# OFFICE OF APPLIED STUDIES 

# Substance Abuse in States and Metropolitan Areas: <br> Model Based Estimates from the 1991-1993 <br> National Household Surveys on Drug Abuse: <br> Methodology Report 

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## 1. Introduction

In 1996, the Substance Abuse and Mental Health Services Administration (SAMHSA) published a report on substance abuse for 26 States and 25 metropolitan statistical areas (MSAs). ${ }^{1}$ That report did not provide much detail on the methodology used to produce those estimates. The report you are now reading has been written to serve two purposes. The first is to give policy analysts a deeper understanding of the properties of the estimates and of the confidence intervals on the estimates. The second is to allow other researchers to replicate the approach and to apply the method to other tasks.

The impetus for developing the local area statistics was based on the increasing demand for such estimates by State and Federal substance abuse planners. While there are existing data systems that provide small area indicators of drug abuse for selected MSAs, like the emergency room drug-related episode reports from the Drug Abuse Warning Network (DAWN) and the voluntary urine test reports among arrestees (DUF), these data systems do not provide estimates of the desired total population statistics on use, dependence, treatment and the need for treatment. Local area surveys designed to provide reliable direct estimates tend to be costly and generally do not provide comparable estimates between areas due to different sampling and data collection methodologies.

The National Household Survey on Drug Abuse (NHSDA) has been the federal government's chief source of information on the magnitude of substance use and abuse in the United States and has been used by policy makers to monitor trends in drug use and to identify problem areas. In addition to assessing prevalence and trends in drug use, SAMHSA uses the NHSDA data to investigate many special topics that are important for understanding the nature of substance abuse, and numerous researchers from around the nation conduct special analyses using the public use files that are produced from the survey. Reports based on the NHSDA are highly valued due to the use in the survey of a rigorous sampling and data collection methodology that has been developed and tested over a number of years.

Despite the value of the NHSDA for national statistics, it is not by itself an adequate source of information about drug abuse at the state and MSA levels. The local area statistics that were published in 1996 rely upon a complex algorithm for combining data from the NHSDA with local data from the Decennial Census and other sources. The algorithm is justified

[^0]through the use of models that relate the available local data to drug abuse as measured in the NHSDA. The use of models was required since national surveys like the NHSDA do not provide large enough samples for direct State level estimation, a limitation that persists even after pooling three years of NHSDA data together. The model-based approach to deriving the small area estimates is similar to approaches that have been used by other government agencies as the demand for local area data has increased and the required statistical and computational tools have improved.

The algorithm that was used to combine NHSDA and local data to produce small area estimates is new. It was developed by a contractor, the Research Triangle Institute. The earlier summary report that provided the estimates also had a simplified description of the algorithm and a report on an evaluation of the algorithm, but that discussion was not detailed enough to allow other researchers to replicate the method. This new report provides a detailed explanation of the methods. Although most of this report is quite technical, the introduction was written for a broad audience of social science researchers and policy analysts.

This report has four main chapters and several appendices. The balance of the introduction provides background on the NHSDA, a description of the variables and areas for which estimates were formed, a review of the need for special methodology different from that used to produce national estimates for the NHSDA and most other federal demographic surveys, a review of other methodologies that have been developed in the past for small areas such as states and MSAs and the need for a new methodology, a discussion of evaluation strategies, and guidance on interpretation of the state and MSA estimates.

Chapter 2 explains the methodology in detail. The material in this chapter is quite technical. Readers will need to be comfortable with calculus, linear algebra, and statistics. However, readers do not need to be national experts on the subject of small area estimation to appreciate this chapter. Specifically, it does not assume past experience on small area estimation.

Chapter 3 discusses the evaluation strategy developed for this project and presents the results. This chapter largely repeats the material in the summary report (SAMHSA, 1996), but there is some new material.

Chapter 4 discusses the lessons learned over the course of this project and ideas that the researchers will pursue in future applications of the methodology.

The appendices provide detail on the classification of drug and alcohol dependence, the definitions of the MSAs involved in the study, more technical information on the software used to create the estimates, more information on geographic predictors of drug and alcohol abuse, tables of actual estimates for the states and MSAs, and tables of confidence intervals on the estimates.

### 1.1 Background on the NHSDA

In this section, the basic design of the NHSDA is reviewed: the sample design, the questionnaire, interviewing procedures, and the data collection schedule.

### 1.1.1 Sample Design

The respondent universe for the NHSDA is the civilian noninstitutionalized population 12 and older within the United States. Since 1991, the NHSDA has included residents of noninstitutional group quarters (e.g., shelters, rooming houses, dormitories), residents of Alaska and Hawaii, and civilians living on military bases. Persons excluded from the universe include those with no fixed household address, e.g., homeless transients not in shelters, and residents of institutional group quarters such as jails and hospitals.

The sample design is a stratified, multistage probability design. The first stage of sampling involves selection of primary sampling units (PSUs) located across the United States. These PSUs are either very large MSAs or individual counties. Then, within each PSU, smaller land areas, or segments, are selected. Once the segments are selected, professional field staff list all of the dwelling units in each selected segment. From the resultant listings, specific dwelling units are selected for screening and/or interviewing. The NHSDA uses an area sampling frame based on block-level geographical units defined by the Decennial Census. Dwelling unit undercoverage bias is largely eliminated by using the half-open interval technique, which asks questions of screened dwelling units to identify unlisted units.

The NHSDA oversamples blacks and Hispanics to ensure an adequate representation of these minority populations in the sample. Young people are also oversampled. From 1991 to 1993, six major metropolitan areas-New York City, Washington DC, Miami, Chicago, Denver and Los Angeles-were oversampled to provide prevalence estimates for those areas. Due to the association between smoking and illicit drug use, oversampling of current smokers aged 18 to 34 was initiated for the 1993 NHSDA.

Exhibit 1.1 summarizes the sample design/size and response rate data for the NHSDA between 1991 and 1993, the years upon which the small area estimates were based.

## Exhibit 1.1 NHSDA Sample Size and Response Rate by Year

|  | 1991 | 1992 | 1993 |
| :--- | ---: | ---: | ---: |
| \# PSUs | 125 | 118 | 117 |
| \# Segments | 3,509 | 3,218 | 3,124 |
| \# DUs screened | 105,311 | 69,996 | 100,340 |
| Screener response rate | $95.0 \%$ | $93.6 \%$ | $94.0 \%$ |
| \# Interviews | 32,594 | 28,832 | 26,489 |
| Interview response rate | $84.3 \%$ | $82.5 \%$ | $79.5 \%$ |
| among screened eligibles |  |  |  |

### 1.1.2 Interviewing Procedures

Prior to the interviewer's arrival at the sample dwelling unit (SDU) a letter was mailed to the resident briefly explaining the survey and requesting their cooperation. Upon arrival at the SDU a few days later, the interviewer referred the respondent to this letter and answered any questions. If the respondent had no knowledge of the lead letter, the interviewer provided another copy, explained that one was previously sent, and then answered any questions. If no one was at home during the initial call at the SDU, the interviewer left a "Sorry I Missed You" card alerting the SDU that the interviewer planned to make another callback at a later date/time. Interviewers made at least four callbacks (in addition to the initial call) to each SDU to complete the screening process and possibly obtain an interview. As necessary and appropriate, the interviewer could make use of the Appointment Card for scheduled return visits with the respondent. When an in-person contact was made with an adult member of the SDU and introductory procedures were completed, the interviewer presented a "Statement of Confidentiality" and answered questions if required. Assuming respondent cooperation, a screening of the SDU was then initiated through administration of the Housing Unit Screening Form for housing units, or the Group Quarters Unit Screening Form for group quarters units.

If a potential respondent refused to be screened, the interviewer was trained to accept the refusal in a positive manner, thereby avoiding the possibility of creating an adversarial relationship and precluding future opportunities for conversion. A conversion was usually attempted by supervisory field staff or specially selected veteran interviewers with established conversion records. If the respondent proceeded with the screening process, the interviewer answered any questions that the screening respondent may have had concerning the study. A number of informational handouts also may have been given to the respondent at this time.

Interviewers screened each sample dwelling unit within a sample segment. The interviewer listed all dwelling unit members on the screening form in order of age, beginning with the oldest. The dwelling unit type was determined based upon the race/ethnicity of the head of household, and the age groups represented in the household. Once the dwelling unit type was determined, the interviewer referred to a selection table that indicates which (if any) age groups were to be interviewed. None, one or two persons may have been selected for interview. The decision was made to limit the number of interviewed persons per household in order to avoid household fatigue, thereby keeping household response rates high.

Assuming the within dwelling unit sampling process selected a member for participation in the study, and if the selected individual was 18 or older and currently available to do the specified study questionnaire, the interviewer moved immediately to begin administering the questionnaire in a private setting within the dwelling unit. If the selected individual was 12 to 17 years of age, parental consent was obtained from the selected individual's parent or legal guardian; then, the minor was asked to participate. Once consent was obtained, the interviewer began the interview process.

The questionnaire and interview methods were designed to retain respondent interest, ensure confidentiality, and maximize the validity of response. The questionnaire was administered in such a way that interviewers would not know respondents' answers to the questions on substance use. Except for tobacco, questions for all substances were self-administered, as respondents recorded their answers on answer sheets. If a respondent was unable to read the questions or preferred not to read them, the interviewer read them out loud. However, only under circumstances of the respondent's physical inability could the interviewer record the answers on the answer sheets. Separate English and Spanish version of the questionnaire were available for each round of the NHSDA.

As the respondent recorded his/her answer choices and completed each answer sheet, they were placed in an envelope. At the end of the interview process, all materials (screening form,
study questionnaire, and answer sheets) were enclosed in this envelope, sealed, and mailed to the data processing site.

For verification purposes, respondents were asked to complete a Verification Form that requested their address and telephone number for possible follow-up to ensure that the interviewer did his/her job appropriately. Respondents were apprised that completion of the Verification Form was voluntary, and they were given the opportunity to decline to complete the verification form. These forms were then placed in a separate envelope and mailed to the data processing site. Respondents were invited to travel with the interviewer to the nearest mailbox to verify that the envelopes were immediately mailed.

A random sample of those who completed verification forms received a telephone call expressing appreciation for their participation in the study. Each respondent also was asked to answer a few questions verifying that the interview took place, whether the answer sheets were used properly, and the amount of time required to administer the interviews. Mail-out of verification letters was used when telephone numbers were unavailable.

### 1.1.3 Data Collection Schedule

Data collection for the 1991 NHSDA took place over a 6 month period from January to June of that year. In 1992, the NHSDA began to operate on a quarterly data collection schedule. That is, data collection extends over the entire calendar year, and is divided into four quarterly components based on the four calendar quarters. This quarterly data collection schedule allows for the realization of several associated benefits and efficiencies, such as increased flexibility in the analysis of trends and in the ability to produce data suitable for public release. Furthermore, such a schedule reduces the burden on the field staff by spreading the data collection over a longer period of time, thus allowing procedures from year to year to be implemented on more of an on-going rather than "start-stop" basis.

### 1.2 Selection of Variables and Areas for Estimation

It was not feasible to develop estimates of all substance abuse rates. It was necessary to pick a few behaviors. Also, there was a reluctance to prepare estimates for areas with very little NHSDA sample in them. In this section, the selected variables and areas are documented, and the choices are explained.

### 1.2.1 Selection of Behavior Measures

The NHSDA collects information on many aspects of substance usage, dependence, and treatment along with background demographic variables that can help provide context. Due to the cost of fitting the area estimation models, it was not feasible to produce estimates for all behaviors of interest. Accordingly, SAMHSA chose 11 critical behavior measures for which state and MSA estimates would be produced.

Alcohol and cigarette use were chosen because of their importance for public health and because independent estimates of the use of these substances are available at the state level for comparison. Three measures of usage of illicit substances were chosen, one broad measure that covers all illicit substances, a narrower measure that excludes marijuana, and a measure that focuses exclusively on cocaine.

Two measures of dependence were chosen: a measure of dependence on illicit drugs with or without dependence on alcohol and a measure of dependence only on alcohol without any dependence on illicit drugs. Persons classified as dependent are among the most severely affected substance abusers who are likely to require some kind of treatment or intervention. The dependence measure developed for the NHSDA is based on an algorithm that approximates the DSM-III-R criteria (Appendix A).

Three measures related to treatment were chosen. Two are based on questions in the NHSDA questionnaire that ask about the receipt of treatment. One covers treatment for illicit drugs (with or without treatment for alcohol abuse), and the other covers treatment for alcohol abuse (without treatment for illicit drugs). A measure of need for treatment for illicit drugs was also chosen that is based on an algorithm developed by SAMHSA's Office of Applied Studies. By subtracting the count of those actually reporting receipt of treatment from those classified as needing treatment, it is possible to measure unmet need. Note, however, that unmet treatment need was not explicitly estimated.

Finally, arrest during the past year for any reason was also chosen. This behavior measure was chosen because of its importance and its correlation with substance abuse. Note that data on arrests are also available from the FBI Uniform Crime Reports, but that the UCR
data are not directly comparable with NHSDA data since the UCR counts all arrests while the NHSDA counts persons with one or more arrests.

The 11 chosen behaviors are:

## Use of legal (licit) substances:

1. Cigarette Use In Past Month - Smoked cigarettes at least once within the past month.
2. Alcohol Use In Past Month - Had at least one drink of an alcoholic beverage, that is, beer, wine or liquor or a mixed alcohol drink within the past month.

## Use of illicit substances:

3. Any Illicit Drug Use In Past Month - Use within the past month of hallucinogens, heroin, marijuana, cocaine, inhalants, or the nonmedical use of sedatives, tranquilizers, stimulants or analgesics.
4. Any Illicit Drug Use Other Than Marijuana In Past Month Past month use of any illicit drug excluding those whose only illicit drug use was marijuana.
5. Cocaine Use In Past Month - Use within the past month of cocaine in any form, including crack.

## Drug or alcohol dependence: ${ }^{2}$

6. Dependent On Illicit Drugs In Past Year - Dependent on marijuana, inhalants, cocaine, hallucinogens, heroin, opiates or nonmedical use of sedatives, tranquilizers, analgesics, or stimulants. Those who are dependent on both alcohol and another illicit substance are included, but those who are dependent on alcohol only are not.
7. Dependent On Alcohol But Not On Illicit Drugs In Past Year Dependent on alcohol but not dependent on any illicit drugs.

Treatment for drug and alcohol problems:
8. Received Treatment For Illicit Drugs In Past Year - Received treatment in the past 12 months at any location (including hospitals, clinics, self-help groups, doctors) for any illicit drug. These estimates include those who received treatment in the past 12 months for both dinking and illicit dugs.

[^1]9. Received Treatment For Alcohol Use, But Not Illicit Drugs, In Past Year - Received treatment in the past 12 months for drinking (including hospitals, clinics, self-help groups, doctors). These estimates exclude those who received treatment in the past 12 months for both drinking and illicit drugs.
10. Needed Treatment For Illicit Drug Use In Past Year (whether or not treatment received) - Persons who either: were dependent on illicit drugs in the past year; were a past year heroin user; received treatment in the past 12 months for any illicit drugs; were a needle user of heroin, stimulants or cocaine in the past 12 months; were a daily marijuana user during the past 12 months; or in the past 12 months were weekly users of hallucinogens, cocaine, inhalants or had weekly nonmedical use of stimulants, sedatives, tranquilizers or analgesics.

## Past year arrest: ${ }^{3}$

11. Arrested For Any Crime In Past Year - Arrested and booked at least once for breaking a law in the past 12 months.

### 1.2.2 States and MSAs for Which Estimates Were Produced

Estimates were only produced for those States and MSAs which had some minimum NHSDA sample in them. Although estimates could have been produced even for States with no NHSDA data, it was thought that these estimates would not have been reliable enough to meet program needs. The States and MSAs selected for small area estimation are presented in Exhibit 1.2. This exhibit shows the number of people who responded to the combined 1991-1993 NHSDA surveys plus information on the NHSDA sample including numbers of the sample MSA/County units, sample block groups, and the estimated 1992 population.

The States and MSAs presented in Exhibit 1.2 were chosen for small area estimation because:

The NHSDA sample size was close to 400 persons or more, a number selected so that at least some instances of even the rarest behaviors of interest such as cocaine abuse would be observed at least once in the state sample,

[^2]The number of distinct sample PSUs was greater than or equal to 4 units, and

The number of distinct sample segments was greater than 40 segments.

Exhibit 1．2 State and MSA Small Areas Selected for Inclusion in the Study Population Size and NHSDA Sample Characteristics

| STATE | $\begin{aligned} & \text { SAMPLE } \\ & \text { MSA/ } \\ & \text { COUNTIES }{ }^{1} \end{aligned}$ | SAMPLE BLOCK GROUPS ${ }^{2}$ | SAMPLE RESPONDING PERSONS ${ }^{3}$ | $\begin{aligned} & 1992 \\ & \text { POPULATION } \\ & \text { PROJECTION } \end{aligned}$ |
| :---: | :---: | :---: | :---: | :---: |
| TOTAL UNITED STATES | 213 | 8，942 | 84，974 | 205，945 |
| NORTH EAST REGION | 34 | 1，489 | 13，681 | 42，236 |
| ivew Jersey | 0 | $10 /$ | 1，5＜3 | 0，443 |
| ivew York | 1 | 845 $10 y$ | 8，5us | 14，8Y4 |
| SOUTH REGION | 85 | 3，271 | 32，346 | 71，396 |
| Fioriaa | 15 | Y04 | 10，บסט | 11，205 |
| Georgia | 5 | 118 | 1，401 | 5，442 |
| кentucky | 0 | 112 | 1，U81 | ¢，US |
| Loussiana | － | 135 | 1，0Yy | 3，08／ |
| Ukıanoma | 4 | 0.3 | 1，4y4 | く，303 |
| soutn carouna | 4 | 48 | 3su | ＜，Ysy |
| 1 ennessee | 4 | Y | ／${ }^{\text {U }}$ | 4，111 |
| ıexas | 13 | sus | 〕，ưく | 15， |
| Virginia ${ }_{\text {vest }}$ | ${ }^{\text {y }}$ | 304 | 3，338 |  |
| NORTH CENTRAL REGION | 49 | 1723 | 15，456 | 48，968 |
| Illinois | 0 | ／yy | 1，¢லชð | 4，3／0 |
| ınaıana |  | 114 | y／8 | 4，581 |
| Kansas | 4 | OU | 515 | ＜，U1U |
| ivircnigan | 3 | 110 | 1，181 | 1，015 |
| lvinnesola | 3 | $1 / 0$ | 1，084 | 3，2／0 |
| Unio | 12 | 404 | ＜， $\mathbf{4}<1$ | 8， 940 |
| wisconsin | 3 | 5 | 4／5 | 4， $\mathrm{U}<1$ |
| WEST REGION | 45 | 2，459 | 23，491 | 43，346 |
| Calliorilid | $\angle$ | 1，3＜4 | 12，504 | 24，344 |
| － | 4 | 14 59 | $0 / 6$ 412 | 1，14y |
| Washington | 3 | 13 | OYU | 4，Uy4 |

${ }^{1}$ MSA／Counties refers to geographic entities formed to estimate random effect terms in the logistic model and which are generally analogous to NHSDA primary sampling units（PSUs）．The exceptions are the distinct MSA constituents of PSUs that crossed State boundaries or combined more than one MSA
${ }^{2}$ Block groups refers to the sample segments that were selected at the second stage of selection in the 1991－1993 NHSDA．
${ }^{3} 87,915$ people responded to the 1991－1993 NHSDA，however 2，941 people were omitted from the small area estimation research because of missing local area indicator variables that were used as potential predictors in the models．
${ }^{4}$ Population projections presented in 1000 s．

Exhibit 1．2 State and MSA Small Areas Selected for Inclusion in the Study Population Size and NHSDA Sample Characteristics（continued）

| MSA | SAMPLE <br> BLOCK <br> GROUPS $^{2}$ | SAMPLE <br> RESPONDING $^{\text {PERSONS }}$ | 1992 <br> POPULATION |
| :---: | :---: | :---: | :---: |
|  |  |  |  |


| Atlanta, GA | $*$ | $*$ | 2,425 |
| :--- | :---: | :---: | :---: |
| Baltimore, MD | $*$ | $*$ | 1,996 |
| Boston, MA | 735 | 7,537 | 3,145 |
| Chicago, IL | $*$ | $*$ | 4,981 |
| Dallas, TX | 719 | 7,585 | 2,120 |
| Denver, CO | $*$ | $*$ | 1,346 |
| Detroit, MI | $*$ | $*$ | 3,593 |
| El Paso, TX | $*$ | $*$ | 456 |
| Houston, TX | 768 | 7,533 | 2,661 |
| Los Angeles, CA | 725 | 8,142 | 7,127 |
| Miami-Hialeah, FL | $*$ | $*$ | 1,600 |
| Minneapolis-St. Paul, MN | 730 | 7,676 | 2,035 |
| Nassau-Suffolk, NY | $*$ | $*$ | 2,178 |
| New York, NY | $*$ | $*$ | 7,086 |
| Newark, NJ | $*$ | $*$ | 1,500 |
| Oakland, CA | $*$ | $*$ | 1,727 |
| Philadelphia, PA-NJ | $*$ | $*$ | 4,037 |
| Phoenix, AZ | $*$ | $*$ | 1,770 |
| San Antonio, TX | $*$ | $*$ | 1,040 |
| San Bernardino, CA | $*$ | $*$ | 2,122 |
| San Diego, CA | 725 | 2,089 |  |
| St. Louis, MO-IL |  | $*$ | 2,006 |
| Tampa-St. Petersburg, FL |  | $*, 822$ |  |
| Washington, DC |  | $*, 345$ |  |

*Number of sample block groups ranged from 40 to 110; number of respondents ranged from 400 to 1200 in these MSAs.
${ }^{2}$ Block groups refers to the sample segments that were selected at the second stage of selection in the 1991-1993 NHSDA.
${ }^{3} 87,915$ people responded to the 1991-1993 NHSDA, however 2,941 people were omitted from the small area estimation research because of missing local area indicator variables which were used as potential predictors in the models.
${ }^{4}$ Population projections presented in 1000 s.
See Appendix B for a list of counties included in each MSA.

Four exceptions to the four or more PSU unit rule were allowed for States that met the sample person and area segment minimums.

### 1.3 Limits of Design-Based Estimates

Design-based estimators are the standard approach used in most national surveys to describe the population. Under the designed-based approach, one treats the substance use status of each person in the population at a particular time as an intrinsic characteristic of the person. A fixed measurement protocol, consisting of a sampling design, a sample size, a questionnaire, a set of procedures for interviewers, a weighting procedure, and an estimator is selected to describe the fixed national population. The goal is to find estimators for various parameters of the national population such as the total number of people using a particular substance, the prevalence of substance abuse in the population, and so on. Estimates of these parameters are calculated based on the sampling design used for the survey, and their expected values and variances are derived by averaging across all possible samples that could be generated using the particular sampling design. (Särndal, Swensson, and Wretman, 1992). The variance across all possible samples can be estimated based upon the data and used to form "randomization-based" or "design-consistent" confidence intervals. With these confidence intervals, statements are possible along the lines of, "If the survey were independently repeated under the same general conditions and a large number of times and a point estimate and a confidence interval were constructed for each replicate, then approximately 95 percent of the confidence intervals formed would include the average of the point estimates." This approach is commonly known as design-based estimation and statisticians who use it can be called randomization-based frequentists or design-based statisticians. This is the procedure used in almost all demographic surveys in the U. S. to produce national estimates.

A key feature of the sampling designs that are used in national surveys is that each member of the population has a nonzero probability of being in the survey. Thus, a national probability sample is also a probability sample of any subgroup within the nation, and one can, in principle, make estimates for any small area within the nation. However, because of the small sample sizes that are obtained for these areas (including some zero sample sizes), the design-consistent confidence intervals can be extremely wide and the normal approximation required for the confidence intervals to be valid may not hold.

The NHSDA sample design was developed with the aim of producing highly precise estimates for the nation, for the four Census regions, and for various demographic subgroups
defined in terms of age, race/ethnicity, and gender. It was not designed to produce state estimates. Thus, although the NHSDA is a valid probability sample of the population of each state, design-consistent confidence intervals for state estimates are likely to be very wide because the portion of the national sample that will happen to fall in a state is small or even zero, particularly for small states. In addition, there are other features of the design that make it less suitable for state estimates. A multi-stage clustered design was used. There was no attempt to construct state level strata to ensure a minimum representation within each state. Rather, the stratification focused on controlling the representation of the important demographic subgroups and employed extensive oversampling of young people, blacks, and Hispanics. Clusters at the first stage (the primary sampling units, PSUs) were large MSAs, individual counties in medium and small MSAs, individual nonmetropolitan counties, and small groups of nonmetropolitan counties. For the 1991-1993 samples, a total of 2,939 PSUs were formed. The largest 45 were selected with certainty. The remainder were then sorted by several variables such as percent minority. A sampling algorithm was used to select an additional 72-80 sample PSUs in a manner that reduced the variance for variables correlated with the sort variables. The set of sort variables did not include a marker for state.

Because there was no attempt to control the distribution within state boundaries, state estimates are extremely unstable. Furthermore, there was 1) extensive oversampling of important demographic domains, 2) clustering at the block level during the second stage of selection to reduce the cost of data collection, and 3) limits placed on the number of persons per sample household to increase the privacy of the interview resulting in people in large households having smaller probabilities of selection. The second-stage clustering and the differential sampling tend to make the estimates even more unstable. Thus, while these procedures are near optimal for national and regional estimates, they are not at all conducive to state estimation.

For example, there were just 330 people in 4 PSUs in the NHSDA in South Carolina from 1991 through 1993. Suppose that the design-based estimated rate of cocaine abuse during this period was 0.66 percent (the same as the estimate provided by the small area estimation project). Using a logit transformation and assuming that the logit of the estimated rate is normally distributed and that the 330 people had come from a simple random sample, the standard design-based 95 percent confidence interval would range from 0.26 percent to 1.65 percent. (Using the logit transform avoids the embarrassment of a negative lower bound on the confidence interval.) The design-based variance based on the NHSDA was not directly estimated for this project but is probably on the order of 2 to 6 times larger than the design-based variance from a simple random sample. Assuming that the factor is 4 , the 95 percent confidence
interval would run from 0.10 percent to 4.05 percent. Such an estimate and confidence interval would be of little use to South Carolina officials.

In addition to the problems that the instability of the design-consistent estimators pose for state planning purposes, this instability also leads to problems for the comparisons and ranking of states. Let $\pi_{i}^{D}$ be the design-consistent estimate of the drug abuse rate for the i-th state and $\pi_{i}$ be the limit of that estimate as the state sample size approaches the state population. The "D" stands for design consistent. The parameter $\pi_{i}$ is defined as the limit of the design-consistent estimator rather than the "true" rate for the state due to the limitations of the measurement protocol. It can be fairly easily demonstrated that the small state sample sizes and large design effects cause

$$
\mathrm{E}\left[\operatorname{Range}_{i}^{\left.\left\{\pi_{i}^{D}\right\}\right]}{ }_{\mathrm{i}}^{\operatorname{Range}_{\left\{\pi_{i}\right\}},}\right.
$$

and that

$$
\mathrm{E}\left[\sum_{i}\left(\pi_{i}^{D}-\pi\right)^{2}\right] » \sum_{i}\left(\pi_{i}-\pi\right)^{2}
$$

meaning that the range among the states and the variance among the states is exaggerated by the design-consistent estimates. This exaggeration of differences could have important consequences on public perceptions and official policy unless corrected. Thus, one of the properties that a sound alternative approach should possess is a capability to shrink the state estimates together toward the national average.

### 1.4 Review of Alternative Approaches to Small Area Estimation

The best current review of alternative approaches to small area estimation can be found in Ghosh and Rao (1994). In order to place the SAMSHA small area estimation project in context with other work on small area estimation, it is recommended that the reader consult this article. A book of case studies edited by Schaible (1996) is also interesting and useful for providing a background on approaches to small area estimation. The article by Ghosh and Rao is terse, requiring a fairly high level of statistical expertise on the part of the reader. For this report, the goal is to extract the kernels of the ideas presented by Ghosh and Rao and to present these ideas at a level accessible to the majority of social policy researchers. It is hoped that this material will leave such readers with an intuitive impression of the shortcomings of the other methods and the benefits of the new method presented here. The discussion in this chapter is at a fundamental level. Chapter 2 and Appendices C and G contain heavier mathematics.

The alternative approaches do not treat the substance abuse status of a person at a particular point in time as an intrinsic characteristic of the person. Instead, these approaches assume that it is a matter of chance for each person but that there are underlying factors that make this chance larger for some people than for others. ${ }^{4}$ Before discussing the details of these alternative approaches, it will be useful to review their theoretical underpinnings. After reviewing these underpinnings, each of the most popular alternative approaches is reviewed including fixed effect models, composite estimators, and mixed effect models. The discussion in Section 1.4 closes with reasons for believing that the new approach is superior to those other alternatives.

### 1.4.1 Theoretical Underpinnings: Conceptions of Reality and Probability

In order to use national data to estimate state and local substance abuse rates, it is necessary to develop a theoretical framework for applying the observed patterns of substance use to groups of persons who were not interviewed. This can be done by considering each person's substance abuse status to be a random variable rather than a fixed characteristic of the person. The actual process leading to an individual's use of a particular substance may, in fact, not have a random component; it could be a complex deterministic function of genetics, family environment, local environment, government activities, and so on. However, since this process is too complex for us to understand, it is very useful to think of the process as being random within groups of people.

Under this approach, the statistician's goal is to identify groups of people within each of which there are no discernible differences in their patterns of substance abuse. It is then assumed that the probability of substance abuse is homogenous within each group. This probability can be thought of in two different ways.

One approach is to assume that there is a fixed but unknown probability for a group. With this approach, one thinks of the collection of persons in a homogenous group as an outcome

[^3]of an underlying random process--as just one possible manifestation of an underlying superpopulation. The statistician defines the fixed but unknown probability of drug abuse for the group as the long-run average that would be obtained if this process were repeated independently a large number of times. The collection of possible manifestations of the underlying process is called the superpopulation. This approach to inference is termed the model-based frequentist approach. Applying this approach, the statistician uses the data to estimate the fixed but unknown probability and also to provide a confidence region about his estimate. The interpretation of such a confidence interval (e.g., a 95 percent interval) is that over all possible manifestations of the superpopulation, 95 percent of all confidence intervals constructed in this manner from samples of the given size from the group will include the fixed but unknown true probability for members of this subgroup. A statement can thus be along the lines of, "Given a sufficiently large number of observed manifestations, 95 percent of confidence intervals constructed in this manner will include the true probability of substance abuse for people in this group."

A second way to think of this probability is to consider it as a random variable as well. This assumes that there is a random process behind the random process theorized by model-based frequentists. In other words, the probability of substance abuse in a certain group at a certain time isn't simply some fixed $p$; instead, there is a random process that determines whether the probability of substance abuse for the group at a certain time is above or below p. This is called the Bayesian approach to inference after an 18th century theologian/mathematician who discovered a theorem that demonstrates how to use observed data to update subjective estimates of probabilities of various events. The Bayesian starts out the inference task with a prior distribution on p . This means that he has a function F (the prior distribution) such that $\operatorname{Pr}\{\mathrm{p} \leq \xi\}=\mathrm{F}(\xi)$ for $0 \leq \xi \leq 1$. This prior is based upon past research, intuition, and personal judgment. He then uses the sample data and Bayes theorem to update his belief about the distribution of p and to derive a posterior distribution on p . This posterior distribution will depend to some extent on the prior distribution, but, if the sample size is very large, then this dependence will be slight. The Bayesian can use the posterior distribution to make point estimates and intervals (called prediction intervals) similar to the confidence intervals of the parametric frequentists. The point estimate is taken to be the mean or modal value of the posterior distribution (the expected and the most likely value of $p$, respectively) and the prediction interval is defined by the percentiles of the posterior distribution. For example, if a 95 percent prediction interval is desired, the lower point will be the 2.5 th percentile of the posterior distribution and the upper point will be the 97.5 th percentile of the same. Prediction intervals are interpreted along the lines of, "After considering the observed data, I now believe
that there is a 95 percent probability that the probability of people in this group abusing the substance in question is in the stated range."

### 1.4.2 Using the Sampling Weights

Having now briefly presented the model-based frequentist and Bayesian perspectives, it is useful to contrast the treatment of sampling weights in these approaches with the treatment of sampling weights in the randomization-based approach. ${ }^{5}$ This is critically important for an understanding of the small area estimation approach adopted for this study since both sampling weights and elements of the model-based frequentist's and Bayesian approaches have been used in developing the method described herein.

Neither the model-based frequentist nor the Bayesian uses sampling weights. They discard information on probabilities of selection and on joint probabilities of selection. They are, in fact, often just as happy to work with a purposely drawn sample as with a random sample. The design-based statisticians, of course, insist on a random sample with known marginal probabilities of selection and prefer having information on the joint probabilities of selection as well.

These differences in the use of sampling weights arise from the different conceptions discussed above. The design-based statistician is interested in estimating the drug abuse rate amongst a certain real population at a particular point in time. The model-based frequentist and the Bayesian on the other hand are not as interested in the real population at a point in time. They are more interested in the process that gave rise to that population. The latter two therefore construct models of the process and are interested in obtaining the most efficient estimates of the parameters of those models. Research has shown that using the sampling weights when estimating the parameters of a correct model only increases the variance. However, research has also shown that if the model is wrong, then using the weights could have reduced or eliminated the bias in the estimates due to model error (Holt, Smith and Winter, 1980). Since the design-based statistician believes that every model is wrong, he would rather have the less efficient but more robust estimates that are obtained by using the sampling weights. The other two groups reply that if the model is wrong, then there is no point in estimating the parameters at all; that all one can do is to use the best models available and then estimate the parameters of those models with as little variance as possible.
${ }^{5}$ For more information on the contrasts between the different schools of statisticians on this issue, see Smith (1994).

The practical importance of these differences in inferential approaches can be illustrated with a simple example. Suppose that there is a group that the modeler (whether frequentist or Bayesian) believes is homogenous, but that there is, in fact, a small difference between two subgroups that is undetected due to small sample sizes and that the sampling weights are different for the two subgroups. Let subgroup $A$ have a process mean rate of substance abuse of 0.3 , a sample size of 5 from a population of 10,000 (resulting in a sampling weight for all 5 sample persons of 2000). Let subgroup $B$ have a process mean rate of substance abuse of 0.35 , a sample size of 25 from a population of 12,500 (resulting in a sampling weight for all 25 persons of 500). The model-based frequentist will tend to estimate a substance abuse rate for the entire group of 0.3417 with an expected standard error of 0.0867 while the designed-based statistician will tend to estimate a substance abuse rate of 0.3278 with an expected standard error of 0.1054 . Note that the expected estimate of 0.3278 is correct for the combined group but that it does not accurately describe the process for either subgroup and that it has substantially higher variance than that obtained by the model-based frequentist. With this small sample size, the estimate and standard error obtained by the Bayesian would depend fairly strongly on the prior distribution assumed.

For national estimates, it is more important to estimate the substance abuse rate for the population unbiasedly rather than to get more efficient estimates by assuming models either with or without prior distributions on the model parameters. The NHSDA sample was designed to do just that. However, as discussed above in Section 1.3, this approach is not feasible at the state or MSA level using current NHSDA data; so an alternative was needed.

In developing small area estimates of substance abuse rates, the various approaches were blended. Models have to be assumed to construct estimators for substance abuse at the state and local level, but it is convenient that the state estimates sum to national estimates that are close to the national estimates obtained using design-based techniques without the models. Furthermore, it was desired that state and MSA estimators, although model-based, would converge to design-consistent estimators where state/MSA sample sizes were sufficiently large.

### 1.4.3 Fixed Effect Models for Small Area Estimation

Fixed effect models include synthetic and regression estimators (domain-indirect estimators in the language of Schaible, 1996). Versions exist for design-based inference,
model-based frequentist inference and Bayesian inference, but the development is perhaps simplest within the model-based frequentist approach.

The model-based frequentist basically assumes that one can model the substance abuse rate in a small area as a function of other information that exists for the small area. For example, suppose that a number of domains have been identified such as demographic subsets of the population for which current estimates are maintained for small geographic areas. The Census Bureau has divided the U.S. land area into a set of nonoverlapping very small areas called block groups and has published considerable information about every block group. Furthermore, information is available at the county level on fairly current arrest rates for illegal drug possession and for illegal drug sales or manufacture, deaths related to alcohol abuse, and alcohol and substance treatment rates. All of this information can be useful in developing models that predict local substance abuse rates.

Let $\pi_{i b}^{d}$ be the true substance abuse rate for persons in domain $d$ who live in block group $b$ of state $i .{ }^{6}$ Let $N_{i b}^{d}$ be the number of people in domain $d$ who live in block group $b$ of state $i$. Let $X_{i b}^{d}$ be a row vector of characteristics for people in domain $d$ who live in block group $b$ of state $i$. Examples of entries could be binary indicator flags for membership in domain $d$ and lack of membership in other domains and median income for the domain within the block group, the percent below poverty, the percent with a high school degree, and so on. A common model would be something like

$$
\begin{equation*}
\operatorname{logit}\left(\pi_{i b}^{d}\right)=\ln \left(\frac{\pi_{i b}^{d}}{1-\pi_{i b}^{d}}\right)=X_{i b}^{d} \beta \tag{1}
\end{equation*}
$$

where $\beta$ is a vector of unknown parameters. Maximum likelihood methods would be used to obtain an estimate $\beta$ for $\beta$ without paying any attention to the sample design. The substance abuse rate for the state would then be estimated as

[^4]\[

$$
\begin{equation*}
\pi_{i}^{F}=\frac{\sum_{d b} \sum_{i b}^{d} \pi_{i b}^{d}}{\sum_{d} \sum_{b} N_{i b}^{d}}=\frac{\sum_{d} \sum_{b} N_{i b}^{d} \frac{1}{1+e^{-X_{i b}^{d} \beta}}}{\sum_{d} \sum_{b} N_{i b}^{d}} \tag{2}
\end{equation*}
$$

\]

where the " $F$ " stands for fixed-effect model.

As an example of how to set up such a model, suppose that there were three domains, two states, two block groups in each state, and no prediction variables other than domain flags. Then the $X$ matrix would be as shown on the left below.

$\mathrm{X}=|$|  |  | Applies to People in |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  |  | Domain | State | Block <br> Group |
| 1 | 0 | 1 | 1 | 1 |
| 1 | 0 | 1 | 1 | 2 |
| 1 | 0 | 1 | 2 | 1 |
| 0 | 1 | 1 | 2 | 2 |
| 0 | 1 | 2 | 1 | 1 |
| 0 | 1 | 2 | 1 | 2 |
| 0 | 1 | 2 | 2 | 1 |
| 0 | 0 | 2 | 2 | 2 |
| 0 | 0 | 3 | 1 | 1 |
| 0 | 0 | 3 | 1 | 2 |
| 0 | 0 | 3 | 2 | 1 |
|  |  | 2 | 2 |  |

Also, $\beta$ would consist of just two parameters, $\beta_{1}$ and $\beta_{2}$. Comparing a person in domain 1 with a person in domain 3 , the difference between the two domains in the logit of the propensity to engage in the behavior of interest is $\beta_{1}$. This translates into odds ratio of $e_{1}^{\beta}$. For example, if $\beta_{1}=1$, then the odds ratio is 2.7 , meaning that someone in the first domain has odds of engaging in the behavior 2.7 time higher than for someone in the third domain. For more background on logistic regression, see Chapter 6 of Breslow and Day (1980), Chapter 4 of McCullagh and Nelder (1989) or all of Cox and Snell (1989).

In presenting such an estimate to an analyst, one could say that the national rate of substance abuse was estimated for combinations of a number of demographic domains in certain types of block groups ("neighborhoods"). One could also say that data from the Decennial Census were used to estimate how many inhabitants the state has in each combination of demographic group and block group. The national rates were applied to these state-specific population counts to estimate expected substance abuse rates for the state. Since there are many
variables that influence the likelihood that a person will abuse substances other than those measured in the decennial census, the estimates would generally be different from those that would be obtained if a large state-specific sample were interviewed using the national procedures. The analyst could then use this estimate for planning purposes, along the lines of, "If there are this many people in need of assistance, then we need to do ... to meet those needs." However, one should be cautious about using the estimates to correlate state action plans with estimated differences across the states. The estimates will not reflect differences across the states due to differences in laws, enforcement activities, advertising campaigns, outreach activities and so on, and will tend, rather, to be quite close to each other since the mix of demographic groups and block groups does not vary dramatically across the states. In essence, the fixed modeling approach shrinks the state estimates too close together. Also, if the estimates were repeated every few years, it would be entirely incorrect to try to correlate changes in the state estimates with any changes in policies or other state activities. The only changes would be due to changes at the national level.

An additional difficulty of using fixed effect models is that the estimated variances on these estimates would be highly misleading. The estimated variances would reflect sampling variability on the national rates only. Since the national rates are estimated with small variance, these estimates would appear to be quite accurate, even though they are not -- at least not in the broader sense of being close to what a large sample for the state would have found. Approaches have been suggested for replacing the variance with a mean squared error across all the states, but such approaches are not very satisfactory, as is discussed further in Section 1.5, Chapter 3, and Appendix H.

Thus, it is apparent that there are several important shortcomings with this approach. Most seriously, analysts who used them to assess the impact of state interventions would end up with seriously flawed analyses. Nonetheless, if there were no state specific data in the NHSDA, this would be the best that could be done. For example, there are no NHSDA sample data for Hawaii for the period of 1991 through 1993. This approach is therefore the best that could be done for Hawaii. However, there are state-specific data for all the states for which substance abuse rates were estimated in this study.

The fact that state-specific data do exist for each of the states and MSAs that were used in this analysis allows consideration of a model along the lines of

$$
\begin{equation*}
\operatorname{logit}\left(\pi_{i b}^{d}\right)=\ln \left(\frac{\pi_{i b}^{d}}{1-\pi_{i b}^{d}}\right)=X_{i b}^{d} \beta+\eta_{i}, \tag{3}
\end{equation*}
$$

where $\eta_{i}$ is a fixed effect for the $i$-th state. However, whereas model (1) will tend to make the states look too much like each other, model (3) will tend to overstate the differences among the states, much as the design-based estimates do. Such a model would produce estimates of $\pi_{i}$ that would be only marginally more precise than the design-consistent estimates. Like the design-consistent estimates, the range and variance of substance abuse rates would be exaggerated. What is needed is a method that shrinks the estimates closer together than the design-consistent estimators but not as close together as the fixed-effect model given in equation (1).

### 1.4.4 Composite Estimators

When at least some survey information is available for a small area, it is possible to use composite estimators that combine information from the survey and from models. The randomization-based approach can be used to create a design-consistent estimator, $\pi_{i}^{D}$, for the substance abuse rate in each state. As discussed previously, this estimator will be subject to intolerably high variance for most states due to small state sample sizes and the lack of state stratification in the first stage of sample selection. However, this estimator is unbiased (or at least design consistent) for actual substance abuse rates in the state at the point in time of interest. If, as is probable, the model alone does not adequately describe the propensity to abuse substances, then $\pi_{i}^{D}$ contains information about whether the state was higher or lower than projected from a model based only on demographic distributions across block groups. A common approach is to average $\pi_{i}^{D}$ with $\pi_{i}^{F}$. Let $\Gamma_{i}$ be the averaging factor for the i-th state.
Then the composite estimator of $\pi_{i}$ is

$$
\begin{equation*}
\pi_{i}^{C}=\Gamma_{i} \pi_{i}^{F}+\left(1-\Gamma_{i}\right) \pi_{i}^{D} \tag{4}
\end{equation*}
$$

The variance of $\pi_{i}^{C}$ is larger than the variance of $\pi_{i}^{F}$, but $\pi_{i}^{C}$ is closer to what would have been obtained with a large sample in the state.

This approach has considerable merit, but the problem is how to decide on values for the $\Gamma_{i}$. Additionally, it becomes more complicated to define what is meant by variance since the randomization-based approach has been mixed with the model-based frequentist approach. Various approaches have been suggested for choosing the $\Gamma_{i}$, but none are very satisfying. It is desired to pick $\Gamma_{i}$ close to 1 when the model applies well for the state and/or the sample size is small for a state and to pick $\Gamma_{i}$ close to 0 when the model doesn't fit well for the state and/or the sample size is large for the state. It is easy enough to decide when the state has a large or small sample size, but deciding when the model fits well in a particular state is impossible unless the state sample size is very large, in which case, it is known that $\Gamma_{i}$ should be selected close to zero without even examining its fit for the state. Ad hoc rules can be developed, but better approaches to the entire problem have recently been developed.

### 1.4.5 Mixed Effect Models for Small Area Estimation

With a mixed effect model, one endeavors to produce estimates for each small area that reflect not only the level of substance abuse expected for an area given the national process means for different domains and types of block groups but to also reflect the impact of unmeasured variables, such as family environments, on the local substance abuse rates. The goal is thus quite similar to the goal for composite estimation -- smaller variance than the design-based estimates but expected values closer to what a large sample in each state would yield. The difference between using a mixed effect model and composite estimation is that fitting a mixed effect model is a somewhat more objective process than picking the $\Gamma_{i}$ in composite estimation.

A one-stage mixed effect model looks like:

$$
\begin{equation*}
\operatorname{logit}\left(\pi_{i b}^{d}\right)=\ln \left(\frac{\pi_{i b}^{d}}{1-\pi_{i b}^{d}}\right)=X_{i b}^{d} \beta+U_{i}, \tag{5}
\end{equation*}
$$

where $U_{i}$ is a random variable with zero expected value and positive variance that is the same for all states and it is assumed that the variables are independent across states; i.e., $\mathrm{E}\left(U_{i}\right)=0$, $\operatorname{Var}\left(U_{i}\right)=\sigma_{u}^{2}$, and $U_{i} U_{i^{\prime}}$, are independent for every $i \neq i^{\prime} .$.

Note the difference between models (3) and (5). In model (3), each state has a fixed deviation on the logit scale from the baseline propensity expected based just on demographic
group and prediction variables. In model (5), each state has normal random variation on the logit scale from the baseline propensity. Over all possible manifestations of the state process, it is expected that each $U_{i}$ will have an average value of zero. Nonetheless, after the period in question, it is possible to talk about the realized value of the random variation. In a particular past year, the deviation for each state must have been positive or negative. Model (5) can be used to get estimates, $U_{i}$, of the value of $U_{i}$ for a particular manifestation of the state process. For example, if a state had a social climate that effectively suppressed substance abuse, one would expect to see a value of $U_{i}<0$. Conversely, a climate that was conducive to substance abuse would lead to a value of $U_{i}>0$.

Unless state sample sizes are large, the $U_{i}$ from model (5) will be closer to zero than the $\eta_{i}$ from model (3). If all the state sample sizes are large, then the models yield similar estimates. This regression to the mean with small state sample sizes is desirable since each of the state processes is being measured with error, thereby exaggerating the differences among the states, and so there is a need to "shrink" the state estimates somewhat toward the national average. This is demonstrated in Section 3.2.2. For a more thorough review of the benefits of making the state effect a random effect rather than a fixed effect, see Robinson (1991).

With this approach, the overall estimated rate of substance abuse for the state is

$$
\begin{equation*}
\pi_{i}^{M}=\frac{\sum_{d} \sum_{b} N_{i b}^{d} \pi_{i b}^{d}}{\sum_{d} \sum_{b} N_{i b}^{d}}=\frac{\sum_{d} \sum_{b} N_{i b}^{d} \frac{1}{1+e^{-\left(X_{i b}^{d} \beta\right.}{ }^{\left.55 \wedge+U_{i}\right)}}}{\sum_{d b} \sum_{b}^{d}} \tag{6}
\end{equation*}
$$

where the "M" stands for mixed effect. From the standpoint of being able to compare the states to determine what sorts of social climates are more resistant to substance abuse than others, it is desired that $\pi_{i}^{M}$ is close to $\lim _{n_{i} \rightarrow N_{i}}\left(\pi_{i}^{D}\right)$, the limit of the randomization-based estimate for the state as the state sample size, $n_{i}$, approaches the total state population, $N_{i}$. Note that this is not the same as desiring that $\pi_{i}^{M}$ is close to $\pi_{i}^{D}$ given the actual state sample size from a national sample. Since $\pi_{i}^{D}$ is very unstable with the small state sample sizes that are available from a national sample, the $\pi_{i}^{M}$ should vary substantially from the $\pi_{i}^{D}$.

Prior efforts to fit this sort of model did not have the same goal of attempting to approximate the asymptotic values of the design-based estimators. Model-based frequentists have developed techniques to estimate $\boldsymbol{\beta}, \boldsymbol{U}_{i}$, and $\sigma_{u}^{2}$ using maximum likelihood techniques. These techniques require that the $U_{i}$ be normally distributed and run into both memory space and time problems on even the largest computers available. Bayesians place prior distributions on $\boldsymbol{\beta}$ and $\sigma_{u}^{2}$ but are free to use distributions other than the normal distribution for $U_{i}$. Bayesians use new techniques called Monte Carlo Markov Chain (MCMC) methods (of which the most well known example is Gibbs sampling) to obtain posterior distributions for $\boldsymbol{\beta}, U_{i}$, and $\sigma_{u^{-}}^{2}$. These techniques use huge amounts of computer time but are conceptually easy to program. A third approach is called empirical Bayesian, in which approximations are used to obtain posterior distributions for $\boldsymbol{\beta}, U_{i}$, and $\sigma_{u}^{2}$ with less computer time than a full Bayesian approach and without assuming prior distributions. For a review of these methods, see Chapter 9 of Diggle, Liang and Zeger (1994). The Bayesian approach is also discussed in Chapter 8 of Schaible (1996).

All of these techniques assume that the basic structure of the model given in (5) is "true." This means that the propensity to abuse substances can be totally explained by knowing the demographic group that a person belongs to, the type of block group that they live in (as characterized by a few variables from the prior Decennial Census), characteristics of the county, and the state that they live in. Even more strongly, all these techniques assume that the logit transform of this propensity is a linear function of fixed effects for the demographic group and type of block group and of a random effect for the state. The actual propensity to abuse substances may, of course, be considerably more complex reflecting things such as the quality of the local transportation network, the quality of the local police department, the proximity to major drug transportation routes, and a score of other fixed and random characteristics of the milieu in which each person lives. Since these techniques assume that the model is true, they make no use of the sampling weights. If the model is not true, they thus cannot be expected to converge to the substance abuse rates that would be estimated by very large state substance abuse surveys. To deal with this lack of convergence, a survey weighted approach was developed for this study.

### 1.4.6 The Survey-Weighted Empirical Bayesian Approach

This is the name given to the approach developed for this study although it could also be called a "survey weighted Penalized Quasi-likelihood" approach since the estimators can be
motivated from either an empirical Bayesian viewpoint or from a frequentist view point. ${ }^{7}$ The goal of this study was to be able to fit a model like (5) in such a manner that estimates would be close to design-based estimates for states with large NHSDA samples and for national domains with large sample sizes such as men and women. In terms of equations, it was desired that

$$
\begin{align*}
& \lim _{n_{i} \rightarrow N_{i}} \frac{\pi_{i}^{D}}{W}=1 \text {, and }  \tag{7}\\
& \pi_{d-}^{W} \pi_{d}^{D} \tag{8}
\end{align*}
$$

where $\pi_{i}^{W}$ is the survey-weighted empirical Bayesian estimate of the substance abuse rate for the state and $\pi_{d}^{W}$ is the survey-weighted empirical Bayesian estimate of the substance abuse rate for the demographic group across all states. ${ }^{8}$

The method was based upon the empirical Bayesian approach because it was thought to be the least expensive in terms of computer time. Even with this approach, large quantities of computer time were consumed in fitting all the models. Equation (8) is useful in terms of the face validity of the estimates. It is certainly awkward to explain why small area estimates do not aggregate up to national estimates. Equation (7) is somewhat useful in states with large sample sizes such as California, but questions do remain about how close $\pi_{i}^{W}$ and $\pi_{i}^{D}$ are to each other when the state sample size is not large. If the model is not true (as it almost certainly is not), the authors believe that their estimates will be better than those from model-based frequentist,
Bayesian or Empirical Bayesian approaches, but it is not claimed that $\pi_{i}^{W}$ will be extremely close to $\lim _{n_{i} \rightarrow N_{i}}\left(\pi_{i}^{D}\right)$ when the state sample size is small. It is not realistic to think that modeling exercises of this type can provide as much information about complex social phenomena as large local surveys. This question of evaluation is discussed further in Section 1.5. Guidance on interpreting the estimates is given in Section 1.6. It is not entirely straightforward to say what

[^5]is meant by $\operatorname{Var}\left(\pi_{i}^{W}\right)$. More information on the mechanics of the survey-weighted empirical Bayesian approach is given in Chapter 2.

### 1.5 Evaluation Strategies

In any small area estimation project, questions arise as to the quality of the estimates. The purpose of using a model-based approach that combined NHSDA data with local data was to produce estimates of substance usage behaviors for States and MSAs that would have smaller variance than the direct estimates based solely upon the NHSDA. As discussed in Section 1.3, the direct design-consistent estimates provided confidence intervals for most States and MSAs that were too wide to be useful to researchers, policy analysts, and public health officials. It was recognized that in order to achieve the desired variance reduction, it would be necessary to let the validity of the resulting estimates depend on the models that were created to relate local data to NHSDA data. To the extent that the local data have good predictive power for the substance abuse behaviors of interest and that the models accurately reflect those relationships, the resulting model-based estimates for States and MSAs should be better than either the design-consistent estimates or simply assuming that the national rates apply to every State and MSA. Several meanings can be given to the word "better" in this context, but, regardless of the definition, actually demonstrating that the model-based estimates are better is a challenging task.

This issue is also being confronted by other government agencies. It is, in fact, at the heart of the debate about whether the Decennial Census should be adjusted for undercount. One of the chief methods for estimating the undercount is a national survey taken shortly after the census. Although there is some controversy about the adequacy of the undercount estimates at the national level, the most vigorous debate is whether adequate models can be developed to apply the national information about undercount to small areas in a way that makes the small area estimates better than the raw counts. This remains an open question despite years of major efforts by some of the best statisticians in the country.

This study had a fairly intensive evaluation component in it, but the results were more suggestive than conclusive. In Chapter 3, there is a thorough discussion of the various approaches that were used and the limitations of each. Results of the various approaches are also presented and discussed. More conclusive results might be achieved with a large scale simulation or perhaps the application of the methodology to variables that are measured well on the Decennial Population Census.

### 1.6 Guidance on Interpretation of Results

As mentioned earlier, the interpretation of confidence intervals provided for the state and MSA estimates of substance abuse is not entirely straightforward. First, it may be better to call these intervals prediction intervals since they are based more on Bayesian concepts than on frequentist concepts. The intervals are based on a model characterized by a national fixed pattern and a series of three random events that jointly determine whether a person abuses substances or engages in other behavior of interest. The national fixed pattern says that a person of a particular age, race and sex living in particular type of block group is going to have a certain baseline propensity to engage in the behavior of interest. The first random event is at the state level. It is assumed to affect everyone in the state in exactly the same manner by adding a small offset to the logit of the propensity to engage in the behavior of interest. The second random event is at the PSU level. It is assumed to affect everyone in the PSU in exactly the same manner by adding a second small offset to the logit of the propensity to engage in the behavior of interest. The third random event is at the person level. Given that the person has a propensity determined by his or her race, sex, age, type of block group of residence, specific PSU and specific state, it is assumed that his or her actual behavior is random with the probability of engaging in the behavior equal to the person's propensity. There was no attempt to explain a mechanism by which the random decision is reached. Statistically, it was treated as if a random number between 0 and 1 was drawn and if the random number was less than the propensity, then the person engaged in the behavior.

One can imagine averaging up the true propensities for some State, MSA or other group of interest and calling the average $\pi$. That hypothetical average $\pi$ is a random variable subject to variance because of the random events at the state and PSU levels. The model states that $\pi$ is normally distributed.

If all the estimated person-level propensities are averaged up for the same group, then another random variable results that is approximately normally distributed. This average is $\pi$, the estimated propensity for the group. The random variable $\pi$ is subject to variance not just because of the random events at the state and PSU levels but also because of uncertainty in the estimated parameters of the fixed national model. The variable $\pi$ is used as an estimate of $\pi$, but it is known that given $\pi$, the conditional expectation of $\pi$ is not $\pi$. Since the conditional variance of $\pi$ is a measure of how close it is to its own conditional expected value, interest does not focus on that conditional variance. There is even less interest in the unconditional variance of $\pi$ since that measures the deviance of the $\pi$ from its expected value over all possible state
outcomes, PSU outcomes, and person outcomes -- rather interest focuses on measuring the deviance of the $\pi$ from $\pi$ given the state and PSU random events that actually occurred.

According with this interest, the "variance" is defined as the expected value of $(\pi-\pi)^{2}$ with respect to the distribution of the state and PSU level random effects and the distribution of the estimated parameters of the fixed national model. This might be called a mean square error, but that would lead to confusion with the design-based concept of mean square error. It would probably be most accurate to call it a mean squared prediction error, but that becomes cumbersome, and so it is referred to in this report as simply the variance.

The validity of the prediction intervals depends largely but not entirely on the correctness of the model. The model can be wrong in various ways. For example, the variance of the state level random effects could be larger in one region than in another; the variance of the PSU level random effects could be larger for larger metropolitan areas than for small rural counties or vice versa; the random effects might follow a different distribution from the normal; there could be correlations between state and PSU-level random effects; there might be additional random events at the county, tract, block group, block or household levels; there might be additional random effects associated with schools and places of work; it might be possible that the behavior of interest has a strong genetic component; everyone may have their own unique propensity that they share with no one else; or everyone's behavior may be predestined with no chance variability at all.

Under some of the milder alternative models, the computed prediction intervals still have meaning, but their coverage properties may be lower than claimed. The use of weights partially protects against model failure since it is known that for large enough samples of large enough populations, the inference procedures come close to design-based inference. However, for predictions for small groups where only small sample sizes are available, the validity of the prediction intervals depends fairly strongly on the validity of the model.

For more information about the procedures that were used to estimate the variances, see Section 2.6 and Appendix G. These sections have some additional information on some acknowledged problems in the variance estimation. Those problems have probably led the prediction intervals to be somewhat too narrow. The degree of the inappropriate shortening is unknown but thought to be small. The estimated prediction intervals are shown in Appendix I.

## 2. The Survey-Weighted Empirical Bayesian Method

This method requires that a model be developed for predicting the propensity to engage in the behavior of interest. As a result of the modeling, it is possible to estimate the propensity to engage in the behavior of interest for every person in a state, whether or not they are in the sample. In Section 2.1, the structure of the models is described. In Section 2.2, the procedures for selecting predictor variables for the models are described. In Section 2.3, there is a sketch of the procedures used to fit the models once the variables had been selected - more details are given in Appendix C. In Section 2.4, there is a description of how separate models were fit for different segments of the population due to problems that prevented the fitting of a single model for the entire U. S. population. In Section 2.5, there is a description of how the final model was used to develop an estimate of the prevalence of the behavior of interest in targeted states and metropolitan areas. In Section 2.6, there is a discussion of how the variance of the estimator was approximated -- more details are given in Appendix G.

### 2.1 Structure of the Model

The full model used for most of the nation is specified here. In part of the nation, it was necessary to use a simpler model. The simpler model is described in Section 2.4.

Let the states be indexed by the subscript $i$, the sample PSUs within the states by the subscript $j$, and the sample persons within the sample PSUs by the subscript $k$. Then

$$
\mathrm{y}_{\mathrm{ijk}}= \begin{cases}1 & \begin{array}{l}
\text { if the } k \text { th person in the jth PSU of the } i \text { th state reported engaging } \\
\text { in the behavior of interest and }
\end{array} \\
0 & \text { otherwise } .\end{cases}
$$

Let $\pi_{i j k}=\left(y_{i j k}\right)=y_{i j k}=1$. This $\pi_{i j k}$ is the propensity for the indicated person to engage in the behavior of interest. A value of $\pi_{i j k}$ close to 0 indicates that the person is very unlikely to engage in the behavior of interest, while a value of $\pi_{i j k}$ close to 1 indicates that the person is nearly certain to engage in that behavior.

Let $U_{\mathrm{i}}$ be a normal random variable associated with the ith state and $U_{\mathrm{ij}}$ be another normal random variable associated with the $j$-th PSU of the ith state. These variables cannot be directly observed. They represent the impact of unmeasured conditions in the state and PSU on the propensity to engage in the behavior of interest, as will be explained more fully below. It is
assumed that $\mathrm{E}\left(U_{\mathrm{i}}\right)=0, \operatorname{Var}\left(U_{\mathrm{i}}\right)=\sigma_{1}^{2}, \mathrm{E}\left(U_{\mathrm{ij}}\right)=0, \operatorname{Var}\left(U_{\mathrm{ij}}\right)=\sigma_{2}^{2}$, and that all the $U_{\mathrm{i}}$ and $U_{\mathrm{ij}}$ are mutually independent. The expectations and variances here are with respect to a superpopulation as was discussed in Section 1.4.

Let $X_{\mathrm{ijkt}}$ be the value of the t -th background variable for the indicated sample person. This can be the average income for the block group that the person lives in, the arrest rate for the county, an indicator variable for a particular type of block group or county, or an indicator variable for a particular type of person (i.e., an indicator for a particular demographic domain). By indicator variable, it is meant that

$$
X_{i j k t}= \begin{cases}1 & \begin{array}{l}
\text { if the person lives in the type of block group or county of interest or belongs to the } \\
\text { demographic group or interest and }
\end{array} \\
0 & \text { otherwise } .\end{cases}
$$

$$
\text { Let } \lambda_{\mathrm{ijk}}=\operatorname{logit} \pi_{\mathrm{ijk}}=\ln \left(\frac{\pi_{i j \mathrm{k}}}{1-\pi_{i j \mathrm{k}}}\right) \text {. Note that } \lambda_{\mathrm{ijk}} \text { is referred to as the logit propensity for }
$$

the individual to engage in the behavior of interest. Also note that the propensity, $\pi_{\mathrm{ijk}}$, must be strictly between 0 and 1 for $\lambda_{\mathrm{ijk}}$ to be defined.

With this notation, the full model can be written as

$$
\lambda_{i j k}=\sum_{t=1}^{p} X_{i j k t} \beta_{t}+U_{i}+U_{i j},
$$

where $\beta_{\mathrm{t}}$ is an unknown parameter that specifies the impact of the $t$-th background variable on the logit propensity. Also note that $p$ is simply the number of background variables in the model.

The model assumes that over all possible manifestations of states and PSUs, for people with characteristics $\mathrm{X}_{\mathrm{ijk} \mathrm{l}}, \ldots, \mathrm{X}_{\mathrm{ijk} \mathrm{p}}$, there is a central tendency for the logit
propensity to engage in the behavior of interest. That central tendency is $\sum_{t=1}^{p} X_{i j k t} \beta_{t}$.

However, the model assumes that this logit propensity varies across the possible manifestations of states and PSUs. This variation is due to unmeasured variables such as family background and peer group influences, efficacy of state and local programs to influence behavior,
cultural differences and random chance. It is assumed that the variation follows a normal law, that the process causing the state variation is independent across the states, and that the process causing the PSU variation is independent across the PSUs. The use of the normal law seems reasonable since so many natural phenomena appear to obey it such as human height, weight, and IQ. However, it is not possible to directly test the reasonableness of this normal assumption. It is possible that these state and PSU random disturbances follow nonnormal distributions.

Some additional aspects of the model are important to note. The model assumes that everyone with the same values for the $p$ background variables has the same central tendency in the logit of the propensity to engage in the behavior of interest. This is somewhat difficult to believe. Variables about the county and about the block group may have a very strong effect on this central tendency, but it seems likely that variables on family background would exert even stronger effects. This disbelief in the model led to the decision to include the sampling weights in the model-fitting procedure as was mentioned in Section 1.4.

This project was probably the first small area estimation project outside of the Census Bureau to use block group level data. Using county level data is a more common approach that is far less expensive to implement, but then the assumption of homogeneity in the central tendency of the logit propensity would have been even harder to believe. Block group-level variables were included in the modeling process in order to make the homogeneity assumption more credible.

The objective of the modeling process was to obtain posterior Bayes predictions of $\beta_{1}, \ldots$, $\beta_{\mathrm{p}}$; all the $U_{\mathrm{i}}$; and all the $U_{\mathrm{ij}}$. (Note that the $\beta_{\mathrm{t}}$ are called fixed effects and that the $U_{\mathrm{i}}$ and $U_{\mathrm{ij}}$ are called random effects.) Variances and covariances on these predictions were also required in order to be able to form prediction intervals around the small area estimates. The parameters $\sigma_{1}^{2}$ and $\sigma_{2}^{2}$ were not directly of interest, but had to be estimated in order to obtain the desired predictions of the fixed and random effects.

Section 2.3 discusses how the long list of potential background variables was narrowed down to the final list of predictors. A sketch of the model fitting procedures is given in Section 2.4, and a detailed description of the model-fitting procedure is given in Appendix C.

This section concludes with an interpretation of the final model for cigarette smoking during the previous month among 18-25 year olds outside of the big cities. There were 117 fixed effects in this model. Their predicted values are given in Appendix E. The first effect is
an intercept term entitled "DUMMY". This means that $\mathrm{X}_{\mathrm{ijkl}}=1$ for everyone in the sample.
The predicted value of $\beta_{1}$ is $=-0.560$. This means that for a person for whom all the other background variables are equal to zero, the predicted central tendency of the logit of the propensity to have used cigarettes in the last month is -0.560 . Taking the inverse of the logit transform, this means that the propensity is
$\pi=\frac{e^{-.560}}{1+e^{-560}}=\frac{1}{1+e^{.560}}=0.364$. On average then, $36.4 \%$ of persons with zero values of the other background variables are expected to report smoking in the past month.

The second effect is for being female. This means that

$$
x_{i j k 2}=\left\{\begin{array}{l}
1 \\
0
\end{array}\right.
$$

The predicted value of $\beta_{2}$ is $\beta 55 \wedge_{2}=0.083$. This means that females with zero values on all the remaining background variables have a predicted logit propensity of $\beta 55 \wedge_{1}+\beta 55 \wedge_{2}$ $=-0.477$. Again taking the inverse of the logit transforms, this means that the propensity is
$\pi=\frac{1}{1+e^{377}}=0.383$. On average then, 38.3 percent of females with zero values on the other
background variables are expected to report smoking in the past month. A property of the logit transform is that the ratio of the odds for males and females is constant under this model for males and females with identical remaining background variables. The ratio is

$$
\left(\frac{\pi_{F}}{1-\pi_{F}}\right) /\left(\frac{s u b M}{\pi_{1-\pi_{M}}^{1}}\right)=\frac{e^{-.477}}{e^{-560}}=1.087, \quad \text { meaning that females are estimated to have an }
$$

odds
for smoking in the past month that is $8.7 \%$ higher than the odds for similar males. Note that this result does not seem intuitive. It was expected that males would have a higher propensity to smoke at this age. When the significance probabilities in Appendix F are examined one sees that the $p$-value for the female term is a rather large 0.1047 , meaning that standard procedures of hypothesis testing with a maximum tolerance for false positive rates of 0.05 or even 0.10 would accept the null hypothesis of no effect of sex on the propensity to smoke in this age range.

Continuing with the third through sixth effects, the modelling yielded a predicted value of $\beta 55 \wedge_{3}=-.273$ for black females and $\beta 55 \wedge_{4}=-1.145$ for other females, $\beta 55 \wedge_{5}=-.903$ for blacks, and -.008 for others. The central tendencies of the logit propensities for all combinations of race and sex are:

$$
\text { Logit }(\pi)
$$

|  | Male | Female |
| :--- | ---: | ---: |
| White | -.560 | -.477 |
| Black | -1.463 | -1.653 |
| Hispanic | -.560 | -.477 |
| Other | -.568 | -1.630 |

and the corresponding propensities are:

|  | Male | Female |
| :--- | ---: | ---: |
| White | .364 | .383 |
| Black | .188 | .161 |
| Hispanic | .364 | .383 |
| Other | .362 | .164 |

It is important to bear in mind that these are not population estimates. These
propensities apply only to persons with zero values for all the other background variables. Since those remaining variables include block-group-level variables for which no one in the sample has a value of zero, these absolute propensities are actually not very interesting. The odds ratios are more interesting. These are shown below with white males as the reference group.

Odds Ratios for Smoking in Last Month

|  | Male | Female |
| :--- | ---: | ---: |
| White | 1.000 | 1.087 |
| Black | 0.405 | 0.335 |
| Hispanic | 1.000 | 1.087 |
| Other | 0.992 | 0.343 |

The next three effects are for regions. The omitted Midwest region has a zero value for all three of these indicator variables. The next four effects are for type of setting the person lives in: large MSA, medium MSA, small MSA, or urban nonmetropolitan (small town distant from any major city). The omitted category here is rural nonmetropolitan (on a farm or out in the wilderness).

The next three effects are for the prevalence of children in the tract that the person lives in. Tracts are roughly the size of ZIP codes areas. There does not appear to be large variation in the percent of the population that is 0 to 18 years of age at such a high geographic level, but some tracts do have unusually high or low proportions of children. In this case, $\mathrm{X}_{\mathrm{ijk}}, 14=$ for a linear trend effect across five categorized levels of percent of population in tract of person ijk that was 0-18 years of age at the time of the last decennial census (April 1, 1990). Also, $\mathrm{X}_{\mathrm{ij}, 15}=$ a quadratic trend effect $X_{i j k, 14}^{2}$ and $X_{i j k, 16}=X_{i j k, 14}^{3} \quad$. So $\beta 55 \wedge_{14}=0.174, \beta 55 \wedge_{15}=-0.020$, and $\beta 55 \wedge_{16}=.094$. Clearly, these parameters are of almost no interest to policy analysts. The most important point of this discussion is to illustrate the mechanisms of using the parameter estimates. The reason for estimating the parameters is only to be able to estimate the average propensity in every block group in the states for which small area estimates were produced.

The random effects are perhaps of somewhat greater interest. They were intended to measure the cumulative impact at the state and PSU levels of all the variables that could not be included in the model, such as official policies and intangible variables such as cultural patterns. In essence, the fixed effects tell us about relationships between known environmental factors and the behavior of interest and the random effects tell us about what is still unexplained. However, this interpretation is muddied somewhat by having county-level arrest and substance treatment data included amongst the background variables, since these variables are more naturally viewed as the results of substance abuse rather than as causes. Instead of representing shifts in the logit propensity to engage in the behavior of interest after controlling for age, race, sex, and local environmental variables, the random effects come to represent shifts after controlling for all those variables and county-level arrest and treatment data on substance abuse. Shifts of this type appear to be difficult to interpret. Although the random effects are not being published, they are available from SAMHSA.

### 2.2 Procedures for Selecting Fixed Effects

A wide range of possible predictor variables were considered. This section presents a description of how the variables were created and a discussion of how the list of actual fixed effects in the model was determined.

NHSDA Data: Although there are many useful background variables collected through the NHSDA survey instrument, most of these cannot be used in the modeling because it is impossible to get reliable estimates at the block group level of how many people possess these characteristics. Accordingly, the only predictor variables that could be used from the NHSDA interview were age, sex, race, and Hispanic origin. From geographic information from the sampling system, additional available variables included: region, size of metropolitan area (if metropolitan), and whether the block group was urban or rural. The four age groups were 12-17, 18-25, 26-34, and over 34. As explained in Section 2.4, separate models were fit for each age group, so age and all interactions of age with other predictor variables were forced into all the models. Sex, race, Hispanic origin, and geography were recoded into the 11 main-effect variables listed in Exhibit 2.1. Additionally, the interactions of sex with race/ethnicity, sex with region, and race/ethnicity with region were tested.

Exhibit 2.1 NHSDA Predictor Variables (fixed effects)

## Female

Hispanic (of any race)
Black but not Hispanic
Neither white, black nor Hispanic
Northeast
South
West
Large MSA (metropolitan statistical area)
Medium MSA
Small MSA
Urban block group outside of any metropolitan area

Note that one category has been excluded from each of the classifications that the variables induce (i.e., male, white but not Hispanic, Midwest, and rural nonmetropolitan). This was done to get unique parameter estimates. It was possible to have set extra constraints to make the parameters unique, but it was easier to exclude categories.

Census data: Exhibit 2.2 lists Census data elements that were considered for use in the modeling. There were eighteen groups of these variables. All of the attributes come from the 1990 U.S. Census long form sample. ${ }^{9}$ About 8 percent of the population was asked to complete a long form in 1990. For most of the variable groups, the possibilities were considered of using average responses both at the block group level and at the tract level.

Note that all of the census variables are approximately continuous at the tract level and block group level. There was concern that the relationship of the logit propensity to the predictor variables might be nonlinear. Frequently, for example, the upper and lower ends of the income distribution have more in common with respect to certain behaviors than the middle of the income distribution. ${ }^{10}$ Consideration was thus given to using powers of the continuous variables as predictor variables, such as the square of the poverty rate, the cube of the poverty rate, and so on. However, using these powers of continuous variables as predictor variables probably would have led to outliers when the model was used to predict block-group level propensities. The reason for this is that when a continuous variable is used as a predictor, any outlying values of the predictor variable can lead to outliers in the predicted propensities.

In order to avoid the problems with outliers while simultaneously being able to estimate linear trends, quadratic relationships, and higher order relationships, some special recodes were created. These recodes were done in the same manner for each of the variables. The procedure was as follows:

Sort the units (counties, tracts or block groups, depending on the variable being recoded) by the variable. Using the poverty rate for tracts as example, that means that all the tracts in the nation were sorted by the tract-level poverty rate. The sorted list was then divided into 5

[^6]
## Exhibit 2.2 1990 Census Variables Used to Model Prevalence of Substance Abuse ${ }^{11}$

1. Race x Hispanic

Percent:
White nonhispanic
Black nonhispanic
Hispanic
Other
2. Education for persons 18 or older

Percent with:
0-8 years
9-12 years and no H.S. diploma
H.S. graduate
some college and no degree
associate degree
bachelors, graduate, or professional degree
3. Age

Percent aged:
$0-18$ years
19-24 years
25-34 years
35-44 years
45-54 years
55-64 years
65 and over
4. Poverty

Percent of:
families below poverty level
5. Public Assistance

Percent of:
households with public assistance income
6. Disability

Percent of:
persons $16-64$ with a work disability
7. Household composition

Percent:
one-person households
of households with female heads (no spouse present) with children under 18
8. Employment

Percent:
of men 16 years and older in the labor force
of women 16 years and older in the labor
force
9.Housing value - owner occupied units

Median value of owner occupied housing units
10. Housing rent - rental units

Median rents for rental units
11. Sex by marital status (persons 16 years and older)

Percent of:
Females currently married and not separated
Females separated, divorced, or widowed
Females never married
Males currently married and not separated
Males separated, divorced, or widowed
Males never married
12. Income

Median Household Income
13. Urbanicity

Percent:
of persons residing in an urban place
14. Urbanized Area

Percent:
of persons in an MSA urbanized area
15. Age of Housing

Percent:
of HUs built before 1939
of HUs built from 1940 to 1949
16. High School Dropout Rate (Tract level only)

Percent:
of high school age children who have dropped out
17. Hispanic Subpopulations

Percent:
of Hispanics that are Cuban
of Hispanics that are Puerto Rican
18. Other Race Subpopulations

Percent of:
Population that is Asian and Pacific Islander
Population that is Native American, Alaskan, or Aleut
${ }^{11}$ From Summary Tape File 3, 1990 Census of Population and Housing. Summaries were used at the tract level and at the block group level. Where a segment consisted of blocks from multiple block groups or even tracts, the summary variables were a weighted average of the statistics from the block groups or tracts that intersected the segment.
categories, each containing 20 percent of the tracts. Such groups are referred to as quintiles. The 20 percent of tracts with the lowest poverty rates are referred to as the first quintile of the tract-level poverty rate distribution. The fifth quintile consists then of the 20 percent of tracts with the highest poverty rates. The trend variables were then defined as shown in Exhibit 2.3.

Exhibit 2.3 Definitions of Trend Variables

| Linear | Quadratic | Cubic | Quartic |  |
| ---: | ---: | ---: | ---: | :--- |
| -2 | 2 | -1 | 8 | if the tract was in the first quintile |
| -1 | -1 | 2 | -5 | if the tract was in the second quintile |
| 0 | -2 | 0 | -6 | if the tract was in the third quintile |
| 1 | -1 | -2 | -5 | if the tract was in the fourth quintile |
| 2 | 2 | 1 | 8 | if the tract was in the fifth quintile |

Creating four variables for every one of the variables in the list of 18 variable groups would produce more variables than could possibly be simultaneously fit. In addition, there were problems with collinearity between variables, ${ }^{12}$ particularly if both the tract-level variables and the block-group level variables corresponding to the same census question (such as average poverty rate for the tract and for the block group) were used. To reduce the collinearity problem, all variables that could be logically determined given other variables were dropped. As an example of this, consider the first group of variables concerning race and ethnicity. If the percent of the tract that is white but not Hispanic, the percent that is black but not Hispanic and the percent that is Hispanic are all known, then one can easily deduce the percent that is neither white nor black nor Hispanic.

To further reduce collinearity problems, block-group level variables were discarded if the correlation between the tract-level version and the block-group level version (across all the block groups in the nation) was above 0.80 . Retention of the tract-level variables was favored over the block-group level variables because of the smaller sampling error on the tract level variables. However, this was a difficult decision. If all work had been done only at the tract level, the tasks of assembling the predictor variables and of obtaining population projections would have been much less expensive. There was substantial initial interest in the block group level data

[^7]because it was thought that they would have greater predictor power than tract level data. Of course, for those variables where the tract-level and block-group level variables are nearly collinear, it didn't matter much which were used since both versions contained roughly equal information in them.

There was also a desire to include some interactions of the Decennial Census variables with the NHSDA variables. For all Census variables that were kept after the preceding step, two-way interactions of the variables with sex and separately with race/ethnicity were generated. No other interactions were tested.

County level (social indicator) correlates of substance abuse: In addition to the Census variables, recoded county level 'social indicators' of substance abuse were also considered. These county level variables were obtained from three sources: The first of these sources was the FBI's Uniform Crime Reports database for 1991. This source yielded data on arrest rates per 10,000 persons for illegal drug possession, drug sales/manufacture by several reported drug categories, and total violent crime arrest rates. The second source combined data from the 1991 and 1992 National Drug and Alcoholism Treatment Unit Survey (NDATUS) conducted by the Substance Abuse and Mental Health Services Administration. From this source, data were obtained on the 1991 and 1992 average treatment rates per 1,000 county residents for (1) alcohol treatment alone and (2) for illicit drug treatment (including treatment for both drug and alcohol use). Thirdly, 1990 alcohol-related death rates per 10,000 county residents were obtained from the National Center for Health Statistics national death certificate registry. Two such rates were considered in this research: (a) the "any related rate" which includes all ICD-8 cause-of-death codes that are deemed to have a significant link to alcohol abuse, and (b) a more restrictive rate which requires explicit mention of alcohol on the death certificate. Appendix D presents the 1990 census block group, census tract, and County level variables that were considered as possible fixed effects. In appendix D, the defining variable labels of block group variables are preceded by the letter B. The tract and County variable labels are preceded by letters T and C respectively.

Underclass Indicator: Finally, there was a variable at the tract level from the Urban Institute that flagged tracts in distressed inner city areas. This was a binary recode of several tract-level census summary variables.

## Further reducing list of possible predictor variables

Despite the work to eliminate collinear census variables, there were still too many variables and some of the variables had structural problems. A variable has such a problem if there exists a level of the variable such that no one in the entire NHSDA sample had the characteristic and also engaged in the behavior of interest. A logistic model always predicts a propensity strictly between 0 and $1--$ never exactly 0 or 1 . If a predictor variable has a value that is associated with an observed propensity of 0 or 1 , then the model fitting will fail. Accordingly, all such variables were dropped. Note that this was done separately for each of the 88 models, as were all the remaining steps in this section.

The next step was to fit a simple linear regression model using all the remaining possible fixed effects. The form of this simple linear regression model was

$$
Y_{i j k}=\sum_{t=1}^{P} X_{i j k t} \beta_{t}+e_{i j k}
$$

where it was assumed that all the $e_{i j k}$ are independently and identically distributed as $\mathrm{N}\left(0, \sigma^{2}\right)$. Since $Y_{i j k}$ can be only 0 or 1 , while the right hand side can predict any real number, this model is not at all satisfactory for most inferences. Nonetheless, models of this type do have several important advantages over logistic models when the analysis is in the exploratory stage. First, the linear models do still produce parameter estimates that are approximately correct. Second, they do not fail when some interaction term is associated with an observed propensity of 0 or 1 . Third, linear models are far faster to run than logistic models since there is no iteration required. Fourth, the software for implementing variable elimination procedures is better written for linear models than for logistic models ${ }^{13}$. The idea was to quickly cull out poor predictors and predictors that were approximately collinear with other predictors. ${ }^{14}$ To be on the safe side, the selection criteria were set loosely for these runs at $\alpha=0.1$. If any interaction terms associated with a main effect were significant, then the interaction and the associated main effects were kept even if the main effects were not significant themselves. (This makes the model somewhat easier to interpret.) Similarly, if a higher order term was significant for one of the recodes for polynomial trends, then all the recodes for lower order trends were kept even if those lower order trends were not significant themselves.

[^8]To improve the accuracy of the p-values, a modified version of the REGRESS procedure from SUDAAN was used to carry out the linear regression runs. SUDAAN increases the variance estimates to reflect the effects of clustering and unequal weighting in the sample design. The stripped-down version was a custom version made to run faster than the more flexible commercial version. SUDAAN requires the input of cluster and stratification structure for the sample design. The same structure information was used as would be used for national models from the NHSDA. This structure is different from the structure implicit in the mixed model, but this was not very important since the program was only being used to further cull out weak predictor variables.

The next step was to run fixed-effect logistic models with the retained variables. This was done using a stripped-down version of the procedure LOGISTIC from SUDAAN. The algorithm was the same as would have been used to fit a fixed-effect logistic model to any dataset from a complex sample survey, but some of the optional features were removed to make the program very fast. The same sample structure information that would have been used for national models from the NHSDA was again used. In these logistic fits, any variables that failed to pass the significance tests outlined above with $\alpha$ reduced to 0.05 were deleted. The fixed effect parameters obtained from these survey weighted LOGISTIC procedure runs were used as the starting $\beta$ values in the mixed logistic model runs.

### 2.3 Fitting the Models

The full model described in Section 2.2 can be written in matrix form as

$$
\lambda=X \beta+Z U,
$$

where $\lambda, X, \beta, Z$, and $U$ are all matrixes. The structure of these matrices is a bit tedious to describe and understand, but the effort is well worthwhile in terms of the simplicity that they allow in describing the extremely complex model fitting procedure.

Let $m$ be the number of states involved in the model fitting. The term "state" is used loosely here. A state-like entity in the model could be either a state, the balance of a state after taking out an MSA, or the balance of a region after taking out all targeted states. Let $r_{i}$ be the number of sample PSUs in the $i$-th state. Let $n_{i j}$ be the number of sample persons in the $j$-th PSU
of the $i$-th state. Let $n=\sum_{i=1}^{m} \sum_{j=1}^{r_{i}} n_{i j}$ be the total number of sample persons used in the model
fitting. The matrix $\lambda$ is an $n \times 1$ matrix (i.e., $n$ rows and 1 column). It is formed by listing all the $\lambda_{\mathrm{ijk}}$ with the first subscript varying the slowest, the middle subscript the next slowest, and the last subscript the fastest. (Recall that $\lambda_{\mathrm{ijk}}$ is the logit propensity to engage in the behavior of interest for the $k$-th person in the $j$-th PSU of the $i$-th state.) This is the same as listing all the logit propensities for the first sample PSU of the first state, then those of the second sample PSU and so on until all have been listed for the first state, and the proceeding to the second state and so on. The last entry is for the last person in the last sample PSU of the last state.

The matrix $X$ is an $n \times p$ matrix (i.e., $n$ rows and $p$ columns), where $p$ is the number of fixed effects in the model. The element in the j -th column of the i -th row is denoted $X_{i j}$ and signifies the value of the $j$-th background variables for $i$-th sample person where the sample persons are ordered by state, PSU, and person, as in the description of $\lambda$ above. The matrix $\beta$ is a $p \times 1$ matrix with elements $\beta_{1}$ through $\beta_{\mathrm{p}}$.

Let

$$
r=\sum_{i=1}^{m} r_{i}
$$

be the number of PSUs in sample. Let $q=m+r$. This is the number of random effects in the model. Then $U$ is a qx1 matrix where $U_{1}$ through $U_{\mathrm{m}}$ are listed first and then $U_{11}$ through $U_{m r_{m}}$ are listed next with all the PSU effects for the same state listed next to each other. The matrix $Z$ is an $n x q$ matrix consisting of 0 s and 1 s . The $j$ th element of the $i$ th row of $Z$ is denoted $Z_{i j}$ and signifies whether the $i$-th sample person is in the state or PSU associated with the $j$-th random effect. Exactly two elements of each row of $Z$ are 1 's since a particular sample person can only belong to one state and one PSU. The other elements of each row are all 0 s. Each column of $Z$ corresponds to either a state random effect or a PSU random effect. If a column corresponds to a state random effect then the number of 1 s in the column is equal to the state sample size.
Similarly, if a column corresponds to a PSU effect, then the number of 1 s in the column is equal to the PSU sample size. The distribution assumptions about the random effects can be written compactly as

$$
U \sim N_{q}(055 \sim, G),
$$

where $\mathrm{N}_{\mathrm{q}}$ denotes a q-variate normal distribution, $060 \sim$ ? is a $q \times 1$ matrix of zeroes and $G$ is the variance-covariance matrix for $U$.

Given the assumptions about independence between the random effects, a uniform variance for the state-level effects, and another uniform variance for the PSU-level effects, the matrix $G$ has a particularly simple form. Let $I_{\mathrm{n}}$ be an $n x n$ identity matrix. (A matrix with 1 s on the main diagonal and 0 s off the main diagonal. Then

$$
G=\left[\begin{array}{ll}
\sigma_{1}^{2} I_{m} & 07 \\
\hline 0 & \sigma_{2}^{2} I_{r}
\end{array}\right]
$$

where, as before, $m$ is the number of states and $r$ is the number of sample PSUs. Note that $G$ is qxq.

The objective of the model fitting was to find the best possible estimates of $\beta$ and $U$. Once these are obtained, they are used to predict a propensity for every person in the population to engage in the behavior of interest. In other words, obtaining best estimates of $\beta$ and $U$ would lead to best estimates of $\lambda$, which would in turn lead to best estimates of $\pi$ for the entire population. If $\pi$ is known for the entire population, then it is easy to estimate the average propensities for small areas. Complicating this simple objective is the fact that statisticians do not agree on the way to obtain best estimates of $\beta$ and $U$. This is an area of very active current research. There is a maximum likelihood approach favored by model-based frequentists, another approach favored by Bayesians, and an approach favored by empirical Bayesians. These various approaches are discussed below. That discussion is prefaced by a quick review of probability distributions and a general discussion of the different approaches to estimation.

By way of quick review, the distribution function for a random variable is usually written $F(\mathrm{y})$ and is defined as $F(\mathrm{y})=\operatorname{Pr}\{\mathrm{Y} \leq \mathrm{y}\}$. If $F$ is differentiable at $y$, then one may define $f(\mathrm{y})=F^{\prime}$ (y) and call $f$ the probability density function (pdf). If $F$ is not differentiable at $y$, then $f$ is defined as

$$
f(y)=\lim 120 \varepsilon \rightarrow 0^{+}(F(y+\varepsilon))-\lim \quad 120 \varepsilon \rightarrow 0^{-}(F(y+\varepsilon))
$$

and it is then called a probability function (pf) since

$$
f(y)=\operatorname{Pr} Y=y .
$$

The modeler usually has a family of possible distributions in mind when making inferences based on a sample. That means that he believes the distribution of $Y$ is known except for the values of a few parameters, labeled by the vector $\theta$. Writing out $f(y)$ will involve the use of $\theta$ in some way. Thus, $\mathrm{f}(\mathrm{y})$ is often written as $\mathrm{f}(\mathrm{y} \mid \theta)$, drawing attention to the fact that the pdf or pf of $y$ depends on $\theta$. Instead of viewing it primarily as a function of $y$ that depends on $\theta$, the
pdf or pf can be viewed as a function of $\theta$ that depends on $y$. When it is viewed in this manner, it is called a likelihood function instead of a pdf or a pf and it is usually written as

$$
L(\theta \mid y) .
$$

Note, however, that $\mathrm{L}(\theta \mid \mathrm{y})=\mathrm{f}(\mathrm{y} \mid \theta)$. Both functions appear identical. The difference is only one of emphasis. When $\mathrm{f}(\mathrm{y} \mid \theta)$ is used, the writer is, thinking about ways to use knowledge about $\theta$ to make predictions about $y$; when $\mathrm{L}(\theta \mid \mathrm{y})$ is used, the writer is thinking about ways to use knowledge about $y$ to make predictions about $\theta$.

Exhibit 2.4 shows the pdf for a standard normal distribution. The pdf reaches its maximum value at the center of the distribution at $\mathrm{Y}=0$. The point that maximizes the pf or pdf is called the mode of the distribution. If one considers trying to balance the graph at a single point along the horizontal axis, the center of gravity is also found at $\mathrm{Y}=0$. The center of gravity is called the mean of the distribution. If one considers trying to find the value of $Y$ such that half the area under the graph is on the left and half the area is on the right, that point is also found at $\mathrm{Y}=0$. The point with half the area on either side is called the median of the distribution. For the normal distribution, all the measures are the same; i.e., the mode, mean and median are all equal to each other. This is not true for all random variables, but since the central limit theorem

## Exhibit 2.4 Standard Normal Probability Density Function


states that the mean of a large random sample of values of a random variable will be approximately normally distributed, the mode of the distribution is close to the mean in many applications.

The shape of the curve in Exhibit 2.4 is similar to the shape of the curve of the likelihood function for the unknown mean of a normal distribution given a simple random sample from that distribution, except for the fact that the likelihood function will be centered at the sample mean.

The method of maximum likelihood is to estimate a parameter by finding the mode of its likelihood function given the sample data. Suppose for example, that it is believed that Y is normally distributed with known variance but unknown mean and that a sample of 30 observations of Y yielded an average value of -34 . The value that maximizes the likelihood function for the unknown mean given that particular random sample is -34 .

Although this method works fine for many applications, there can be problems when the likelihood function is not symmetric or has multiple local maxima as in Exhibit 2.5. The likelihood function can look like this when the variable being measured (the $Y$ variable) is not normal and the sample size is small. Note that for this random variable, the mean, median, and mode are all different. The median is 0.5 , the mean is 0.4 , and the mode is 1.5 . For such a random variable, maximum likelihood estimation would not be a good method for finding the mean based on a small sample.

Despite the dangers of using maximum likelihood estimators for small samples, they have excellent properties when based on large samples. It has been demonstrated that for many classes of random variables, the maximum likelihood estimators of their parameters are asymptotically unbiased and exhibit minimum possible variance. In addition, the MLE

## Exhibit 2.5. Probability Density Function for Mixture of Normal Variables


estimators are asymptotically normally distributed which is useful for forming confidence intervals.

The Bayesian approach to estimation would be to place a prior distribution on the parameter $\theta$, then derive the posterior distribution of $\theta$ given the sample data, then find the mean of the posterior distribution. If $\mathrm{p}(\theta)$ is the prior distribution on $\theta$, then the posterior distribution of $\theta$ given $Y$ is

$$
p(\theta \mid y)=\frac{f(y \mid \theta) p(\theta)}{\int_{f(y \mid \theta) p(\theta) d \theta}}
$$

Note that if $\mathrm{p}(\theta)=1$ for all $\theta$ and if $\int f(y \mid \theta) d \theta$ exists, then $\mathrm{p}(\theta \mid \mathrm{y})=\mathrm{L}(\theta \mid \mathrm{y})$, so the two methods are very similar for a flat $\mathrm{p}(\theta)$. Such a prior distribution is called an uninformative prior because it states that all real numbers are equally likely to be the correct value of $\theta$. Such a prior is an improper prior because a proper probability distribution has finite area underneath its graph. For some applications, use of an uninformative prior will result in the denominator of the posterior being infinite so that the posterior is not well defined. For other applications, the use of an uninformative prior is adequate. In general, use of uninformative priors is the biggest difference between the empirical Bayes approach used in this study and a fully Bayesian approach. With a fully Bayesian approach, only proper priors would be used.

If there are two random variables of interest, $Y$ and $Z$, then the joint distribution of the two together is frequently of interest, as well as the marginal distributions of each by itself, and the conditional distributions of each given the other. These various distributions are related to each other as follows. Let the marginal probability functions or probability density functions for $Y$ and $Z$ be $f(y)$ and $g(z)$, let the joint pf or pdf of $Y$ and $Z$ be $h(x, y)$, and let the conditional pf or pdf of $Y$ given $Z$ be $f(y \mid z)$, and the conditional pf or pdf of $Z$ given $Y$ be $g(z \mid y)$. Then
$f(y \mid z)=\frac{h(y, z)}{g(z)}$,
$g(z \mid y)=\frac{h(y, z)}{f(y)}$,
$h(y, z)=f(y \mid z) g(z)=g(z \mid y) f(y) \quad$,
$f(y)=\int h(y, z) d z=\int f(y \mid z) g(z) d z$
$g(z \mid y)=\int h(y, z) d z=\int g(z \mid y) f(y) d y$
where the integrals are Lebesgue integrals that correspond to summation when $h$ is a pf instead of a pdf.

If there is a sample of $n$ random observations of $Y$, then the joint pdf or pf for the entire set of observations is

$$
f_{n}\left(y_{1}, \text { DOTSAXIS, } y_{n} \mid \theta\right)=\prod_{i=1}^{n} f(y \mid \theta)
$$

where the $\Pi$ notation means to multiply all $n$ factors together.

Returning from general review to this specific study, the pf for a single observation of substance abuse or other behavior is

$$
f\left(y_{i} \mid \beta, U, G\right)=\left[\pi_{i}^{y_{i}}\left(1-\pi_{i}\right)^{1-y_{i}}\right],
$$

for $y_{i}=0$ or 1. (This is a standard result for Bernoulli random variables.) Using the general rule given above, the pf for the entire $y$ vector of behavior observations given $\beta$, $U$, and $G$ is

$$
f(y \mid \beta, U, G)=\prod_{i=1}^{n}\left[\pi_{i}^{y_{i}}\left(1-\pi_{i}\right)^{1-y_{i}}\right] .
$$

The pdf for the vector of random effects given the assumption of a $q$-variate normal distribution is

$$
f(U \mid G)=\frac{1}{(\sqrt{2 \pi}) q \sqrt{|G|}} \exp \left\{-\frac{1}{2} U^{t} G^{-1} U\right\},
$$

where $|G|$ denotes the determinate of $G, U^{\mathrm{t}}$ denotes the transpose of $U$, and $G^{-1}$ indicates the inverse of G (a matrix such that $G G^{-1}=G^{-1} G=\mathrm{I}$, the identity matrix).

Using the rules given above for conditional and joint distributions, the joint $\mathrm{pf} / \mathrm{pdf}$ for $y$ and $U$ is

$$
f(y, U \mid \beta, G)=f(y \mid \beta, U, G) f(U \mid \beta, G)
$$

Since the distribution of $U$ does not depend on $\beta$, this can be simplified to

$$
\begin{aligned}
& f(y, U \mid \beta, G)=f(y \mid \beta, U, G) f(U \mid G) \\
& \quad=\left\{\begin{array}{l}
n \\
\prod_{i=1}^{n}\left[\pi_{i}^{y_{i}}\left(1-\pi_{i}\right)^{\left.1-y_{i}\right]}\right.
\end{array}\right\} \frac{\exp ^{\{ }\left\{\frac{1}{2} U^{t} G^{-1} U^{\prime}\right\}}{(\sqrt{2 \pi})^{q} \sqrt{|G|}}
\end{aligned}
$$

If this function is now viewed as a function of $\beta$ and $U$ given fixed $y$ and $G$ instead of a function of $y$ and $U$ given fixed $\beta$ and $G$, something very similar to a likelihood function is obtained:

$$
L(\beta, U \mid y, G)=\left\{\begin{array}{l}
n \\
\prod_{i=1}^{n}\left[\pi_{i}^{y_{i}}\left(1-\pi_{i}\right)^{\left.1-y_{i}\right]}\right.
\end{array}\right\} \quad \frac{\exp ^{\{ }\left\{\frac{1}{2} U^{t} G^{-1} U^{\prime}\right\}}{(\sqrt{2 \pi})^{q} \sqrt{|G|}}
$$

Finding $\beta$ and $U$ that maximize this penalized quasi-likelihood has substantial intuitive appeal as a means for estimating $\beta$ and $U$. However, there are two problems. The first is that G is unknown. The second is that $L(\beta, U \mid y, G) \quad$ is not a true likelihood function since $U$ is a latent variable rather than a parameter. A latent random variable is a random variable that, by definition, can not be observed. When the existence of a latent random variable is theorized, it is standard practice to also speculate on the nature of the joint distribution of the observable and the latent random variables. However, maximum likelihood estimation requires that the marginal distribution of the observable random variables given the distribution parameters be found, and that this marginal distribution be maximized to find the maximum likelihood estimates of the parameters. Using a procedure that is similar to maximum likelihood estimation but not exactly the same raises some questions about the properties of the estimators. As was mentioned above, maximum likelihood estimators are known to have good properties when sample sizes are large. Little is known about the properties of estimates obtained by maximizing $L(\beta, U \mid y, G) \quad$ even when $G$ is known.

This is the situation that was faced in this project. The random $Y$ is observable, but the random vector $U$ is not $\quad$ So $U$ is a latent random vector. The distributions of both $Y$ and $U$ depend on the parameter $G$. In addition, the distribution of $Y$ depends of the parameter $\beta$. The parameter $\beta$ is the real parameter of interest. It governs the relationship between the census background variables and the observed behaviors. The marginal conditional distribution of $Y$ given the parameters $\beta$ and $G$ is, however, quite computer intensive to calculate. Using the relationships on marginal and conditional distributions given above, the marginal distribution of of $Y$ given the parameters $\beta$ and $G$ is

This can be turned around into a likelihood function for $\beta$ and $G$ given $Y$ :

$$
\begin{aligned}
& L(\beta, g \mid y)=\frac{\left\{\begin{array}{c}
n \\
\prod_{i=1}^{n}\left[\pi_{i}^{y i}\left(1-\pi_{i}\right)^{1-y_{i}}\right]
\end{array}\right\} \frac{\exp _{\left\{\frac{1}{2} U^{t} G^{-1} U^{\prime}\right\}}^{(\sqrt{2 \pi})^{q} \sqrt{|G|}}}{\text { l } 1}}{\substack{ \\
l}} \\
& \int\left\{\prod_{i=1}^{n}\left[\pi_{i}^{y i}\left(1-\pi_{i}\right)^{1-y_{i}}\right]\right\} \frac{\left.\exp ^{\{ }-\frac{1}{2} U^{t} G^{-1} U\right\}}{(\sqrt{2 \pi})^{q} \sqrt{|G|}} d U
\end{aligned}
$$

The model-based frequentist would evaluate the integral in the denominator and then find the values $\beta 55 \wedge$ and $G$ that jointly maximize $\mathrm{L}(\beta, \mathrm{G} \mid \mathrm{y})$. He would then use $G$ to make predictions $U$ for $U$, and then use $\beta 55^{\wedge}$ and $U$ to make predictions for $\lambda$ and hence for $\pi$.

The difficulty with this approach is that the integration to find $L(\beta, G \mid y)$ is $q$-dimensional and each of those $q$ dimensions must be integrated with numerical techniques since closed-form integrals of $L(\beta, U \mid y, G)$ do not exist. Some methods exist to reduce the dimensionality of the integration to the number of levels of random effects. For just a state effect, it is possible to reformulate the task as one involving $\mathrm{q}=\mathrm{m}$ single-dimensional integrations; for a model with both state and PSU effects, the task can be reformulated into some number of two-dimensional integrations. This approach was, in fact, tried for this project. However, the computer time required for the integration was found to be unacceptable even with the 2-level nested random effect model. Since at the time, there were plans to develop 3-level and even 4-level nested random effect models (with random effects for separate segments and even households), this approach was abandoned.

The estimation approach of maximizing $L(\beta, U \mid y, G) \quad$ can be easily justified from an empirical Bayes point of view. (That is the reason why the method is called an empirical Bayes method.) To see this, note that if an uninformative joint prior is placed on $\beta$ and $U$, then the joint posterior of $\beta$ and $U$ given the data $y$ and the variance matrix $G$ is

$$
p(\beta, U \mid y, G)=\frac{\left\{\begin{array}{l}
n \\
\prod_{i=1}^{n}\left[\pi_{i}^{y_{i}}\left(1-\pi_{i}\right)^{1-y_{i}}\right]
\end{array}\right\} \frac{\exp ^{\left\{,-\frac{1}{2} U^{t} G^{-1} U^{\prime}\right\}}}{\left.\int \sqrt{2 \pi}\right)^{q} \sqrt{|G|}}}{\int\left\{\prod_{i=1}^{n}\left[\pi_{i}^{y_{i}}\left(1-\pi_{i}\right)^{\left.1-y_{i}\right]}\right\}, \frac{\left.\exp ^{\{ }, \frac{1}{2} U^{t} G^{-1} U^{\prime}\right\}}{(\sqrt{2 \pi})^{q} \sqrt{|G|}} d \beta d U\right.}
$$

Since the denominator of this posterior is not a function of $\beta$ or $U$ (they have been integrated out), maximizing $p(\beta, U \mid y, G) \quad$ is identical to maximizing $L(\beta, U \mid y, G)$. Thus, the method of maximizing the joint quasi-likelihood assuming known $G$ is identical to the
empirical Bayesian method, also assuming known $G$. The fact that the two approaches agree was comforting, as was the fact that it had been previously invented, tested, generalized, and alternately motivated by Stiratelli, et al (1984), Schall (1991), and Breslow and Clayton (1993). This was the approach adopted for this study.

The problem in applying this method is that $G$ must also be estimated. If $U$ were known then it would be possible to estimate $G$ by maximizing $L(G \mid U)=\mathrm{f}(U \mid G)$. This can be motivated through the maximum likelihood perspective or through the empirical Bayes perspective by placing an uninformative prior on $G$. Thus, there is a slight conundrum. Given the true value of $G$, it is possible to reasonably estimate $\beta$ and $U$. On the other hand, given the true value of the unobservable $U$, it is possible to reasonably estimate $G$. If one knows neither $U$ nor $G$, then it is difficult to know how to estimate either of them or $\beta$. Following, the work of the authors mentioned above, this conundrum was resolved through the use of an iterative technique.

In this iterative technique, there is an initial guess at a reasonable value for $G$. Using this guess, $\beta$ and $U$ are estimated by maximizing $L(\beta, U \mid y, G) \quad$. The resulting estimate of $U$ is used to estimate $G$ through maximization of $L(G \mid U)$. This procedure cycles back and forth until convergence is obtained.

A fully Bayesian approach would have been to put a joint prior distribution on $\beta, U$, and $G$. The Bayesian would then find the posterior means $\beta 55 \wedge, U$, and $G$ and use these to estimate $\lambda$ and hence $\pi$. Until recently, the Bayesian approach involved even more intense integrations than did the maximum likelihood approach of the model-based frequentists. Now, with new Monte Carlo Markov Chain methods such as Gibbs Sampling, this approach may be computationally tractable. However, since these methods are new, reported to converge very slowly, and require the specification of prior distributions (a step with which SAMHSA was not very comfortable), this approach was not pursued.

As discussed in Section 1.4, the empirical Bayesian approach was modified slightly for this study to use the survey weights. The intent of this modification was to make the method more robust to model misspecification and to make the method design-consistent.

The modification to the method involves the insertion of the survey weights into the posterior distribution for $y$ and $U$. Rather than maximizing

$$
\left.L(\beta, U \mid y, G)=\left\{\prod_{i=1}^{n}\left[\pi_{i}^{y_{i}}\left(1-\pi_{i}\right)^{1-y_{i}}\right]\right\} \frac{\exp \left\{-\frac{1}{2} U^{t} G^{-1} U\right\}}{\sqrt{2 \pi}} \sqrt{|G|}\right)
$$

the expression to be maximized is

$$
\left.L_{w}(\beta, U \mid y, G)=\left\{\prod_{i=1}^{n}\left[\pi_{i}^{w_{i} y_{i}}\left(1-\pi_{i}\right)^{w_{i}\left(1-y_{i}\right.}\right]\right\} \frac{\exp \left\{-\frac{1}{2} U^{t} G^{-1} U\right\}}{\sqrt{2 \pi}} q \sqrt{|G|}\right)
$$

where $w_{\mathrm{i}}$ is the sampling weight for the $i$-th person, scaled so that the sum of the weights is equal to the total sample size. The procedure for estimating $G$ is the same although the use of the weights does change the estimate of $G$.

If all persons in the 1991-93 NHSDA had the same sampling weight, then the estimators resulting from maximizing $L$ and $L_{\mathrm{w}}$ would be the same. Also, if the background variables reflected in $X$ totally explained the variation in sampling weights, the estimators would be the same. However, the sampling weights vary according to a more complex pattern than is reflected in $X$. As discussed in Section 1.1, the NHSDA oversampled by age and race and undersampled persons in large households. Also the sampling rates in six large metro areas were markedly higher than the national sample rates. Finally, block groups with high percentages of Hispanics and Blacks were oversampled to reduce the cost of overrepresenting Hispanics and Blacks. There is further unplanned variation caused by undersampling of blocks that were much larger at the time of listing than had been anticipated based on Decennial Census information and by adjustments for nonresponse and undercoverage. Since most of the weight variation due to age and race is reflected in the $X$ matrix, and since separate models were fit for the collection of 6 oversampled metro areas, the most important differences between $L$ and $L_{\mathrm{w}}$ concern the planned oversampling of concentrated Hispanic and Black neighborhoods and the undersampling of large households and unexpectedly large blocks.

The frequentist properties of the survey-weighted empirical Bayes estimates are not well understood. Since the only prior distributions used were noninformative (also called improper or vague), it is theoretically possible to derive the frequentist properties of these estimates, but this is quite difficult and has not yet been rigorously resolved. Breslow and Clayton (1993) point out that for estimating $\beta$ and predicting $U$, this method is approximately equivalent to a maximum likelihood approach. They also point out structural similarities to estimators proposed by Harville (1977) for normal $y$ variables. They also report on two small simulation
studies, the results of which are moderately encouraging. As discussed in Section 1.5, larger, more varied, and more realistic simulation studies would be useful for evaluating the survey-weighted empirical Bayes model fitting procedure. This idea is discussed further in section 3.4.

### 2.4 Need for Multiple Models

The ideal modeling procedure would have been to fit one national model for each of the 11 behaviors of interest. For technical reasons, however, it was necessary to fit 8 models for each of the 11 behaviors for a total of 88 models. Separate models were fit for four age groups in each of two oversampling strata. The four age groups were 12-17, 18-25, 26-34, and over 34 . The oversampling strata were defined by the set of metropolitan areas that were given sufficiently large sample sizes to allow design-based estimates with good precision. There were 6 such metropolitan areas. The combination of these 6 metropolitan areas constituted one of the strata for which separate models were fit. The other stratum consisted of the rest of the nation. The models for the collection of 6 targeted MSAs are referred to as the "Big City Models." The models for the balance of the country are referred to as the "Remainder Models."

There was an initial attempt to fit just one national model for each behavior for several reasons. First, a single national model would have yielded more stable estimates of the fixed effects. Second, the estimates of the fixed effects would not vary by age or stratum as they do when 8 different models are fit. Third, the estimates of mean square error of the small area estimates would have been more accurate. Lastly, it would have been somewhat easier to organize the file handling aspects of the task.

The reason for having to fit a different set of models for the oversampled MSAs was that the average sampling weight in the oversampled MSAs was much smaller than the average sampling weight in the balance of the country. The large disparity in weights caused a critical matrix in the model-fitting procedure to become ill-conditioned, meaning that it could not be inverted. (See Appendix C for a more detailed explanation of this point.) Larger and faster computers probably would not have solved this problem. It appears that although the method can make the small area estimates more robust through reflection of the sampling weights, if the variation in the sampling weights is too extreme, then the analysis must fail.

The reason for having to fit a different set of models for each age group was related to computer size and speed. Since age is the most important predictor of the behaviors of interest, it was desired to include many interactions of age with other variables. The X matrix of
predictor variables became too large to read in at acceptable speeds. It was thus decided that the best way to shorten the X matrix without giving up very much predictive power was to fit separate models by age group. With a larger and faster machine, there would not have been a need to fit separate models by age group. Another solution might have been to use fewer fixed effects. At the time, there was a reluctance to give up prediction power by using fewer fixed effects, but since the evaluation in Chapter 3 seems to indicate that the fixed part of the model was overfit (too rich, meaning too many fixed effects), this might be the best solution to the problem in future applications.

The big city models had a simpler structure than the remainder models. The structure given in Section 2.1 is for the remainder models. For the big city models, the terms for the PSU-level random effects ( $U_{\mathrm{ij}}$ ) were forced equal to zero. Although it might seem natural to fit a model with 6 state-level random effects corresponding to the 6 MSAs, it was felt that the estimates of $\sigma_{1}^{2}$ would be very unstable if they were based upon just 6 realizations of $U_{\mathrm{i}}$. Accordingly, each of the six oversampled MSAs were divided in two. Although it would have been possible to split each MSA by county, it was felt that it would be more useful to split each MSA into two strata of block groups, one with higher SES (socio-economic status) than the other. SES was measured by rent levels and housing values. The cut points on rent and housing values were set so that about 30 percent of the population in each MSA was in the low SES stratum. Thus, for the big city models, $m=q=12$.

After the sample in the oversampled MSAs was dropped out from the remainder models, those models converged nicely. However, there was still too much variation in the weights within the 6 oversampled MSAs. The reduced models did not converge initially. The problem was that Denver and Miami are much smaller MSAs than New York, Los Angeles, Chicago, and Washington. In order to obtain the desired sample sizes for Denver and Miami, these two MSAs had to be oversampled at rates considerably higher than in the other four MSAs. To resolve this problem, the weights were standardized within each of the 12 random-effect groups defined by MSA and by SES stratum. This means, that within each of these groups, the sampling weights were forced to add up to the nominal sample size. This was done by simply dividing every weight by the sum of all weights for the group. This adjustment preserved the variation of weights within each group but clearly changed the variation across groups considerably.

This adjustment to the weights means that the big city estimates are no longer nearly as design consistent as the remainder estimates are, but comparisons of the model-based estimates
and the design-consistent estimates (unpublished) still show good agreement between the two, leading to the belief that the effect of these weight adjustments was fairly minor.

### 2.5 Form of the Estimator Given a Fitted Model

The population was divided into 32 domains by age, sex and a combination of race and Hispanic origin. The four age groups were 12-17, 18-25, 26-34, and over 34. The four race/ethnicity groups were white but not Hispanic, black but not Hispanic, other but not Hispanic, and Hispanic. (The "other but not Hispanic" group consists primarily of American Indians, Eskimos, and Aleuts; and Asians and Pacific Islanders.) For each behavior of interest, there were eight models covering different age groups and parts of the country as described in Section 2.4. After concatenating the predictions from the eight models, an estimated propensity to engage in a behavior of interest was available for each of 32 domains inside every one of the block groups in the 50 states and the District of Columbia. (There were about 230,000 block groups defined for the 1990 Decennial Census.)

In this report, the age domains are indexed by $a$, the sex-race/ethnicity subdomains with each age domain by $d$, the states and targeted metropolitan areas by $i$, and the block groups within each state and targeted metropolitan area by $b$. The list of targeted states and metropolitan areas is shown in Exhibit 1.2. In order to apply the fitted model, the $X$ and $Z$ matrices originally defined in Section 2.3 had to be redefined. When fitting the model, both of these matrices have one row per sample person. When applying the model, they both have one row for every domain defined by age, sex and race/ethnicity in every block group in every state of interest, whether or not the block group is in a sample PSU. Where the meaning is clear, $X$ can mean either the matrix with one row per sample person or the matrix with one row per domain per block group. Where both matrices appear in the same equation or there is a desire to stress the choice of matrix, $\boldsymbol{X} \mathbf{4 5}{ }^{\boldsymbol{*}} \boldsymbol{?}$ is used for the matrix with one row per domain per block group. The same convention is followed for the matrix $Z$. The rows of $X 45^{*}$ ? are denoted by $X_{i b}^{\text {ad }}$. Similarly, the rows of $\boldsymbol{Z} \mathbf{4 5}^{*}$ ? are denoted by $\boldsymbol{Z}_{i b}$, dropping the $a$ and the $d$ subscripts since all the rows of $\boldsymbol{Z} \mathbf{4 5}$ *? in the same block group are identical. The row vector $\boldsymbol{X}_{\boldsymbol{i b}}^{\text {ad }}$ consists of flags for the age group and domain, census data about the county, tract, and block group, and administrative data about the county as described in Section 2.2. For the remainder models, the row vector $Z_{i b}$ consists mostly of zeros with two 1 's in each row to indicate the state and PSU to which the block group belongs. For the big city models, the row vector $Z_{i b}$ has just one 1 to indicate the city and SES stratum of the block group.

Let $\beta 50{ }_{a}$ be the column vector of estimated fixed effects for the $a$-th age group and let $U 50 \wedge_{a}$ be the column vector of estimated state-level and PSU-level random effects for the $a$-th age group. Here, it is important to note that the PSU effect was taken to be zero if the PSU was not in sample. Also, to avoid conflicting predictions for the big cities, the state level random effects for states containing oversampled MSAs were actually defined as balance-of-state random effects. Finally, in order to be able to make national estimates, all the states in a region not targeted for separate estimates were combined to form a pseudo state. Each pseudo state was assigned a separate state-level random effect. Give this notation, the propensity for persons of the indicated age, sex, race and ethnicity in the indicated block group to engage in the behavior of interest was calculated as:

$$
\pi 55_{i b}^{\wedge d}=\frac{1}{\left.1+e^{-\left(X_{i b}^{a d} \beta\right.} 50{ }_{a}^{a}+Z_{i b}{ }^{U} 5 \wedge_{a}\right)^{.}} .
$$

As an example, if $\pi \underset{i b}{55}{ }_{i b}^{\text {ad }}=0.1$, this means that the model predicts that 10 percent of these people are likely to engage in the behavior of interest.

Using data from Claritas (a private firm specializing in current demographic data), the number of people in the specified area who have the indicated demographic characteristics was estimated. Let $N_{i b}^{a d}$ be that estimated population size. Then the estimated number of people in that block group who engaged in the behavior of interest at the midpoint of the 1991-1993 period is $N_{i b}^{a d} \pi 5_{i b}^{a d}$.

By summing this number up across all the block groups in the $i$-th area, a state/local estimate of the number of people in the age-sex-race-ethnicity domain $a d$ who engaged in the behavior of interest at that time is obtained. By summing further on $i$, regional and national estimates are obtained for the domain $a d$. Summing alternatively on $b, d$, and $a$, one can obtain small area estimates for all ages, sexes, races, and ethnic groups combined.

Using formulas, the average rate of engaging in the behavior of interest in the $i$ th small area is estimated to be

$$
\pi 55 \wedge_{i}^{W}=\frac{\sum_{a d} \sum_{b} N_{i b}^{a d} \pi 5_{i b}^{a d}}{\sum_{a d} \sum_{d} N_{i b}^{a d}} .
$$

Similarly, the average rate of engaging in the behavior of interest in the $d$-th subdomain of the $a$-th age group is

$$
\pi 55 \wedge_{a d}^{W}=\frac{\sum_{i} \sum_{b} N_{i b}^{a d} \pi 5_{i b}^{a d}}{\sum_{i} \sum_{b} N_{i b}^{a d}} .
$$

### 2.6 Estimating Variance

The estimated prevalence rate for the $i$-th state or other small area is

## Error!

where $a$ indexes the four age domains for which separate models were run, $d$ indexes the eight race/ethnicity by gender domains which were modeled by fixed effects in $\beta 55{ }_{a}$, $b$ indexes block groups within the area, $N_{i b}^{a d}$ is the domain-ad population of the indicated block group, $X_{i b}^{\text {ad }}$ is the row vector of characteristics of the fixed predictor variables for the block group, $Z_{i b}$ is the row vector of flag variables for the block group that indicated which random effects apply, and $\beta 55{ }_{a}$ and $U_{a}$ are the vectors of fixed and random effects peculiar to the model for age group $a$.

This is clearly a nonlinear estimator for which one can only hope to approximate the variance. First the types of errors that need to be reflected must be conceptualized. As discussed in Section 1.4, one could be interested in variability and bias across replications of the survey, across possible manifestations of the population, etc. In the empirical Bayes approach, there are three random events that determine each person's propensity to engage in a behavior of interest. The first is a random event at the state level that determines the $U_{\mathrm{i}}$ component of the person's propensity. The second is a random event at the PSU level that determines the $U_{\mathrm{ij}}$ component of the person's propensity. The third is the flip of the biased coin that decides whether or not the person will actually engage in the behavior, where the probability of "heads" on the coin is equal to the person's realized propensity given their PSU, state, and background variables.

If $\pi_{i b}^{a d}$ is interpreted as the uniform propensity for persons in domain ad, block group $b$, and state $i$ to engage in the behavior, interest focuses on how closely the estimate $\pi_{i}^{W}$ is expected to track the average of these propensities

$$
\pi_{i}=\frac{\sum_{a d} \sum_{b} N_{i b}^{a d} \pi_{i b}^{a d}}{\sum_{a} \sum_{d} \sum_{b} N_{i b}^{a d}}
$$

across all possible outcomes of the three variables across all members of the population; that is, it was decided to estimate $E\left(\pi_{i}^{W}-\pi_{i}\right)^{2}$, where both $\pi_{i}^{W}$ and $\pi_{i}$ are random variables and the expectation is with respect to the posterior distributions of $\pi_{i}^{W}$ and $\pi_{\mathrm{i}}$ given the observed data.

It was decided not to try to reflect any extra variation in ( $\pi_{i}^{W}-\pi_{i}$ ) across all possible samples of a fixed population caused by the segment and household-level clustering in the sample design. That is, of course, of some concern for a hybrid method that incorporates design-based weights in the Bayesian approach, but there would be severe technical difficulties in trying to reflect that extra variation.

Also for reasons of technical difficulty, it was decided not to reflect the extra variation in ( $\pi_{i}^{W}-\pi_{i}$ ) caused by the estimation of $\sigma_{1}^{2}$ and $\sigma_{2}^{2}$, the components of variance. Instead, the mean was calculated as if $\sigma_{1}^{2}=\sigma_{1}^{2}$ and $\sigma_{2}^{2}=\sigma_{2}^{2}$ were fixed and known. This is not the desired procedure from a Bayesian viewpoint but seems to be unavoidable in the empirical Bayes approach. The magnitude of the error in estimating $E\left(\pi_{i}^{W}-\pi_{i}\right)^{2}$ caused by treating $\sigma_{1}^{2}$ and $\sigma_{2}^{2}$ as fixed is unknown, but some discussion in Appendix $G$ indicates that the underestimation of $\sqrt{\left(\pi_{i}^{W}-\pi_{i}\right)^{2}}$ could be in the range of 5 to 20 percent.

Another technical difficulty prevented reflection of the fact that $\operatorname{Cov}\left(\pi_{i b}^{a d},,_{i b}^{a^{\prime d}}\right) \neq 0$ for $a \neq a^{\prime}$. Computing constraints required that this covariance be treated as zero. Since these covariances will generally be positive, this problem also led to the underestimation of $E\left(\pi_{i}^{W}-\pi_{i}\right)^{2}$ . Again, the magnitude of the underestimation is unknown.

Perhaps most seriously, the overfitting discussed in Chapter 3 probably led to underestimation of the variance. The link between overfitting a model and underestimation of model error can perhaps best be understood with a simple extreme example. Consider the linear regression of a single continuous variable on $n$ independent binary variables with a total sample size of $n$ cases. Suppose further that all the predictor variables are independent of the continuous variable. In this case, the model fit will be perfect even though the predictor variables have no predictive value. Estimated model error will be zero. Actual prediction error will equal the variance of the continuous variable. Nothing that extreme was done on this project, but there were hundreds of predictor variables in some of the models. The sizes of the random effects were almost certainly underestimated due to the large number of predictor variables. This then probably led to underestimation of the error in the model.

Finally, there was an error in the variance formula that affected models with two stages. Corrected variances have been calculated for some of the estimates but are not shown in this report. The impact of the correction on standard errors was small ( $0-10 \%$ ) for past month cigarette use, past month cocaine use, past month use of any illicit substances other than marijuana, and past year alcohol treatment. The impact of the correction on standard errors was moderate ( $0-30 \%$ ) for past month alcohol use and past month use of any illicit substance. Appendix I shows the original confidence intervals prior to correction of the error. For a further discussion of these issues and a detailed description of the variance estimation procedure, see Appendix G.

## 3. Evaluation

This chapter discusses the work that was done to evaluate the quality of the small area estimates. This work can best be thought of as a partial evaluation since it is difficult to evaluate the quality of estimates based upon a mixture of models and data when the phenomenon being described is never actually measured. The purpose of small area estimation methodology is to have narrow confidence intervals without paying for extensive data collection. But it is precisely that kind of data that is needed to evaluate the methodology. If the data required for a stringent evaluation were available, then there would be no need for the small area estimation program. Despite this central dilemma, three types of partial evaluation were carried out.

The first type was to compare the model-based estimates with alternate estimates for the small areas of interest. This is a popular method with a fairly long history, but it was only marginally useful for this application. The second type of partial evaluation was to compare the model-based estimates with alternate estimates for artificial domains where theoretical considerations lead one to believe that agreement between the methods should be good. This method yielded more information, particularly for the more common behaviors of interest such as alcohol use, but is still subject to serious caveats. The third type of partial evaluation was to compare the model-based estimates with data from other federal data systems for the small areas of interest. Comparisons of this type are, of course, interesting, but methodological differences between the data systems make these comparisons difficult to interpret.

None of the three types of partial evaluation were very conclusive by themselves. The summary report for this study (SAMHSA, 1996) found that the joint preponderance of evidence favored the survey-weighted empirical Bayes approach over the alternatives and that for most of the estimates developed, there was evidence that the estimates adequately reflect the prevalence of substance abuse characteristics for States and MSAs. Upon further review of the evaluation methodology, it appears that some of the evaluation findings in the summary report should perhaps have been somewhat less definitive. The basic conclusions have not changed, but they are slightly more tentative in this report.

Another result of the methodology review has been some discussion of what could have been learned from a well crafted simulation study. In favor of the simulation study approach, it might be argued that the central reasons for using the survey-weighted empirical Bayes procedure were that it was thought to provide: (1) estimates with smaller errors than the design-based methods, (2) better error estimates than methods based only on fixed effect models, (3) better consistency with national estimates than could be achieved through the use of mixed models
without survey weights, and (4) computational savings relative to a fully Bayesian or maximum likelihood approach. The evaluation work presented in this report does not address any of these points. At this time, it is strongly suspected but unproven that the first two assertions are true. The third assertion appears to be true on theoretical grounds alone, but the magnitude of the improvement associated with using the weights is unmeasured. The fourth assertion appears to be subject to change as the methodology for each approach improves with additional research.

The central questions from the users' point of view are whether the prediction intervals really are nearly certain to include the truth and whether the intervals are short enough to be useful. Only the user can determine whether the intervals are short enough to be useful to them, but the quality of the coverage of the prediction intervals is an open question that needs additional research. A computer simulation study would address this question directly. This point is discussed further in Section 3.4.

### 3.1 Comparisons with Alternate Estimates for the Small Areas of Interest

Estimates based on different models were compared to see whether theories about the properties of the various models are borne out. Specifically, there was interest to see (1) if the survey-weighted empirical Bayes estimates for California would agree better with the design-based estimates for that state and (2) how the dispersion of the state estimates varied by method. California was of interest because the very large sample size of 12,000 people in California makes the design-based estimate the most believable estimate for that state.

Regarding dispersion, it was expected that estimates based upon the leanest fixed-effect model would have the most compressed dispersion. Estimates based upon a mixed model were expected to have broader dispersion but not as broad as the design-based estimates. If there had been a fixed effect model with broader dispersion of state estimates from the national average than what was observed with a mixed model or even with the design-based estimates, then this would have constituted strong evidence that the fixed effect model had been overfit.

The estimates from the different models were not compared with the idea of deciding which set was best in some sense. Other workers in the field of small area estimation have used comparisons of this type to try to decide which set is best, but there are some serious problems with that approach that are discussed in detail in Appendix H. Very briefly, the standard definition of the best small area estimator is usually stated in terms of design-based mean square
error. By definition, the design-based mean square error of an arbitrary estimator $\pi_{i}$ is $\operatorname{MSE}_{\mathrm{D}}\left(\pi_{i}\right)=\operatorname{Var}_{\mathrm{D}}\left(\pi_{i}\right)+\operatorname{Bias}_{\mathrm{D}}^{2}\left(\pi_{i}\right)$. The design-based estimates have large variance and almost no bias. Estimates based upon a lean fixed-effects model have very small variance and large bias. Composite estimates have average variance and bias. Estimates based upon mixed-effect models also have average variance and bias and can be applied to areas with no sample in them. Furthermore, procedures exist for estimating errors based upon mixed models that appear to have better validity than those based upon fixed effect models. Design-based variances can be estimated for each of the methods, but estimation of the design-based bias is not possible for composite estimates nor for estimates based upon mixed effect models. With no way to estimate the bias of these estimators, it is impossible to decide which of them is best. It was for this reason that the various estimates were compared across the small domains of interest primarily to see whether the expected dispersion patterns were realized.

## Results

Exhibit 3.1 contrasts different estimators of past month alcohol use. Exhibits 3.2, 3.3 and 3.4 do the same for past month cigarette use, past year drug treatment, and past year arrest. The first column of estimates are the design-based estimates for the 26 states with nontrivial NHSDA samples in them. Recall from Section 1.3 that these estimates are unstable and vary too much across the states. The second column of estimates shows the results of using mixed-effect models with survey weighting. As desired, the mixed models compressed the dispersion of the state estimates. The range, the standard deviation and the interquartile range are all smaller for all four behaviors examined in the four exhibits.

If the random effects are removed but all the same fixed effects are kept as in the full mixed model, then the state estimates are equal to the statistics shown in the third column of estimates. For most behaviors and measures of dispersion, using a fixed effect model instead of a mixed effect model results in greater compression of the dispersion across the states, as expected.

The next three columns of estimates show the results of applying three different fixed effect models. The fixed effect model with only county and demographic effects does not contain any tract level and block group level summary variables, but does include some additional

## Exhibit 3.1 Relationship of Survey-Weighted Empirical Bayes Estimates of Past Month Alcohol Consumption to Design-Based Estimates <br> and <br> Estimates Based on Fixed Effect Models

|  | Design- <br> Based <br> NHSDA <br> 1991-1993 | Survey- <br> Weighted <br> Empirical <br> Bayes <br> (Mixed <br> Model) | Estimators Based on Fixed Models |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | Same Fixed Effects as in Mixed Model | County and Demographic Effects Only | Separate <br> Demographic <br> Effects for Big <br>  <br> Remainder | Demographic Effects Only |
| Total United States | 53.01 | 53.46 | 53.43 | 53.01 | 53.41 | 53.40 |
| California | 57.69 | 56.67 | 58.07 | 56.05 | 53.08 | 52.55 |
| Florida | 49.67 | 48.45 | 48.52 | 49.75 | 52.43 | 52.78 |
| Georgia | 48.78 | 48.57 | 48.21 | 47.48 | 52.28 | 52.78 |
| Illinois | 55.73 | 54.43 | 55.26 | 55.48 | 55.18 | 53.27 |
| Indiana | 44.95 | 47.70 | 52.40 | 52.36 | 54.07 | 54.65 |
| Kansas | 60.82 | 56.51 | 54.33 | 56.40 | 54.10 | 54.60 |
| Kentucky | 32.03 | 41.18 | 44.26 | 40.97 | 54.18 | 54.79 |
| Louisiana | 56.62 | 49.40 | 44.13 | 44.66 | 51.53 | 52.02 |
| Michigan | 58.26 | 56.08 | 55.23 | 54.44 | 53.33 | 53.86 |
| Minnesota | 64.96 | 63.32 | 57.06 | 56.56 | 54.74 | 55.29 |
| Missouri | 44.10 | 54.04 | 52.22 | 54.71 | 53.49 | 54.07 |
| New Jersey | 61.10 | 59.94 | 62.03 | 60.32 | 52.62 | 52.91 |
| New Mexico | 56.21 | 53.98 | 51.57 | 57.40 | 52.41 | 51.88 |
| New York | 56.96 | 57.04 | 56.60 | 56.51 | 53.60 | 52.52 |
| North Carolina | 43.04 | 46.73 | 48.17 | 46.44 | 52.49 | 53.01 |
| Ohio | 50.45 | 52.24 | 53.18 | 55.30 | 53.56 | 54.14 |
| Oklahoma | 36.50 | 39.81 | 44.02 | 44.22 | 52.84 | 53.16 |
| Oregon | 59.72 | 55.95 | 54.83 | 59.81 | 53.97 | 54.45 |
| Pennsylvania | 52.70 | 55.82 | 53.75 | 55.90 | 53.39 | 53.96 |
| South Carolina | 47.03 | 46.84 | 46.67 | 41.34 | 51.83 | 52.36 |
| Tennessee | 35.76 | 40.70 | 45.10 | 39.07 | 53.06 | 53.65 |
| Texas | 55.23 | 52.88 | 48.80 | 50.07 | 53.10 | 53.06 |
| Virginia | 48.16 | 51.21 | 52.28 | 47.34 | 54.18 | 53.42 |
| Washington | 59.55 | 58.33 | 57.32 | 59.97 | 54.05 | 54.43 |
| West Virginia | 38.41 | 38.61 | 39.48 | 38.58 | 53.99 | 54.63 |
| Wisconsin | 67.92 | 59.15 | 55.95 | 56.31 | 54.38 | 54.94 |
| Range | 35.9 | 24.7 | 22.6 | 21.7 | 3.7 | 3.4 |
| Standard Deviation | 9.4 | 6.6 | 5.4 | 6.8 | 0.9 | 1.0 |
| Interquartile Range | 12.6 | 8.5 | 7.1 | 9.7 | 1.4 | 1.6 |
| Correlation with |  |  |  |  |  |  |
| Design-Based | -- | 0.917 | 0.769 | 0.769 | 0.172 | 0.020 |
| Rank Correlation with Design-Based | -- | 0.916 | 0.804 | 0.835 | 0.212 | 0.063 |

Exhibit 3.2 Relationship of Survey-Weighted Empirical Bayes Estimates of Past Month Cigarette Use to Design-Based Estimates and Estimates Based on Fixed Effect Models

|  | Design- <br> Based <br> NHSDA <br> 1991-1993 | Survey- <br> Weighted <br> Empirical <br> Bayes <br> (Mixed <br> Model) | Estimators Based on Fixed Models |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | Same Fixed Effects as in Mixed Model | County and Demographic Effects Only | Separate <br> Demographic <br> Effects for Big <br>  <br> Remainder | Demographic Effects Only |
| Total United States | 27.66 | 27.16 | 27.68 | 27.73 | 27.49 | 27.43 |
| California | 25.52 | 24.35 | 24.97 | 25.81 | 26.35 | 26.70 |
| Florida | 26.34 | 25.75 | 27.29 | 26.62 | 27.15 | 27.03 |
| Georgia | 28.41 | 28.55 | 28.81 | 29.18 | 28.59 | 28.14 |
| Illinois | 27.40 | 27.87 | 27.01 | 27.15 | 26.15 | 27.54 |
| Indiana | 24.65 | 26.04 | 28.20 | 28.13 | 28.14 | 27.77 |
| Kansas | 24.55 | 25.78 | 27.69 | 27.17 | 27.95 | 27.54 |
| Kentucky | 34.97 | 33.74 | 31.17 | 29.55 | 28.15 | 27.78 |
| Louisiana | 24.21 | 27.90 | 30.75 | 29.35 | 28.55 | 28.09 |
| Michigan | 29.45 | 28.78 | 29.89 | 29.41 | 28.26 | 27.84 |
| Minnesota | 25.42 | 24.16 | 26.30 | 28.99 | 28.11 | 27.70 |
| Missouri | 27.53 | 26.76 | 28.29 | 28.25 | 28.08 | 27.68 |
| New Jersey | 25.43 | 26.08 | 26.24 | 26.37 | 27.75 | 27.25 |
| New Mexico | 28.56 | 30.67 | 27.29 | 28.02 | 26.61 | 26.02 |
| New York | 24.18 | 25.13 | 26.57 | 26.06 | 26.10 | 27.24 |
| North Carolina | 30.49 | 28.26 | 28.69 | 28.59 | 28.43 | 27.97 |
| Ohio | 31.80 | 31.18 | 29.26 | 29.10 | 28.16 | 27.77 |
| Oklahoma | 25.85 | 29.00 | 31.09 | 29.36 | 27.87 | 27.20 |
| Oregon | 25.20 | 27.11 | 28.59 | 27.42 | 27.65 | 27.20 |
| Pennsylvania | 30.06 | 28.56 | 28.47 | 28.24 | 27.92 | 27.53 |
| South Carolina | 30.38 | 31.00 | 30.61 | 29.76 | 28.61 | 28.17 |
| Tennessee | 31.39 | 31.44 | 30.33 | 30.44 | 28.22 | 27.82 |
| Texas | 27.51 | 28.38 | 27.16 | 26.74 | 27.54 | 27.11 |
| Virginia | 28.14 | 26.49 | 27.16 | 27.81 | 27.47 | 27.98 |
| Washington | 25.00 | 25.16 | 27.33 | 28.27 | 27.92 | 27.37 |
| West Virginia | 34.39 | 32.67 | 31.58 | 29.50 | 27.75 | 27.40 |
| Wisconsin | 27.98 | 24.94 | 27.13 | 28.21 | 28.03 | 27.63 |
| Range | 10.8 | 9.6 | 6.6 | 4.6 | 2.5 | 2.2 |
| Standard Deviation | 3.0 | 2.6 | 1.8 | 1.2 | 0.7 | 0.5 |
| Interquartile Range | 4.5 | 3.1 | 2.6 | 2.1 | 0.6 | 0.6 |
| Correlation with |  |  |  |  |  |  |
| Design-Based | -- | 0.844 | 0.584 | 0.583 | 0.287 | 0.244 |
| Rank Correlation with Design-Based | -- | 0.762 | 0.508 | 0.575 | 0.340 | 0.329 |

Exhibit 3.3 Relationship of Survey-Weighted Empirical Bayes Estimates of Past Year Drug Treatment to Design-Based Estimates and Estimates Based on Fixed Effect Models

|  | Design- <br> Based <br> NHSDA <br> 1991-1993 | Survey- <br> Weighted <br> Empirical <br> Bayes <br> (Mixed <br> Model) | Estimators Based on Fixed Models |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | Same Fixed Effects as in Mixed Model | County and Demographic Effects Only | Separate <br> Demographic <br> Effects for Big <br>  <br> Remainder | Demographic Effects Only |
| Total United States | 0.62 | 0.70 | 0.70 | 0.68 | 0.65 | 0.64 |
| California | 1.04 | 0.97 | 0.92 | 0.77 | 0.65 | 0.65 |
| Florida | 0.47 | 0.69 | 0.73 | 0.69 | 0.60 | 0.60 |
| Georgia | 0.75 | 0.71 | 0.71 | 0.70 | 0.70 | 0.70 |
| Illinois | 0.46 | 0.54 | 0.59 | 0.53 | 0.63 | 0.65 |
| Indiana | 0.53 | 0.52 | 0.53 | 0.63 | 0.64 | 0.64 |
| Kansas | 0.48 | 0.66 | 0.66 | 0.63 | 0.63 | 0.63 |
| Kentucky | 0.41 | 0.57 | 0.57 | 0.66 | 0.63 | 0.63 |
| Louisiana | 0.35 | 0.64 | 0.66 | 0.61 | 0.70 | 0.70 |
| Michigan | 0.85 | 0.76 | 0.77 | 1.01 | 0.66 | 0.65 |
| Minnesota | 0.59 | 0.84 | 0.82 | 0.54 | 0.64 | 0.63 |
| Missouri | 0.78 | 0.70 | 0.64 | 0.79 | 0.63 | 0.63 |
| New Jersey | 0.42 | 0.68 | 0.68 | 0.67 | 0.64 | 0.63 |
| New Mexico | 0.25 | 0.77 | 0.80 | 0.76 | 0.64 | 0.61 |
| New York | 0.68 | 0.64 | 0.60 | 0.67 | 0.62 | 0.64 |
| North Carolina | 0.58 | 0.64 | 0.66 | 0.85 | 0.68 | 0.68 |
| Ohio | 0.34 | 0.70 | 0.70 | 0.66 | 0.64 | 0.64 |
| Oklahoma | 0.60 | 0.86 | 0.88 | 0.71 | 0.66 | 0.63 |
| Oregon | 0.69 | 0.90 | 0.88 | 0.80 | 0.60 | 0.59 |
| Pennsylvania | 0.45 | 0.56 | 0.60 | 0.62 | 0.62 | 0.62 |
| South Carolina | 0.39 | 0.53 | 0.54 | 0.79 | 0.69 | 0.70 |
| Tennessee | 0.27 | 0.60 | 0.60 | 0.62 | 0.65 | 0.65 |
| Texas | 0.65 | 0.61 | 0.66 | 0.68 | 0.66 | 0.65 |
| Virginia | 0.47 | 0.65 | 0.66 | 0.63 | 0.67 | 0.69 |
| Washington | 0.61 | 0.85 | 0.89 | 0.73 | 0.65 | 0.63 |
| West Virginia | 0.49 | 0.49 | 0.47 | 0.42 | 0.59 | 0.59 |
| Wisconsin | 0.19 | 0.61 | 0.63 | 0.50 | 0.63 | 0.62 |
| Range | 0.9 | 0.5 | 0.5 | 0.6 | 0.1 | 0.1 |
| Standard Deviation | 0.2 | 0.1 | 0.1 | 0.1 | 0.0 | 0.0 |
| Interquartile Range | 0.2 | 0.1 | 0.2 | 0.1 | 0.0 | 0.0 |
| Correlation with |  |  |  |  |  |  |
| Design-Based | -- | 0.536 | 0.446 | 0.509 | 0.065 | 0.070 |
| Rank Correlation with Design-Based | -- | 0.472 | 0.391 | 0.509 | 0.037 | 0.131 |

## Exhibit 3.4 Relationship of Survey-Weighted Empirical Bayes Estimates of Past Year Arrest to Design-Based Estimates and Estimates Based on Fixed Effect Models

|  | Design- <br> Based <br> NHSDA <br> 1991-1993 | Survey- <br> Weighted <br> Empirical <br> Bayes <br> (Mixed <br> Model) | Estimators Based on Fixed Models |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | Same Fixed Effects as in Mixed Model | County and Demographic Effects Only | Separate <br> Demographic <br> Effects for Big <br>  <br> Remainder | Demographic Effects Only |
| Total United States | 1.57 | 1.64 | 1.62 | 1.66 | 1.61 | 1.60 |
| California | 1.90 | 1.90 | 1.68 | 1.74 | 1.58 | 1.65 |
| Florida | 1.66 | 1.54 | 1.48 | 1.72 | 1.50 | 1.51 |
| Georgia | 2.50 | 2.57 | 2.04 | 1.99 | 1.91 | 1.80 |
| Illinois | 1.35 | 1.58 | 1.46 | 1.56 | 1.38 | 1.62 |
| Indiana | 2.68 | 2.29 | 1.88 | 1.73 | 1.64 | 1.57 |
| Kansas | 2.46 | 2.37 | 1.84 | 1.73 | 1.62 | 1.55 |
| Kentucky | 1.31 | 1.59 | 1.69 | 1.77 | 1.63 | 1.57 |
| Louisiana | 1.47 | 2.26 | 2.14 | 2.06 | 1.89 | 1.78 |
| Michigan | 1.41 | 1.89 | 1.97 | 1.76 | 1.69 | 1.62 |
| Minnesota | 1.75 | 1.50 | 1.70 | 2.01 | 1.58 | 1.52 |
| Missouri | 1.70 | 1.83 | 1.91 | 1.69 | 1.61 | 1.54 |
| New Jersey | 1.18 | 1.18 | 1.23 | 1.26 | 1.63 | 1.55 |
| New Mexico | 1.79 | 2.43 | 2.02 | 1.87 | 1.65 | 1.54 |
| New York | 0.66 | 1.18 | 1.16 | 1.05 | 1.40 | 1.59 |
| North Carolina | 1.46 | 1.70 | 1.95 | 2.21 | 1.82 | 1.73 |
| Ohio | 2.03 | 2.07 | 1.96 | 1.81 | 1.63 | 1.56 |
| Oklahoma | 2.07 | 1.27 | 1.52 | 1.79 | 1.54 | 1.47 |
| Oregon | 1.67 | 1.70 | 1.66 | 1.55 | 1.46 | 1.41 |
| Pennsylvania | 1.07 | 1.21 | 1.26 | 1.19 | 1.56 | 1.50 |
| South Carolina | 1.15 | 1.71 | 1.90 | 1.66 | 1.91 | 1.80 |
| Tennessee | 1.10 | 2.07 | 1.60 | 1.54 | 1.69 | 1.61 |
| Texas | 1.92 | 1.77 | 1.68 | 2.03 | 1.85 | 1.73 |
| Virginia | 1.31 | 1.40 | 1.60 | 1.77 | 1.67 | 1.73 |
| Washington | 1.21 | 1.51 | 1.77 | 1.60 | 1.56 | 1.50 |
| West Virginia | 1.75 | 1.17 | 1.35 | 1.74 | 1.47 | 1.42 |
| Wisconsin | 1.91 | 1.29 | 1.74 | 1.95 | 1.60 | 1.54 |
| Range | 2.0 | 1.4 | 1.0 | 1.2 | 0.5 | 0.4 |
| Standard Deviation | 0.5 | 0.4 | 0.3 | 0.3 | 0.1 | 0.1 |
| Interquartile Range | 0.6 | 0.6 | 0.4 | 0.2 | 0.1 | 0.1 |
| Correlation with |  |  |  |  |  |  |
| Design-Based | -- | 0.560 | 0.468 | 0.545 | 0.178 | -0.043 |
| Rank Correlation with Design-Based | -- | 0.445 | 0.413 | 0.587 | 0.080 | -0.079 |

county-level variables, particularly those associated with NDATUS and UCR (as described in Section 2.2). This model is interesting since it is less work to construct models with only county-level variables. Looking across the four tables, it appears that this model sometimes produced greater compression than the full fixed model and sometimes less. On balance, it does not appear that dropping tract and block group variables causes much, if any, stronger compression of the dispersion across the states than using the full fixed model (although of course the compression is stronger than using the full mixed model). This leads to the idea that perhaps for future applications, it would be satisfactory to use a mixed model where the only geographic fixed-effects were at the county level.

The fifth column shows the results from using a fixed effect model that includes only demographic effects except for one set of effects for the six oversampled metropolitan areas and a second set of effects for the remaining areas. This model resulted in very strong compression of the range and a rank correlation with the design-based estimates approaching zero. The simplest model with only demographic fixed effects was even worse.

Another estimator that would have been interesting to include in the tables is the design-consistent logistic regression estimator. The survey-weighted empirical Bayes estimates are asymptotically approximate composites of the estimates from the full fixed effect model with design-consistent logistic regression estimators. Thus, it is expected that the survey-weighted empirical Bayes estimates would lie between the other two. It is noted that while the survey-weighted empirical Bayes estimates frequently lie between the estimates from the full fixed effect model and the design consistent expansion estimators (simple Horwitz-Thompson estimates with some post-stratification), this is not always the case.

It is obvious from these tables that the survey-weighted empirical Bayes estimator performs at least some of the required compression of the dispersion across the states, but does it more lightly than is possible to do with a fixed-effect model. The correlations and rank correlations across the states indicate that using the modeling did change the ordering compared to using the design-based approach. The strength of the impact varies considerably across the behaviors examined. While it is hoped that the rank ordering was improved through the use of modeling, these tables do not contain adequate information to make such a judgment.

One could intently study the complete set of individual state statistics and try to make sense of them individually, but there is no statistical basis to support such analysis. For example, estimates of past-month alcohol use in Tennessee vary from $35.76 \%$ to $53.65 \%$. Which is best? Even if individual estimates were determined to be bad in some sense, there
would still be the possibility that the bad value was a fluke and that on average, the method does provide better estimates than the alternatives.

The only state where it makes sense to look at the individual values is California. The California sample size was over 12,000 people, so the design-based estimates are quite reliable. Exhibit 3.5 highlights the comparisons of the California estimates. Note that an RSE is shown only for the design-based estimates. While all the columns are subject to sampling error, and the columns are correlated with each other (making testing of differences for statistical significance difficult), the RSE at least helps place the relative deviations of the model-based estimates in perspective. The full mixed model does best for arrest and drug treatment. It also is almost the best for alcohol use. It is just as bad for cigarette use as the simple fixed model with only demographic effects. The reason for this is not clear. On average, the full mixed model provides the closest agreement with the design-based estimates for California, as expected given the large sample size in California.

Comparisons of the national estimates are highlighted in Exhibit 3.6. Although the agreement between the survey-weighted empirical Bayes estimates and the design-based estimates at the national level are generally satisfactory, the agreement is not as close as was hoped would be the case, particularly for drug treatment in the past year. Even though the survey-weighted mixed model gives better consistency with design-based estimates at the national level than could be obtained with an unweighted mixed model, the consistency is not as good as can be obtained with a weighted fixed model. (The fixed models were weighted, so they are design consistent.) The problem is that even though the number of sample people is large, the number of sample PSUs is fairly small.

### 3.2 Comparison with Alternate Estimates for Artificial Domains

The second type of partial evaluation that was done was to compare the estimates from the survey-weighted empirical Bayesian method with alternative estimates on artificial domains where good agreement was expected. The idea behind this approach was that all good methods should produce similar estimates for large homogenous domains, where a homogenous domain is defined to be a group of people all of whom have the same propensity to engage in the behavior of interest. However, the study did not attempt to identify naturally occurring large homogenous domains upon which this theory could be tested. Instead, an idea due to Lemeshow and Hosmer (1982) was adapted to this application to create artificial domains that were large and expected to be fairly homogenous.

Exhibit 3.5 California Estimates

|  | Design- <br> Based <br> NHSDA <br> 1991-1993 | RSE on Design-B ased | Survey- <br> Weighted <br> Empirical Bayes <br> (Mixed Model) | lative Deviation from Design Based |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  | Same Fixed <br> Effects as in <br> Mixed <br> Model | stimators Base <br> County and Demographic Effects Only | on Fixed Effect <br> Separate <br> Demographic <br> Effects for Big <br>  <br> Remainder | odels <br> Demographic Effects Only |
| Alcohol use | 57.69 | 1\% | -2\% | 1\% | -3\% | -8\% | -9\% |
| Cigarette use | 25.52 | 2\% | -5\% | -2\% | 1\% | 3\% | 5\% |
| Any illicit | 8.43 | 3\% | -2\% | -7\% | -14\% | -31\% | -32\% |
| Any illicit but marijuana | 3.96 | 4\% | -1\% | -13\% | -8\% | -36\% | -36\% |
| Drug treatment | 1.04 | 9\% | -7\% | -12\% | -26\% | -38\% | -38\% |
| Arrest | 1.90 | 7\% | 0\% | -12\% | -8\% | -17\% | -13\% |
| Average relative deviation |  |  | -3\% | -7\% | -10\% | -21\% | -21\% |

Exhibit 3.6 U.S. Estimates


3-10
deviation $1 \quad 1 \quad 1 \quad 1$

This methodology exploits the fact that as a result of fitting logistic regressions, each sample person in the three years of the NHSDA that were used to fit the models has a predicted propensity to exhibit the behavior of interest (e.g., smoke cigarettes, need treatment for substance abuse, etc.). By sorting the sample persons by the predicted propensity as in Exhibit 3.7, and then cutting the list into a fairly small number of contiguous pieces of equal size, it should be possible to develop a partition that meets the desired criteria of large groups that are internally homogenous. Note that these groups don't represent any specific area or demographic domain; rather, each consists of people who, according to a model, have similar propensities to exhibit the characteristic of interest.

This methodology was used to partition the sample population into $L$ mutually exclusive and exhaustive groups of equal size, each with a distinct average estimated propensity to exhibit the behavior of interest. According to the model used to create the partition, it is impossible to partition the sample into equal sized groups in a manner that would result in greater homogeneity within each group. The groups were ordered by increasing estimated propensity and indexed by d.

It was not expected that the various methods would agree exactly on each group due to variance on the estimates. A test was developed to determine whether the observed differences between the design-based estimates and each of the alternative estimators were significant. Two measures of agreement were also developed -- a correlation coefficient and a ratio of ranges. The construction of the test and measures of agreement is discussed in Section 3.2.1. The statistical properties of these statistics on the full sample are discussed in Section 3.2.2. Their properties on cross-validation samples are discussed in Section 3.2.3. The results of applying this method are presented in Section 3.2.4.

### 3.2.1 Construction of the Test and Measures of Agreement

Let $\pi_{d}^{F}, \pi_{d}^{M}, \pi_{d}^{W}$, and $\pi_{d}^{D}$ be fixed-effect model estimates, mixed effect model estimates, survey-weighted empirical Bayes estimates, and design consistent estimates for the $d$-th large homogenous group. These were calculated as

$$
\pi_{d}^{F}=\frac{\sum_{i \in d} w_{i} \pi_{i}^{F}}{\sum_{i \in d} w_{i}} \quad \pi_{d}^{D}=\frac{\sum_{i \in d} w_{i} y_{i}}{\sum_{i \in d} w_{i}}
$$

where $\pi_{i}^{F}$ is the propensity to engage in the behavior of interest predicted by a fixed model for the $i$-th sample person and $y_{i}$ is a binary flag indicating whether or not the person reported engaging in the behavior of interest. The average group propensities $\pi_{d}^{M}$ and $\pi_{d}^{W}$ were calculated analogously to $\pi_{d}^{F}$. Let $\left.\pi 50 \sim\right\}^{F}$ be the vector of the $L$ estimated average propensities from the fixed model. The propensity vectors $\left.\pi 50 \sim\}^{M}, \pi 50 \sim\right\}^{W}$, and $\left.\pi 50 \sim\right\}^{D}$ were defined similarly.

The test for agreement between the estimates from the fixed effect model with the design-based estimates was calculated as

$$
\left.\left.\left.\left.T=(\pi 50 \sim\}^{F}-\pi 50 \sim\right\}^{D}\right)^{〔} \Psi^{-1}(\pi 50 \sim\}^{F}-\pi 50 \sim\right\}^{D}\right),
$$

where

$$
\left.\left.\left.\left.\left.\left.\Psi=\operatorname{Var}(\pi 50 \sim\}^{F}-\pi 50 \sim\right\}^{D}\right)=\mathrm{E}(\pi 50 \sim\}^{F}-\pi 50 \sim\right\}^{D}\right)^{t}(\pi 50 \sim\}^{F}-\pi 50 \sim\right\}^{D}\right) .
$$

The tests for comparing the survey-weighted empirical Bayes estimates with the design-based estimates were constructed similarly. Tests of this form are called Wald tests. The details of how the variance-covariance matrix was calculated are given in Appendix G, Section G.4. Under assumptions that appear fairly reasonable, $T$ has a chi-square distribution with about L degrees of freedom under the null hypothesis that the two sets of estimates are in good agreement with each other. The power of this test is only fair, with about 40 degrees of freedom for alcohol use and cigarette use and about 20 degrees of freedom for the other behaviors. Also, there were many replications of the test for different behaviors and age groups. Accordingly, attention did not focus on just whether any p-values below 0.05 were found. While a p-value below 0.05 is certainly strong evidence that the model does not fit the data, a preponderance of p -values below 0.5 would also indicate problems with the model. This can be seen by noting that if the two sets of estimates were in good agreement, p-values for the test should be randomly spread across the interval from zero to one with an expected value of 0.50 . Small p-values would indicate that the two estimators do not have the same expected values even for large homogenous domains, a finding that would be troubling. However, there are some difficulties in the interpretation of $T$ as are discussed further in the next section.

The correlation of the estimates from the fixed model with the design-based estimates was calculated as

$$
\rho^{F}=\frac{\sum_{d=1}^{L}\left(\pi_{d}^{F}-\pi_{d}^{D}\right)^{2}}{\sqrt{\sum_{d=1}^{L}\left(\pi_{d}^{F}-\pi 45^{F}\right)^{2}} \sqrt{\sum_{d=1}^{L}\left(\pi_{d}^{D}-\pi 45^{D}\right)^{2}}} .
$$

Similar definitions were used for $\rho^{M}$ and $\rho^{W}$. The initial idea was that large correlations would indicate that the model fit the data well and that smaller correlations would indicate a less satisfactory fit. This correlation coefficient is a descriptive measure of model fit in the spirit of the multiple $\mathrm{R}^{2}$ of linear regression. Since the design-based estimates are subject to more sampling error than the model-based alternatives, one would expect the correlations to be less than one even when the model fits. For this reason, there is uncertainty regarding how small the correlation should be to suggest serious lack of fit.

Let $R^{F}$ equal the observed range of $\pi_{1}^{F}$ to $\pi_{L}^{F}$. The ranges $R^{M}, R^{W}$, and $R^{D}$ were calculated comparably. The range ratio for the fixed model relative to the design-based estimates was defined to be $R^{F} / R^{D}$. The range ratios for the mixed model and for the survey weighted empirical Bayes method were defined similarly. The initial idea was that range ratios close to one would indicate that the model fit the data well and that smaller or larger range ratios would indicate a less satisfactory fit. However, further review of this methodology has raised some questions about the interpretation of small range ratios when the variance of the characteristic under consideration across the domains is not large relative to the variance within the domains. (Since the domains were formed to be fairly internally homogenous, one would expect strong heterogeneity across the domains, but the degree of heterogeneity across the domains depends on the strength of the predictors in the model.) When the heterogeneity across groups is not large relative to the within-domain sampling variance, the design-based estimates will be overdispersed, resulting in a value of $R^{D}$ that will tend to be larger than the true range. Since estimates based on a good model are designed to correct the overdispersion of the design-based estimates, it is not clear how much less than one the range ratio can be before serious lack of fit is suggested. These issues are discussed in the next section.

### 3.2.2 Statistical Properties of the Test and Measures of Agreement

In this section, there are some slight contradictions with the interpretation of evaluation results presented in the summary report (SAMHSA, 1996). Further review of the test and measures of agreement has established interpretation difficulties that can probably be ignored for common characteristics such as smoking and consumption of alcohol but that may be more serious for rare characteristics such as cocaine use. The Wald test is discussed first. The measures of agreement are then discussed under the simplifying assumption that the partition is fixed. Then there is further discussion of the consequence of the random nature of the partition when there is model overfitting.

## Wald Test

The Wald test that was used in this study derives from a standard result in statistics. If $y$ is a random vector of dimension $L$ with a multivariate normal distribution with mean 0 and variance-covariance matrix $\Psi$, then

$$
T=y^{t} \Psi^{-1} y^{\sim} \chi^{2}(L)
$$

A statistic with this form is called a Wald statistic. Wald statistics are a generalization of t-statistics to allow the simultaneous testing of whether a vector of (possibly correlated) random variables all have zero means. If the observed value of $T$ is too large relative to what is expected for a statistic with a chi-square distribution, then it is concluded that one of the variables in the vector must have a nonzero mean. Even if $y$ is not normally distributed and if $\Psi$ is not known but has to be estimated, there are conditions under which $T$ is still approximately distributed as a chi-squared variable with $L$ degrees of freedom (Stroud, 1971). The quality of the approximation will depend on the severity of the nonnormality of the components of $y$, on the stability of the estimated variance-covariance matrix, and on the correlation between $y$ and $\Psi$ 65^?. The approximation is better when $y$ is close to normal and $\Psi 65 \wedge$ ? is stable and independent of $y$.

For this application, $y$ is replaced by either $\left.\pi 50 \sim\}^{F}-\pi 50 \sim\right\}^{D}$ or $\left.\left.\pi 50 \sim\right\}^{W}-\pi 50 \sim\right\}^{D}$, depending upon whether the test is being applied to estimated propensity vectors from a fixed-effect model or to survey-weighted empirical Bayes estimates. Thus, instead of testing whether $\mathrm{E} y=0$, the test is for whether $\left.\left.\mathrm{E}(\pi 50 \sim\}^{F}-\pi 50 \sim\right\}^{D}\right)=0$ or $\left.\left.\mathrm{E}(\pi 50 \sim\}^{W}-\pi 50 \sim\right\}^{D}\right)=0$.

The assumption that $\left.\pi 50 \sim\}^{F}-\pi 50 \sim\right\}^{D}$ and $\left.\left.\pi 50 \sim\right\}^{W}-\pi 50 \sim\right\}^{D}$ each has a multivariate normal distribution is reasonable since the groups were formed large enough for the central limit theorem to indicate that the weighted mean of the predicted or observed propensities in the group has an approximately normal distribution. The more serious problem was how to define the
meaning of the expected value in the definition of $\Psi$. This is also an issue in defining what is meant by saying that the two estimators have the same expected values. There are four sets of random events with respect to which the expected value could be defined. The first is the random selection of persons for the NHSDA sample. The second consists of the set of state-level random effects. The third consists of the set of PSU-level random effects. The fourth consists of the person level random outcomes. In addition, it is possible to define the expectation as a conditional expectation, conditioning on various statistics and/or outcomes. Ideally, one should condition the expectation on as little as possible. It would have ben most satisfying to have defined the expectation as over all possible samples, over the distribution of the state and PSU random effects, and over the distribution of person level random outcomes. However, the contractor was not able to derive a method of doing this within the time and budget available. Accordingly, something simpler was done. The variances were conditioned on the state and PSU random effects, on the estimated $\beta$ vector, on the estimated set of random effects, and on the partition induced by the fitted model. This means that the expectation was just over all possible samples and over the conditional distribution of the person level random events given that state and PSU random effects are fixed and equal to the estimated state and PSU random effects and that the true $\beta$ vector is equal to the estimated $\beta$ vector.

A less conditional definition of the expectation in the equation for $\Psi$ might have resulted in either larger or smaller variances. Focusing on the variance of $\left.\pi 50 \sim\}^{W}-\pi 50 \sim\right\}^{D}$, less conditioning would have resulted in larger variances on $\pi 50 \sim\}^{W}$ and on $\left.\pi 50 \sim\right\}^{D}$, which would, in turn, have led to less significant test results since $T$ would have tended to be smaller. On the other hand, less conditioning would also have resulted in the estimation of a positive correlation between $\pi 50 \sim\}^{W}$ and $\left.\pi 50 \sim\right\}^{D}$. A positive correlation would have reduced the variance on the difference between the two, thereby leading to more significant results since $T$ would have tended to be larger. Since the results in section 3.1.4 do show strong correlations, the p-values for the Wald tests are probably not as small as they should be. This means that there is probably stronger evidence of lack of fit than what the tests showed.

Although it would probably have been possible with more work to derive the variance not conditioning on the random effects or on the estimated parameters, there was another difficulty. Since the partition is random, the distribution of $\left.\pi 50 \sim\}^{W}-\pi 50 \sim\right\}^{D}$ depends on the order statistics of the entire set of person-level predicted propensities. The effects of the random partition can be quite strong, particularly for rare characteristics if there was any overfitting of the model. It is doubtful that it would be possible to derive the variance of $\left.\pi 50 \sim\}^{W}-\pi 50 \sim\right\}^{D}$ without conditioning on the partition induced by the model.

## Measures of Agreement

To understand the statistical properties of the measures of agreement across the $L$ artificial domains, it is useful to have a model for the domain propensities. Indeed, without a model, it is impossible to make any inferences from those measures. However, the method for constructing the domains makes it difficult to conceive of an adequate model. As a first step, a model was developed assuming that the partition was fixed prior to fitting the model or even collecting the NHSDA data.

Let the $d$-th domain be labeled $\pi_{d}$. The model is that there is an underlying random process that leads to the propensity for each domain. This process is assumed to have mean $\pi$ and variance $\varphi$, where $0<\varphi<\pi(1-\pi)$. This means that $\pi_{d}$ is a random variable constrained to lie between 0 and 1, according to the model. Referring back to Section 1.4, this is a Bayesian interpretation of the propensity $\pi_{d}$. The model is rationalized by accepting that since it is not known why the propensity is different in each domain, it is best to treat the propensity in each domain as a random variable with some overall mean and variance. The parameter $\pi$ can be thought of as the national average propensity to engage in the behavior of interest. The parameter $\varphi$ quantifies the expected dispersion of the domain propensities from the national average. Since $\varphi$ quantifies the variability in the process among the domains, it is referred to as the process variance. In a survey, there is interest in both estimating the national propensity and how much that propensity varies across domains. For example, there may be interest in identifying the domains with the highest and lowest realized propensities or in comparing the propensities for two specific domains.

The importance of the process variance depends on its size relative to the overall propensity. Clearly, a large process variance for either a rare or a nearly universal characteristic is more important than the same level of process variance for a characteristic that is neither rare nor nearly universal. This relationship is quantified through the intraclass correlation, defined as

$$
\delta=\frac{\varphi}{\pi(1-\pi)}
$$

If the intraclass correlation is large, then the underlying process leads to sharp differences in group propensities. If the intraclass correlation is small, then the underlying process leads to only mild differences in group propensities. Since the idea of the partition is that propensity is uniform within each group, if the intraclass correlation is small, that says that everyone in the nation has about the same propensity to engage in the behavior of interest.

Generally, the desirability of close agreement between model-based and design-based estimates depends strongly on the intraclass correlation and on the sample size per group. Close agreement between the two sets of estimates is desirable only when the intraclass correlation is high and the sample size per group is large. This can be demonstrated by noting that the dispersion of the design-based estimates is too large unless both conditions are met. After demonstrating this assertion, implications are drawn for the interpretation of both the range ratio and the correlation coefficient.

The expected dispersion in the design-based domain estimates can be derived fairly easily. The dispersion of $\pi_{1}^{D}$ through $\pi_{L}^{D}$ depends on two sources of random variability. There is the random variation that caused $\pi_{1}$ through $\pi_{L}$ to be different from $\pi$ and there is sampling variance on each of the estimates given the true propensity for the domain. The first type of random variation depends only on $\varphi$ while the second type depends on $\pi, \varphi$, and $n_{d}$, the direct sample size for the domain. Let $\mathrm{E}_{\mathrm{M}}$ denote expectation with respect to the model and $\mathrm{Var}_{\mathrm{M}}$ denote variance with respect to the model. Similarly, let $\mathrm{E}_{\mathrm{D}}$ denote expectation with respect to the design and $\operatorname{Var}_{\mathrm{D}}$ denote variance with respect to the design. Then the unconditional expected squared deviation of $\pi_{d}^{D}$ from $\pi$ over all possible samples of a given manifestation and over all possible manifestations of the superpopulation is

$$
\begin{aligned}
& \mathrm{E}_{\mathrm{M}} \mathrm{E}_{\mathrm{D}}\left\{\frac{1}{} \frac{1}{L} \sum_{d=1}^{L}\left(\pi_{d}^{D}-\pi\right)^{2}\right\}_{\zeta} \\
& =\frac{1}{L} \sum_{d=1}^{L} \operatorname{Var}\left(\pi_{d}^{D}\right) \\
& =\frac{1}{L_{d=1}} \sum_{1}^{L}\left\{\mathrm{E}_{\mathrm{M}} \operatorname{Var}_{\mathrm{D}}\left(\pi_{d}^{D} \mid \pi_{d}\right)+\operatorname{Var}_{\mathrm{M}} \mathrm{E}_{\mathrm{D}}\left(\pi_{d}^{D} \mid \pi_{d}\right)\right\} \quad \text { by a basic statistical theorem }{ }^{15} \\
& =\frac{1}{L} \sum_{d=1}^{L} \mathrm{E}_{\mathrm{M}}\left[\frac{\pi_{d}\left(1-\pi_{d}\right)}{n_{d}}\right]+\frac{1}{L_{d=1}^{L}} \sum_{\mathrm{M}}^{\mathrm{L}} \operatorname{Var}_{\mathrm{M}}\left(\pi_{d}\right) \\
& =\frac{1}{L} \sum_{d=1}^{L}\left[\frac{\pi(1-\pi)-\varphi}{n_{d}}\right]+\varphi \\
& =\frac{[\pi(1-\pi)-\varphi]}{n_{d}}+\varphi \text {. }
\end{aligned}
$$

[^9]The left hand side of the final line is the measurement variance due to sampling, while the right hand side is the process variance. Note that the sum of the two must be larger than $\varphi$ by itself. This is the same as saying that the expected dispersion of $\pi_{1}^{D}$ through $\pi_{L}^{D}$ is greater than the expected dispersion of $\pi_{1}$ through $\pi_{L}$. The difference between the two expected dispersions is measurement variance. In other words, it is a mistake to think that true propensities for the domains are as spread out as the design-based estimates of those propensities unless measurement variance is negligible. Exhibit 3.8 illustrates this with some numbers. For this example, the left most column shows invented propensities for four domains. Six simple random samples of 1,062 were then drawn from each domain. (This was a common domain sample size actually used in this study.) As the table shows, the standard deviation among the estimated domain propensities can be smaller than the true standard deviation but is more often larger -- sometimes far larger. Furthermore, when the estimated standard deviation is too large, then the range is also too large. If the estimated range of the design-based estimates is too large, then the ideal model-based procedure will produce a range ratio less than one.

By means of both the derivation of the total dispersion and the illustration, it is now clear that a range ratio of one is ideal only when measurement error is negligible. This can be achieved by having a large intraclass correlation and a large sample size per domain. In light of this discussion, it is evident that the best model is not necessarily the one that most closely tracks the values of the design-based statistics across the domains. If the variation in the process is large relative to the measurement variance, then close tracking to the design-based statistics is ideal, but otherwise the goal is to obtain a tighter set of statistics with a smaller population variance across the domains and a smaller range across the domains.

Exhibit 3.8 Illustration of Extra Variation in Domain Estimates Due to Sampling Error


| Standard deviations |  |  |  |  |
| ---: | ---: | ---: | ---: | ---: |
| 0.31 | 0.29 | 0.42 | 0.66 | 0.82 |

The effect of measurement error on the correlation coefficient is more difficult to determine. More theoretical work or perhaps simulations would be useful. Note that the Wald test accounts for measurement error. Thus, the overdispersion of the design-based estimates does not mean that the ideal model should produce estimates that demonstrate lack of fit.

Given the effect of measurement variance on the range ratio, the question then becomes, what is the ideal value for the range ratio? This research did not establish the ideal value. However, Exhibit 3.9 does show the relative overdispersion of the design-based estimates for illustrative values of the intraclass correlation and for the group sample size. For example, if the intraclass correlation is $\delta=0.1$ (a large value) and the group sample size is 1,062 , then the overdispersion in the design-based estimates is trivial. For such a situation, the ideal range ratio is equal to one, the ideal correlation coefficient is one, and the best model-based estimator would not shows signs of a lack of fit. On the other hand, when the intraclass correlation is just 0.01 and the sample size per group is just 266, then the overdispersion is 37 percent, meaning that the ideal model-based estimator will have 37 percent smaller dispersion across the domains than the design based estimator. Unfortunately, no measures of intraclass correlation were calculated for this study. Given a value for the observed variance in the design-based estimates across the groups and an overall mean, it would be fairly easy to compute the intraclass correlation, but this idea was only conceived as the final report was being written. At that point, there was inadequate time and funding to conduct more analysis.

## Exhibit 3.9 Relative Overdispersion in Design Based Estimates by Intraclass Correlation and Group Sample Size

|  | Sample Size <br> per Domain |  |  |
| :--- | ---: | ---: | ---: |
| Intraclass <br> correlation | 1,062 | 531 | 266 |
|  |  |  |  |
| 0.100 | $0.8 \%$ | $1.7 \%$ | $3.4 \%$ |
| 0.050 | $1.8 \%$ | $3.6 \%$ | $7.1 \%$ |
| 0.025 | $3.7 \%$ | $7.3 \%$ | $14.7 \%$ |
| 0.010 | $9.3 \%$ | $18.6 \%$ | $37.2 \%$ |
| 0.005 | $18.7 \%$ | $37.5 \%$ | $74.8 \%$ |
| 0.001 | $94.1 \%$ | $188.1 \%$ | $375.6 \%$ |
|  |  |  |  |

However, it is noted here that intraclass correlation where the classes are defined to be states was estimated to be $3 \%$ for alcohol use, $0.4 \%$ for cigarette smoking, and less than $0.1 \%$ for drug treatment and arrest. When the model fits, the procedure used to form the artificial domains should maximize the intraclass correlation for a given number of the domains. Also, the number of artificial domains formed for alcohol and cigarette usage were 40 each per age domain. Only 20 artificial domains were formed per age domain for the other behaviors. Since the average sample size per age domain was 21,244 , the sample size per artificial domain was 531 for alcohol and cigarettes and 1,062 for the other behaviors. (The column with 266 per domain reflects the situation when 20 groups are formed per age group for a one-quarter sample as was used for the cross-validation discussed in Section 2.2.3 below.) It is hoped that the intraclass correlations for the artificial domains should be at least 5-10\%, indicating that range ratios for good models should be only slightly below one.

## Model Overfitting and Random Partitions

Recall that all of the discussion of the measures of agreement so far have been preconditioned on the existence of a partition that was fixed prior to analyzing the data. The interpretation becomes more difficult when one considers the random nature of the partition. For a fixed partition, it is expected that the model-based estimators will have less variation across the groups than the design-based estimator. For a model-dependent partition, the opposite can easily be true due to model overfitting.

When the model contains inappropriate (nonsignificant) predictors, or predictors with poorly estimated coefficients, the model will tend to produce predictions for individual cases that are outliers; that is, cases with inordinately big or small propensity predictions. Such models are
referred to as "overfit" since they include too many predictors. If there are only a small number of potential predictor variables, this problem does not arise since rigorous techniques exist to decide which of the predictor variables should be retained in the model. When, however, there are hundreds of potential predictor variables, as was the case on this project, those procedures tend to keep too many variables in the model.

Choosing prediction variables is an aspect of the statistician's task that was discussed in Chapter 1. Recall that the goal of any modeling exercise is to find internally homogenous groups. In this study, all the potential predictor variables were categorical variables. Picking predictor variables for the logistic regression was therefore equivalent to finding groups of sample persons that were internally homogeneous with respect to the propensity to engage in the behavior of interest. By the same logic, finding the largest set of significant predictor variables was equivalent to searching for the smallest set of groups such that it was impossible to break any of the groups into subgroups with different true propensities. However, all that was observed for each person was a yes or a no ( a 1 or a 0 ). As different ways to break a tentative group into subgroups were examined to see if their propensities were different, their observed rates of engaging in the behavior of interest were calculated. If the observed rates were different enough, then it was concluded that the true propensities for the subgroups must be different. Each time that this test is conducted, there is only a small probability that two subgroups with identical propensities will be mistakenly classified as having truly different propensities. However, when the test is repeated hundreds of times, the number of errors that are made of this type can become nontrivial. This problem can probably be ameliorated by having more stringent variable selection rules that minimize overfitting. For this study, predictors were kept in the models if their p-values were at least 0.05 using SUDAAN as described in Section 2.2.

Recall that the artificial partition was created by sorting on the predictions. When the model is overfit, all the outliers get grouped together -- the low outliers in the first group and the high outliers in the last group. As a result, on a partition created from an overfit model, the design-based estimator will tend to vary less across the groups than the model-based estimator that was used to create the partition. Note that this is the opposite relationship from what is expected for a fixed partition. As a result, the statistical properties of the range ratio on a model-dependent partition are sharply different from those on a fixed partition.

Let the true range $R$ of propensities for a partition be defined as the range of $\pi_{1}$ through $\pi_{\mathrm{L}}$ for a particular manifestation of the superpopulation. Let $R^{F}$ be defined as the range of $\pi_{1}^{F}$ through $\pi_{L}^{F}$. Let $R^{M}, R^{W}$, and $R^{D}$ be defined similarly. As discussed above, for a fixed partition,
$E R^{D}>R$ because of measurement error. For a fixed partition, a range ratio less than one ( $R^{F}$ $<R^{D}$ ) could thus mean either that the model is not rich enough or that $R^{F}$ is less biased than $R^{D}$. On the other hand, a range ratio greater than one $\left(R^{F}>R^{D}\right)$ is a strong sign that the model is too rich (i.e., overfit).

When the partition depends upon a model, it is expected that the positive bias in $R^{D}$ will increase since the same data that led to the model also get used to calculate the $\pi_{d}^{D}$. The behavior of the range of the model-based estimates is more complex. The behavior of the range will depend strongly upon whether the partition is induced by the same model that yielded the model-based estimates and upon the extent of overfitting in the model that induced the partition. If the partition is induced by the same model that is being evaluated and that model is overfit, then the range statistic is likely to be inflated due to the impact of outliers. With worse overfitting, the inflation will also become worse. It is difficult to quantify the relationship between overfitting and inflation of the range, but range ratios greater than one are likely to be signals of overfitting.

If a very rich model is used to create a partition, and the model is capturing real signal rather than just generating noise, and a lean model is used to generate the estimated propensities, then the range ratio for the lean model-based estimators will be substantially less than one.

A correlation substantially less than 1 could signal a nonlinear monotone relationship between the model-based and design-based statistics but is more likely to signal either model lack-of-fit (either underfitting or overfitting) or large measurement variance in the design-based estimators. An examination of a graph can rule out a nonlinear monotone relationship, but it will generally be impossible to tell whether a value less than one means model lack-of-fit (underfitting or overfitting) or unstable design-based estimators. At any rate, values substantially less than one are not expected for a model-dependent partition since the data that led to the model also influence the design-based estimators, tending to create relatively high correlations.

### 3.2.3 Cross-Validation

Methods to assess the degree of overfitting in models do exist. One way is to divide the sample into groups prior to fitting the model, develop the model based on the sample in one group, and evaluate the fit using the other group. This method is quite rigorous with properties that are well understood. However, this method does not produce the best possible models since there is less sample available for identifying significant predictors and for estimating model
parameters. For this study, it was decided to use cross-validation after the model fitting by dividing the sample into groups, refitting the model on one group and evaluating the refit model on the other group.

Choosing the group sizes was difficult since it was desired to have a large subsample both for the model refitting and for the evaluation of the refitted model. The subsample for the model refitting had to be large since the final models were too rich (i.e., contained too many variables) to fit on samples much smaller than the original sample. The subsample for the evaluation of the refitted model also had to be large because of the problems for the range ratio discussed above when the artificial domains are small and because the Wald test requires a large sample size to be valid and to have respectable power to detect lack of fit. Accordingly, it was decided to divide the sample into four equal parts, where each part contained a uniform slice of every state and sample PSU. For each model that was evaluated using this cross-validation procedure, the parameters were estimated for the final model using three of the four subsamples pooled together; then the fit was evaluated using the remaining subsample. This operation was repeated four times, so that all possible combinations of three out of the four subsamples were used for parameter estimation and each of the four subsamples were used for model evaluation. The four results were then averaged.

Given the already high computational burden of the model-fitting procedure, it was decided that it was not feasible to refit all 88 models. To keep the cost down, the cross-validation was done for only 12 of the models. These consisted of models for six of the eleven characteristics on the 26-34 age group, both inside and outside of the oversampled MSAs.

Note that the structure of a model was not changed when it was cross-validated, meaning that the set of fixed and random effects remained the same. Since the models were refit on a sample 25 percent smaller than the full sample, the refit parameters are less stable than the original parameters. This means that there are likely to be more outliers at the person level, meaning that range ratios will tend to be inflated. This is further exacerbated by the fact that only one-fourth of the original sample was available for the validation. Taken together, these two factors led to the expectation that the range ratios would be much larger for the cross-validated sample than for the original sample.

One of the improvements that cross validation offers when combined with the model-dependent partitions discussed in 3.2.2 is that some of the difficulties in interpreting range ratios and correlation coefficients are ameliorated. Specifically, the bias in $R^{D}$ when
computed on the reserved one-quarter sample is no worse than its bias on a fixed partition. It is still a biased estimator of $R$ due to the measurement variance in the $\pi_{d}^{D}$, but because the partition is independent of the data used to compute $R^{D}$, the extra bias discussed above disappears. Offsetting that to some degree is the fact that the smaller sample sizes worsen the bias due to measurement variance. Which effect will be stronger depends on the situation. The range for the model-based methods, however, does not become any better behaved since the partition is still based on the predicted propensities for the units in the quarter sample. Therefore, the range of the model-based predictions is still expected to be biased upwards by the effect of outliers. The fact that the model parameters were fit on a separate data set (the other three quarters of the full data set) does not change this fact. It is still the case that model-based estimators will look quite different on partitions induced by themselves versus other models.

Another benefit of the cross-validation is that the estimated variance-covariance matrix $\Psi 65 \wedge$ ? has better validity. Recall that for the full sample, this variance was estimated as a conditional variance given the random effects, the fixed effects, and on the partition induced by the fitted model. This conditional definition meant that the covariance between $\pi 50 \sim\}^{W}$ and $\pi 50 \sim\}^{D}$ was estimated to be zero, even though it is clear that there is a substantial unconditional covariance between them due the fact that both use information in the $y$ vector for each domain. In the cross-validation, the $y$ vector for the one-quarter evaluation sample was not used in the estimation of $\pi 50 \sim\}^{W}$, meaning that the unconditional covariance is zero. Since the lack of a positive correlation between the two will tend to increase the size of $\left.\pi 50 \sim\}^{W}-\pi 50 \sim\right\}^{D}$, this means that cross-validated Wald statistics are expected to be larger than the ordinary Wald statistics, thereby leading to small (more significant) p-values.

### 3.2.4 Results

Exhibit 3.10 shows the results of comparing the survey-weighted empirical Bayes estimates with the design-based estimates for the artificial domains described in Section 3.2.1. Each domain is predicted by the model to be fairly internally homogenous with respect to the propensity to engage in the behavior of interest. The correlations are high for most of the behaviors and age groups, as expected with a model-dependent partition of the population. A few of them are below 0.9 , a possible sign of poor model fit. The p-values tend to range fairly

Exhibit 3.10 Tracking of Survey-Weighted Empirical Bayes Estimates with Design-Based Estimates Across Model-Homogenous Subgroups

| Behavior | Statistic | Age Group |  |  |  | $\begin{array}{r} \text { All } \\ \text { Ages } \end{array}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35 Plus |  |
| Licit Drugs |  |  |  |  |  |  |
| Past Month Cigarette Use | Correlation $\chi^{2}$ probability Range Ratio | $\begin{gathered} 0.917 \\ 0.038 \\ 0.870 \end{gathered}$ | $\begin{aligned} & 0.952 \\ & 0.054 \\ & 0.934 \end{aligned}$ | $\begin{aligned} & 0.952 \\ & 0.136 \\ & 1.016 \end{aligned}$ | $\begin{aligned} & 0.946 \\ & 0.846 \\ & 1.027 \end{aligned}$ | $\begin{aligned} & 0.978 \\ & 0.788 \\ & 0.985 \end{aligned}$ |
| Past Month Alcohol Use | Correlation $\chi^{2}$ probability Range Ratio | $\begin{aligned} & 0.871 \\ & 0.056 \\ & 0.878 \end{aligned}$ | $\begin{aligned} & 0.960 \\ & 0.066 \\ & 0.872 \end{aligned}$ | $\begin{aligned} & 0.972 \\ & 0.049 \\ & 0.894 \end{aligned}$ | $\begin{aligned} & 0.981 \\ & 0.984 \\ & 0.968 \end{aligned}$ | $\begin{aligned} & 0.990 \\ & 0.759 \\ & 0.948 \end{aligned}$ |
| Illicit Drugs |  |  |  |  |  |  |
| Past Month Any Illicit Drug | Correlation | 0.939 | 0.973 | 0.962 | 0.942 | 0.990 |
| Use | $\chi^{2}$ probability | 0.340 | 0.639 | 0.384 | 0.474 | 0.450 |
|  | Range Ratio | 0.905 | 0.827 | 0.880 | 0.881 | 0.868 |
| Past Month Any Illicit But | Correlation | 0.916 | 0.926 | 0.941 | 0.845 | 0.973 |
| Marijuana Use | $\chi^{2}$ probability | 0.611 | 0.089 | 0.774 | 0.566 | 0.609 |
|  | Range Ratio | 0.923 | 0.801 | 1.028 | 0.821 | 0.879 |
| Past Month Cocaine Use | Correlation | 0.824 | 0.878 | 0.920 | 0.903 | 0.970 |
|  | $\chi^{2}$ probability | 0.864 | 0.094 | 0.803 | 0.611 | 0.607 |
|  | Range Ratio | 0.856 | 0.740 | 0.880 | 0.889 | 0.849 |
| Dependence |  |  |  |  |  |  |
| Past Year Dependence On | Correlation | 0.912 | 0.868 | 0.827 | 0.723 | 0.966 |
| Illicit Drugs | $\chi^{2}$ probability | 0.871 | 0.778 | 0.625 | 0.670 | 0.537 |
|  | Range Ratio | 1.031 | 0.882 | 0.894 | 1.147 | 1.000 |
| Past Year Dependence On | Correlation | 0.787 | 0.898 | 0.943 | 0.927 | 0.978 |
| Alcohol | $\chi^{2}$ probability | 0.221 | 0.007 | 0.688 | 0.523 | 0.020 |
|  | Range Ratio | 0.892 | 0.716 | 0.899 | 0.878 | 0.807 |
| Treatment |  |  |  |  |  |  |
| Past Year Treatment For Illicit Drugs | Correlation | 0.908 | 0.772 | 0.918 | 0.884 | 0.962 |
|  | $\chi^{2}$ probability | 0.489 | 0.437 | 0.539 | 0.354 | 0.184 |
|  | Range Ratio | 0.879 | 0.920 | 0.923 | 0.984 | 0.944 |
| Past Year Treatment For Alcohol | Correlation | 0.776 | 0.842 | 0.763 | 0.878 | 0.948 |
|  | $\chi^{2}$ probability | 0.428 | 0.680 | 0.612 | 0.037 | 0.159 |
|  | Range Ratio | 0.978 | 0.748 | 0.899 | 0.814 | 0.826 |
| Needing Treatment In Past Year | Correlation | 0.899 | 0.910 | 0.923 | 0.934 | 0.980 |
|  | $\chi^{2}$ probability | 0.112 | 0.255 | 0.355 | 0.859 | 0.403 |
|  | Range Ratio | 0.892 | 0.851 | 0.937 | 0.823 | 0.872 |
| Arrest |  |  |  |  |  |  |
| Past Year Arrested | Correlation $\chi^{2}$ probability Range Ratio | 0.961 | 0.883 | 0.911 | 0.878 | 0.977 |
|  |  | 0.623 | 0.225 | 0.902 | 0.589 | 0.416 |
|  |  | 0.778 | 0.883 | 0.952 | 1.123 | 0.950 |

*Probability of observing the calculated difference in the predicted and direct estimates across evaluation subgroups given that there is no difference.
uniformly over the interval $(0,1)$, a good sign for acceptance of the model as discussed in the prior section. The actual median of the values in the table is 0.467 . The range ratios are close to 1. Taken together with the high correlations, this is a sign that the two sets of estimates track closely over the artificial domains.

A somewhat different pattern emerges from a table of cross-validated statistics as discussed in Section 3.1.4. Exhibit $\mathbf{3 . 1 1}$ shows the cross validation results for the Survey-weighted Empirical Bayes method and for several fixed effect models. Note that the correlations are sharply smaller than in Exhibit 3.10, the p-values are usually slightly more significant, and range ratios are larger, all of which indicates a lack of agreement between the model-based and design-based estimators.

As discussed in Section 3.2.3, the attenuation of the cross-validated correlation coefficients and the increases in the cross-validated range ratios (both relative to the ordinary versions in Exhibit 3.10) are expected consequences of the reduced domain sample sizes available for the evaluation. These smaller sample sizes lead to higher measurement error on the design-based estimates for the domains and also more instability in the random partition since the first and last groups will have fewer observations in them. For these descriptive statistics, there does not appear to be a good way of judging whether the cross-validated results are more dramatic than one would expect and are therefore symptomatic of lack of fit. Nonetheless, the large range ratios substantially greater than one are certainly suggestive of overfit models.

There are good theoretical reasons, on the other hand, to place more confidence in the cross-validated p-values from the Wald statistics than on the original p-values, as discussed in Section 3.2.3. Note that the p-values in Exhibit $\mathbf{3 . 1 1}$ are mostly below the corresponding values for 26- to 34-year olds in Exhibit 3.10 despite the lesser power of the cross-validated test given the smaller sample sizes for the cross-validation. This tendency illustrates the danger of excessive conditioning in the definition of $\Psi$. Since there are other random events upon which there is still conditioning and since not conditioning upon those random events would tend to increase variances, these p-values may be a little too small. Nonetheless, the fact that all the p-values in Exhibit 3.11 are below 0.5 and some are substantially below 0.5 constitutes reasonably strong evidence of lack of fit. This is seen in all the columns, including the column for the mixed models. Evidence of lack of fit is disturbing since it impinges on the validity of the prediction intervals, but the impact on prediction interval coverage was not quantified in this study.

Exhibit 3.11 Cross-Validating the Survey-Weighted Empirical Bayes Estimates and Several Fixed Effect Models

| Behavior | Statistic | Survey- <br> Weighted <br> Empirical <br> Bayes <br> (Mixed Model) | Estimators Based on Fixed Effect Models |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | Same <br> Fixed <br> Effects as <br> in Mixed <br> Model | County and Demographic Effects Only | Separate <br> Demographic <br> Effects for <br>  <br> Remainders | Demographic Effects Only |
| Past Month Cigarette Use | Correlation $\chi^{2}$ probability Range Ratio | $\begin{aligned} & 0.765 \\ & 0.015 \\ & 1.095 \end{aligned}$ | $\begin{aligned} & 0.737 \\ & 0.007 \\ & 1.084 \end{aligned}$ | $\begin{aligned} & 0.622 \\ & 0.008 \\ & 0.956 \end{aligned}$ | $\begin{aligned} & 0.514 \\ & 0.000 \\ & 0.440 \end{aligned}$ | $\begin{aligned} & 0.584 \\ & 0.000 \\ & 0.272 \end{aligned}$ |
| Past Month Alcohol Use | Correlation $\chi^{2}$ probability Range Ratio | $\begin{aligned} & 0.866 \\ & 0.280 \\ & 0.969 \end{aligned}$ | $\begin{aligned} & 0.858 \\ & 0.231 \\ & 0.841 \end{aligned}$ | $\begin{aligned} & 0.832 \\ & 0.108 \\ & 0.966 \end{aligned}$ | $\begin{aligned} & 0.824 \\ & 0.023 \\ & 0.685 \end{aligned}$ | $\begin{aligned} & 0.839 \\ & 0.001 \\ & 0.524 \end{aligned}$ |
| Past Month Any Illicit Drug Use | Correlation $\chi^{2}$ probability Range Ratio | $\begin{aligned} & 0.728 \\ & 0.043 \\ & 1.618 \end{aligned}$ | $\begin{aligned} & 0.704 \\ & 0.036 \\ & 1.500 \end{aligned}$ | $\begin{aligned} & 0.659 \\ & 0.132 \\ & 1.038 \end{aligned}$ | $\begin{aligned} & 0.573 \\ & 0.080 \\ & 0.510 \end{aligned}$ | $\begin{aligned} & 0.637 \\ & 0.109 \\ & 0.310 \end{aligned}$ |
| Past Month <br> Any Illicit Drug Use But Marijuana | Correlation $\chi^{2}$ probability Range Ratio | $\begin{aligned} & 0.636 \\ & 0.412 \\ & 1.450 \end{aligned}$ | $\begin{aligned} & 0.615 \\ & 0.249 \\ & 1.451 \end{aligned}$ | $\begin{aligned} & 0.392 \\ & 0.242 \\ & 1.213 \end{aligned}$ | $\begin{aligned} & 0.212 \\ & 0.131 \\ & 0.256 \end{aligned}$ | $\begin{aligned} & 0.297 \\ & 0.131 \\ & 0.153 \end{aligned}$ |
| Past Year Treatment For Illicit Drugs | Correlation $\chi^{2}$ probability Range Ratio | $\begin{aligned} & 0.588 \\ & 0.287 \\ & 1.420 \end{aligned}$ | $\begin{aligned} & 0.481 \\ & 0.275 \\ & 1.509 \end{aligned}$ | $\begin{aligned} & 0.407 \\ & 0.386 \\ & 1.348 \end{aligned}$ | $\begin{aligned} & 0.532 \\ & 0.294 \\ & 0.278 \end{aligned}$ | $\begin{aligned} & 0.561 \\ & 0.297 \\ & 0.219 \end{aligned}$ |
| Past Year <br> Arrested | Correlation $\chi^{2}$ probability Range Ratio | $\begin{aligned} & 0.641 \\ & 0.418 \\ & 1.552 \end{aligned}$ | $\begin{aligned} & 0.662 \\ & 0.399 \\ & 1.537 \end{aligned}$ | $\begin{aligned} & 0.543 \\ & 0.324 \\ & 1.430 \end{aligned}$ | $\begin{aligned} & 0.639 \\ & 0.278 \\ & 0.373 \end{aligned}$ | $\begin{aligned} & 0.635 \\ & 0.165 \\ & 0.425 \end{aligned}$ |
| MEAN | Correlation $\chi^{2}$ probability Range Ratio | $\begin{aligned} & 0.704 \\ & 0.243 \\ & 1.351 \end{aligned}$ | $\begin{aligned} & 0.676 \\ & 0.199 \\ & 1.321 \end{aligned}$ | $\begin{aligned} & 0.576 \\ & 0.200 \\ & 1.159 \end{aligned}$ | $\begin{aligned} & 0.549 \\ & 0.134 \\ & 0.424 \end{aligned}$ | $\begin{aligned} & 0.592 \\ & 0.117 \\ & 0.317 \end{aligned}$ |

Note: These tests were restricted to the 26 - to 34 -year-old age group due to the cost of computations.
*Probability of observing the calculated difference in the predicted and direct estimates across evaluation subgroups given that there is no difference.

An important methodological issue in the table concerns how the random partition of the data set was created for each column. For the first three columns, the same model was used to generate the partition as was being evaluated. For the last two columns, the full weighted mixed effect model was used to generate the partition. This accounts for most of the dramatic difference between the range ratios in the last two columns and the other columns. If the simple models in the last two columns had been evaluated with respect to the partitions induced by themselves, the range ratios would have been near one.

When a model is cross-validated with respect to the partition induced by itself, the range ratio is almost always above one. This is true for the full mixed effects model, for the model with the random effects removed but all the fixed effects retained, and for the model with the random effects and all of the tract and block group level fixed effects removed. This model with only demographic and county-level fixed effects is leaner than the full fixed model and yet there are still range ratios above one. This is probably good evidence that the models are overfit-even the models with just demographic and county-level variables. Note that the overfitting appears to be worse for the rarer behaviors.

Another interesting observation about the table concerns the low correlations, small p -values and small range ratios in the last two columns. Since the partition for these columns was induced by the full mixed model, this demonstrates that the full mixed model is capturing important information that the simple models cannot. The design-based estimator does vary significantly across the cells of the partition, and the simple models are not sensitive enough to mirror that variation.

### 3.3 Comparisons with External Data Sources

This approach is useful and important for any study where a census is occasionally conducted of the population of interest with respect to the behavior of interest. For example, this approach is often used to judge the quality of small area estimators for labor force statistics since the Decennial Census has several labor-related questions. Even in that application, however, there are difficulties since the questions are worded slightly differently than in the Current Population Survey and in other surveys that measure employment and unemployment. Systematic measurement biases tend to make evaluation of comparisons difficult.

This is all the more true with a topic as sensitive as substance abuse. It is known that reporting of substance abuse is extremely sensitive, not just to question wording, but also to the setting of the interview, the procedures that the interviewer uses, the assurances of confidentiality
and so on. Furthermore, a substantial portion of the population that engages in the behaviors of interest (such as getting arrested) may not be accessible through a household survey since they reside in prisons at the time of interview or have such a tenuous relationship with any one household that they are not included in any household roster. Administrative databases are also subject to systemic biases. Also, the data collectors for administrative systems are often quite autonomous and thus may develop reporting idiosyncracies that compromise the comparability of the data across states and MSAs.

Despite the concern for the potential for differential nonsampling biases, comparisons were made between the NHSDA estimates and estimates from other sources. Data from three external sources were used: the Behavioral Risk Factor Surveillance System (BRFSS), the National Drug and Alcoholism Treatment Unit Survey (NDATUS), and the FBI’s Uniform Crime Reports (UCR). Each of these external sources are first described. Then comparisons are made.

Behavioral Risk Factor Surveillance System (BRFSS): The BRFSS is a telephone survey conducted in all 50 States under cooperative agreements with the Centers for Disease Control and Prevention with no representation of persons living in households without telephones. State sample sizes are larger for many states than in the NHSDA, but different survey data collection agents are used in every State, making comparability across the states a difficult issue. However, definitions used for alcohol consumption and cigarette use are comparable to NHSDA definitions, since the BRFSS estimates reflect past month use. BRFSS estimates of alcohol consumption and cigarette use were compared to the survey-weighted empirical Bayes estimates. Studies have shown that reporting of substance use behaviors may be lower in telephone surveys than in face-to-face surveys, particularly for illicit drugs. The BRFSS State estimates are simple averages over the three years 1991 through 1993.

National Drug and Alcoholism Treatment Unit Survey (NDATUS): NDATUS is an inventory of all specialty substance abuse treatment facilities in the U.S. Based on reporting by State substance abuse agencies, it provides estimates (including adjustments for nonresponse) of the number of clients in treatment at a given point in time. NDATUS estimates of drug treatment volumes were compared to the survey-weighted empirical Bayes estimates. To develop an estimate of persons treated during a year, the NDATUS client counts (including drug only and combined drug and alcohol clients) were multiplied by the reciprocals of average lengths of stay, and adjusted to account for multiple treatment episodes in a year by the same individual. Estimates of length of stay and multiple episodes were obtained from the Drug Services Research Survey, conducted in 1990. These calculations were done within categories of treatment modality and applied separately to each State. No adjustment was made to account for the inclusion in the NHSDA estimates of persons reporting treatment through self-help groups, private physicians, or emergency rooms, none of which are counted in NDATUS. The State estimates are averages over only 1992 and 1993 since the 1991 estimates could not be adequately adjusted for nonresponse.

Uniform Crime Reports (UCR): The UCR compiles data from local jurisdictions on the number of arrests. UCR estimates of past year arrests were compared to the survey-weighted empirical Bayes estimates. For comparison with the NHSDA estimates, an adjustment to the UCR data was made to account for persons arrested more than once during a year, so the adjusted UCR estimates reflect number of persons arrested at least once. This adjustment was made within the four Census regions, using data on multiple arrests reported by arrestees in the NHSDA sample. The State estimates are simple averages over the three years 1991 through 1993.

Exhibit 3.12 summarizes the results of the comparisons across the 26 states for which NHSDA estimates were prepared. One positive finding is that the ratio of the range of the design-based NHSDA estimates across the 26 examined states was almost always smaller than the range in the external estimates across the same states for three out of the four characteristics. Similarly, relative standard error across the states is smaller with the design based estimates than with external estimates for two out of the four characteristics. Given the earlier discussion in this chapter about the impact of measurement error on the ranges and dispersion, the expectation had been that the design-based estimates would be more dispersed than the external estimates. The fact that this is not true constitutes reasonable evidence that there are important differences in nonsampling errors between the data systems.

Turning attention to the other range ratios in Exhibit 3.12, one observes the same sorts of patterns as in Exhibits 3.1 through 3.4. The survey-weighted empirical Bayes estimates always had a tighter range across the states than the design-based NHSDA estimates, as desired. Whether the reduction in range is too much or too little is impossible to say, but it is clear that all the estimators based on fixed models almost always produce greater shrinkage than the mixed effect model, as expected. The simple demographic model, with or without a separate set of effects for oversampled metropolitan areas, seems to produce clearly undesirable levels of

Exhibit 3.12 Comparison of Alternative Small Area Estimators to Estimates from External Sources

| State | Estimate from External Source | Survey-Weighted Empirical Bayes (Mixed Models) |  | Estimators Based on Fixed Effect Models |  |  |  | $\begin{gathered} \begin{array}{c} \text { Design-B } \\ \text { ased } \\ \text { 91-93 } \\ \text { NHSDA } \\ \text { Estimates } \end{array} \end{gathered}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | With Full NHSDA Sample | Big City Sub-Sam pled Model | Same Fixed Effects as in Mixed Model | County and <br> Demographic Effects Only | Separate Demographic Effects for Big City \& Remainder | Demographic Effects Only |  |
| Alcohol Use National Estimate | $\begin{array}{r} \text { BRFSS } \\ 50.90 \end{array}$ | 53.46 |  | 53.43 | 53.01 | 53.41 | 53.40 |  |
|  |  |  | 53.59 |  |  |  |  | 53.01 |
| Rank Correlation ${ }^{1}$ | . | 0.861 |  | 0.841 | 0.765 | 0.278 | 0.097 |  |
|  |  |  | 0.854 |  |  |  |  | 0.807 |
| Range Ratio ${ }^{2}$ | 1.000 | 0.597 |  | 0.545 | 0.525 | 0.088 | 0.082 |  |
| RSE ${ }^{3}$ | 21 | 12 | 0.598 13 | 10 | 13 | 2 | 2 | 0.867 18 |
| Cigarette Use | BRFSS |  |  |  |  |  |  |  |
| National Estimate | 23.10 | 27.16 |  | 27.68 | 27.73 | 27.49 | 27.43 |  |
|  |  |  | 27.27 |  |  |  |  | 27.66 |
| Rank Correlation |  | 0.491 |  | 0.631 | 0.670 | 0.485 | 0.472 |  |
|  |  |  | 0.610 |  |  |  |  | 0.473 |
| Range Ratio | 1.000 | 0.930 |  | 0.642 | 0.449 | 0.244 | 0.208 |  |
|  |  |  | 0.786 |  |  |  |  | 1.048 |
| RSE | 10 | 10 | 8 | 6 | 4 | 3 | 3 | 11 |
| Drug Treatment | (NDATUS) |  |  |  |  |  |  |  |
| National Estimate | 0.85 | 0.70 | 0.71 | 0.70 | 0.68 | 0.65 | 0.64 | 0.62 |
| Rank Correlation |  | 0.375 | 0.523 | 0.406 | 0.289 | -0.160 | -0.240 | 0.063 |
| Range Ratio | 1.000 | 0.349 | 0.326 | 0.324 | 0.432 | 0.079 | 0.080 | 0.615 |
| RSE | 38 | 18 | 16 | 17 | 18 | 4 | 5 | 31 |
| Arrest | (UCR) |  |  |  |  |  |  |  |
| National Estimate | 4.10 | 1.64 | 1.69 | 1.62 | 1.66 | 1.61 | 1.60 | 1.57 |
| Rank Correlation |  | 0.350 | 0.351 | 0.389 | 0.356 | 0.510 | 0.450 | -0.066 |
| Range Ratio | 1.000 | 0.361 | 0.415 | 0.252 | 0.298 | 0.136 | 0.100 | 0.518 |
| RSE | 27 | 26 | 24 | 16 | 16 | 9 | 7 | 30 |

${ }^{1}$ Correlation calculated by first ranking states and then calculating the correlation of the ranks.
${ }^{2}$ Ratio of the range of the predicted values to the range of data from the external source.
${ }^{3}$ Relative standard error among state estimates as a percentage.
Note: Estimates of prevalence rates have been multiplied by 100 .
Source: SAMHSA, Office of Applied Studies, National Household Survey on Drug Abuse. Model-based estimates using 1991-1993 NHSDA data.
shrinkage. The range ratios for the county demographic model for drug treatment and arrest are higher than for the full fixed model. This is a sign that it is possible to induce as much variation in state estimates of drug treatment and arrest with just county-level variables as with a combination of county, tract, and block-group level variables. Whether the extra induced variation is good or not constitutes an open question.

The data on rank correlations are difficult to interpret. First, since it is not known which set of estimates is best, it is hard to say whether a high rank correlation is desirable. Second, the patterns are not consistent across the behaviors. The full mixed model resulted in the highest rank correlation with the external data source only for alcohol. The very lean fixed effect models (basic demographic and basic demographic with big city effects) generally produced the lowest rank correlations, but by some fluke, produced the highest rank correlations for arrests.

It is interesting that the design-based estimates for drug treatment and arrests show essentially no correlation with the NDATUS and UCR data. This would appear to indicate that the two systems are measuring different phenomena while attaching the same name to those phenomena. The fact that the models with county level predictors have substantial rank correlations with NDATUS and UCR is probably due to the fact that variables from these databases were in those models. ${ }^{16}$ It is not clear though how those variables got picked for inclusion in the model, when at the state level there is no correlation. It may be that these variables are part of the overfitting problem. The fact that the NDATUS and UCR statistics vary more across the states than the design-based estimates despite the fact that they are not subject to sampling error and the fact that there is no rank correlation between them and the design-based estimates raises some concerns about the appropriateness of variables from these databases as predictors in the models. Although these variables may have better face validity than census variables for some data consumers, the potential that they are not consistently collected across the states means that their presence in the models could be undermining the purpose of creating a set of state estimates that will fairly rank the states.

The column for a big city subsampled model describes the results when the survey-weighted empirical Bayes procedure is applied to a subset of the 1991-1993 NHSDA. This subsample was drawn by dropping the oversample of the six targeted metropolitan areas. Dropping the oversamples (so that the areas were sampled at national rates) allowed the fitting of

[^10]a single mixed model for each age group and behavior instead of having to fit separate models for the big cities. The fact that the two survey-weighted empirical Bayes columns are so similar indicates that the oversample in the six MSAs had little effect on most state estimates.

### 3.4 Ideas for Future Evaluations

The evaluation focused on trying to determine whether the model-based estimates were more accurate than the design-based estimates. This effort was partially successful, and it is hard to see what more could be done. While it would be interesting to compare the variances of the model-based estimates with those of the design-based estimates, the variances are almost certainly smaller with the model-based approach. The reason that this comparison was not done is that the estimates of the variances on the design-based estimates for states and MSAs would be highly unstable. It would be difficult to make the comparisons. Also, there are questions about underestimation of the variances for the model-based estimates.

One area, however, where it does appear to be possible to do more concerns the coverage of the prediction intervals, both when the model is true and when the model is not true. Two ideas are presented in this section on how the coverage could be evaluated. These methods were not used in the study since they cannot be used to evaluate the accuracy of the small area estimates themselves, but they could be useful for assessing coverage properties.

Since the labor force items are fairly consistent between the Decennial Census and the Current Population Survey, a good test of the methodology for estimating the variances for the model-based estimates would be to prepare model-based estimates and their estimated variances using variables from the CPS from April of 1990 as outcome variables and variables from the 1980 Census as predictor variables. (It is possible to link the 1990 CPS back to the 1980
Census.) By using ten-year-old predictors, it would be possible to simulate the effects of having imperfect predictors. Another advantage of such an approach is that it would have an evaluation data set completely independent of the data set used to create the predictions. Such a study would be useful for assessing the coverage properties of the prediction intervals. The actual mean squared error reductions that would be achieved for labor force statistics could, however, be quite different from the reductions expected for NHSDA statistics.

If the logistics of matching 1980 Decennial Census data to 1990 CPS data are too difficult, ${ }^{17}$ the coverage of the prediction intervals could also be assessed through a simulation study. For such a study, it would be necessary to specify a model for the U.S. population and then to create a simulated population of very large size. Various models could be utilized to simulate the population. The methods could then be tested using either the same model structure that was used to create the simulated population or some other model. Although it might seem to be a weak test of the methodology to evaluate it assuming that the modeler knows the correct model structure, it would be of interest for the NHSDA project since approximations were used in fitting the model and in estimating the variances for the estimates. Without simulation studies, the effect of these approximations remains unknown.

Using a different model structure in the modeling than in the population simulation constitutes a much more stringent test of a methodology, but such an approach requires more judgment to design and interpret. If the model used to simulate the population is sufficiently pathological, then no reasonable method can be designed. This is even true of design-based methods since these methods assume that domain totals are normally distributed across all possible samples. It is quite difficult to decide how severe a pathology to use in testing.

One possibility to avoid having to create the population is to assemble more years of old NHSDA sample and to treat the conglomeration as a population from which samples are drawn. The problem with this approach would be the population sizes of the clusters. Fairly large clusters are required for representative testing.

A related idea would be to rerun the model on only a subsample of the 1991-1993 NHSDA, dropping out large states like California from the modeling in order to see how well the model works in predicting the behavior rates for those states when no sample was available. Although this idea has the appeal of being simple, it seems like a statistically unstable decision method. By this, it is meant that luck of the draw could easily result in the method either being accepted or rejected. It is sort of similar to making a major decision based on a single coin toss. A more complex simulation program would be more costly but would also yield much more information for the decision.

[^11]
### 3.5 Summary of the Evaluations

As noted previously, all of the evaluation measures that were carried out have limitations. However, some useful findings do arise from the evaluation. First, the California estimates agree well with the design-based estimates. The method was designed to provide such agreement for domains with large sample sizes, so even though this says nothing about the quality of estimates for domains with small sample sizes, it is at least comforting that the method functioned as intended. National estimates agreed fairly well with the design-based estimates but not as well as hoped. Estimates based on simple fixed models actually fit better at the national level for several of the behaviors of interest. This is because weights were used in the fixed models, making estimates based on this design consistent, and because the number of sample PSUs was not large enough to make the national aggregates from the mixed models converge to the design-based estimates.

Second, the survey-weighted empirical Bayes estimates displayed less dispersion across the states than the design-based estimates and more dispersion than the estimates based only upon fixed effects. The method was designed to provide this sort of compression of the dispersion, so this outcome is not surprising, but it is again comforting that the method functioned as intended.

Third, there is some indication that the fixed parts of the models were overfit. Since overfitting results in negatively biased variance estimates, it might have been better to set a higher hurdle for fixed effects to enter the model. On the other hand, there is also evidence that there was genuine predictive value in at least some of the county, tract and block group level summary data, so it would have been a mistake to set the hurdle so high that only demographic variables could have entered the model. For this study, the maximum p-value for a variable to be retained was set at 0.05 . It might have been better set at 0.01 .

Fourth, estimates from BRFSS, NDATUS and UCR for alcohol use, cigarette use, drug treatment, and arrest vary as much or more than the NHSDA design-based estimates across the states. Since theory indicates that the NHSDA design-based estimates vary too much across the states, it might be reasonable to conclude that the estimates from the other sources also vary too much across the states. If this is true, then it might have been better not to use NDATUS and UCR county-level variables in the modeling. Variables from the decennial census may not appear as relevant and can be updated only once every ten years, but at least they are collected consistently across the states.

These findings verify that the methodology is basically functioning as intended. That is reassuring in the sense that it appears to rule out major conceptual or programming errors. The findings also indicate small ways in which the methodology can be improved. However, open questions remain about the reduction in variance achieved through the use of modeling and whether the prediction intervals have the claimed coverage levels. More research is needed to prove that these objectives were actually attained.

## 4. Thoughts for Future Applications

There are a number of important areas for further research. Most critically, work needs to be done on improving the variance estimates and then using simulation studies to demonstrate that the revised prediction intervals have good coverage properties, thereby establishing the validity of the methodology. Once more accurate variance estimates are obtained, it would also be important for planning purposes to determine the relationship between the variances on survey- weighted empirical Bayes estimates and design-based variances. This information could then be used to predict the width of model-based prediction intervals prior to actually preparing the estimates. Additionally, there is room for improvement in the point estimates themselves. Finally, it is important to consider the quality of the change estimates that would be obtained from model-based estimates. Each of these issues is discussed in turn below.

### 4.1 Improvement of Estimated Variances

There were several problems in the estimation of variance. First, a small component of variance due to sampling PSUs was inadvertently omitted. The previously published estimates reflect only the variance of the fixed part of the model in nonsample PSUs, neglecting the variance due to assuming a zero random effect for all nonsample PSU, as explained in detail in Appendix G, Section G.1. Revised variance estimates have been prepared that show a modest impact of the error on most estimates. This correction would need to be routinized for future applications.

Second, the variance due to estimating components of variance was intentionally omitted due to the lack of theory on how to properly reflect this component of variance. There are some ideas on how to proceed in this area, but progress will not be easy. As a temporary measure, one could approximate an upper bound on this effect and then use that upper bound, thereby providing prediction intervals with conservative coverage properties; i.e., one would deliberately overestimate the mean square error so that when $95 \%$ coverage is claimed, the actual coverage would be higher than $95 \%$. For a better solution to this problem, it might be necessary to adopt a fully Bayesian approach to the small area estimation. This would require developing an entirely new software system and documentation. Since such development would be costly, it would only be recommended if simulation studies indicated that neglecting the variance on the estimated variance components was seriously affecting the coverage of the prediction intervals and that a simple upper bound did not remedy those coverage problems.

Third, estimated variances for domains that span the age groups are too low because the methodology ignored the positive covariance between the age groups across areas. There was a plan to approximate this effect, but it could not be implemented due to budget constraints. If one could fit a single model for all the age groups, this problem would disappear, although one would need to rewrite sections of the software to maintain separate random effects by age group.

Fourth, there is some evidence that the models were overfit. This means that too many predictor variables were used. If this is true, this also resulted in underestimation of the variances. The problem is that when the model is overfit, all of the estimated random effects tend to be too small. Since the variance estimate involves a term with the sum of the expected squared random effects, the overfitting thereby results in variance estimates that are too small. This problem can be fixed by keeping the models leaner.

### 4.2 Validation

Validation is an intrinsically difficult task with small area estimation unless there is an occasional census on the variables of interest using the same measurement techniques. Short of a census, simulation studies are the best that can be done to assess the coverage properties of the prediction intervals. The internal measures that were done for this study were innovative and interesting, but don't provide sufficiently strong evidence of validity. Comparisons with other surveys are of limited value because methodologies across surveys differ and because each has sampling error.

Various simulation studies could be designed. These can be grouped into two broad categories. The first category includes studies in which the simulated population is created according to the same model that will be used to analyze it. The second category includes studies in which pathologies are introduced into the population so that the model applies only approximately. Although the first category might appear to be an easy test of a method, it would be of interest for the NHSDA project since approximations were used in fitting the model and in estimating the variance for the estimates. Without simulation studies, the effect of these approximations is unknown.

The second category of simulation study is a much more stringent test of a methodology, but requires more judgment to design and interpret. If the pathologies are severe enough, then no reasonable method can be designed to cope with them. This is even true of design-based methods. It is quite difficult to decide how severe a pathology to use in testing.


#### Abstract

Ideally, both sorts of simulation studies would be conducted. The second category should, of course, be delayed until the results of the first category can be studied. There is no reason to test the method on pathological pseudo populations until it has passed the test on model-conforming pseudo populations.


### 4.3 Reduction in Variance Due to Modeling

Before accurate predictions can be made of the variance reduction achievable through the SAE methodology, it is necessary to improve the estimates of variance as discussed above. The correction of the problem regarding a neglected bias-squared term is particularly important. After making that correction, however, more theoretical work is required since the variance of the model-based estimates is not strictly inversely proportional to the sample size. As the sample size increases, the reduction in variance due to modeling is likely to decrease. A reasonable guess is that the reduction is somewhere in the range of 10 to 75 percent. More time and study would be required to make more precise projections.

### 4.4 Improvement of Point Estimates

The point estimates appear to be of good quality. However, the quality could probably be improved by fitting leaner models. The overfitting mentioned earlier has several consequences for the quality of the point estimates. First, the small area estimates are not shrunk quite as close together as they should be. Another outcome of overfitting is that resulting computer time problems force one to run separate models by age. If a single model could be run including all ages, then the parameters for effects that do not interact with age would be estimated more accurately. A third outcome is that the ordering of the states may not be as stable as it could be. For all three reasons, the models should not be allowed to be as rich on a repetition of the project.

One of the ways that this could be achieved is to reverse the order of elimination for county-level summaries vis-à-vis tract or block-group level summaries. Before, the county-level summaries were only admitted to the model if they were significant after accepting the tract and block-group level summaries for the same characteristics. It may be better to let the county-level variables in first and then to accept the tract and block-group level summaries if they are marginally significant. It may also be better to require higher significance for each variable prior to admitting it to the model, perhaps $\alpha=.01$ or even smaller instead of $\alpha=.05$.

### 4.5 Validity of Change Estimates

Estimates of change can be made by using the survey-weighted empirical Bayes procedure to prepare estimates for each time period and then forming the differences between the two sets. Estimates of change made in this manner will be more stable than estimates of change made using purely design-based methods. However, the model-based estimates of change for particular states reflect a blend of changes at the state and national level. Particularly for states with small sample sizes, the estimates are likely to mostly reflect nation changes. The validity of these change estimates will depend on the extent to which the national changes are uniform within the cells defined by the fixed effects in the model.

### 4.6 Sample Design

In this study, the methodology for small area estimation was developed after the sample had already been designed and the survey had been conducted. The 1991-1993 NHSDA was designed to be nearly optimal for national estimates by race-ethnicity domain by age group. If the objective of state specific estimates is fixed in advanced, it is possible to develop a sample design that is better suited to the objective. Specifically, if state estimates were made an objective, the number of sample PSUs should be increased, the PSUs should be stratified by state, and the sample of people should be more equally allocated across the states instead of being massed in the large states. Since all of these design features would be less than optimal for national estimates by race, ethnicity and age, deciding whether to adopt these features is a difficult question.

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## Appendix A: Classification of Drug and Alcohol Dependence

## CLASSIFICATION OF DRUG AND ALCOHOL DEPENDENCE

The Diagnostic and Statistical Manual of Mental Disorders, Revised Third Addition (DSM-III-R), published by the American Psychiatric Association is designed to be used by clinicians as well as researchers for making diagnosis of psychiatric disorders. Substance abuse and dependence are considered psychiatric disorders under DSM-III-R. DSM-III-R defines a person as dependent on a substance if they meet 3 out of 9 criteria for that substance. The method for estimating dependence from the NHSDA is based on the NHSDA questionnaire items that are assumed to approximate five of the nine DSM-III-R criteria. These five criteria include: unable to cut down on use; reduced social, occupational, or recreational activities; continued use despite knowledge of having a problem; tolerance; withdrawal. In the NHSDA algorithm, respondents are defined as dependent on a substance if they responded affirmatively to at least two of the five NHSDA criteria for that substance.

To evaluate this method for estimating dependence, NHSDA dependence estimates were compared to estimates from the National Comorbidity Survey (NCS). ${ }^{1,2}$ Conducted in 1991, the NCS was designed to provide nationally representative estimates of 14 psychiatric disorders, including substance abuse and dependence, using a structured diagnostic interview. It employed a multistage area probability sample of 8,098 respondents in the household population.

Based on this analysis it was concluded that the approximation to the DSM-III-R definition of drug dependence produces dependence estimates which are comparable to the NCS. The table below indicates estimates of dependence from the NHSDA from 1991 through 1993 and estimates of dependence from the NCS.

Twelve Month Estimates of Dependence from the NCS and NHSDA (Old and New Methods) for Persons 15-54 Years of Age (1991-1994)

| DRUG | NCS | NHSDA |  |  |
| :--- | :---: | :---: | :---: | :---: |
|  | 1991 | 1991 | 1992 | 1993 |
| Any Illicit | $1.8 \%$ | $1.8 \%$ | $1.4 \%$ | $1.5 \%$ |
| Marijuana | 0.9 | 1.2 | 0.9 | 0.9 |
| Cocaine | 0.4 | 0.5 | 0.4 | 0.3 |
| Alcohol | 4.4 | 5.7 | 4.7 | 5.2 |

${ }^{1}$ This is included in a paper by Joan Epstein and Joe Gfroerer, A Method for Estimating Substance Abuse Treatment Need from a National Household Survey, that was presented at the 37th International Congress on Alcohol and Drug Dependence, August 20-25, 1995.
${ }^{2}$ Lifetime and 12-Month Prevalence of DSM-III-R Psychiatric Disorders in the United States. Results from the National Comorbidity Survey. R.C. Kessler, PhD; K.A.McGonagle, PhD; S. Zhao, PhD; C.B. Nelson, MPH; M. Hughes, PhD; S. Eshleman, MA; H.U. Wittchen, PhD; K.S.Kendler, MD. Arch Gen Psychiatry, Vol.51, P.P. 8-19, January 1994.

## Appendix B: Definition of 25 MSAs Selected for Small Area Estimation

## Appendix B. Definition of $\mathbf{2 5}$ MSAs Selected for Small Area Estimation

1992
Population
Projection

1. Anaheim-Santa Ana, CA ..... 1,996,343
California, Orange County ..... 1,996,343
2. Atlanta, GA ..... 2,424,882
Georgia, Barrow County ..... 25,179
Georgia, Butts County ..... 12,970
Georgia, Cherokee County ..... 77,733
Georgia, Clayton County ..... 151,319
Georgia, Cobb County ..... 391,285
Georgia, Coweta County ..... 45,782
Georgia, De Kalb County ..... 463,515
Georgia, Douglas County ..... 59,987
Georgia, Fayette County ..... 55,556
Georgia, Forsyth County ..... 38,659
Georgia, Fulton County ..... 546,808
Georgia, Gwinnett County ..... 310,368
Georgia, Henry County ..... 51,116
Georgia, Newton County ..... 35,030
Georgia, Paulding County ..... 35,385
Georgia, Rockdale County ..... 46,428
Georgia, Spalding County ..... 45,367
Georgia, Walton County ..... 32,395
3. Baltimore, MD ..... 1,996,133
Maryland, Anne Arundel County ..... 357,569
Maryland, Baltimore County ..... 588,006
Maryland, Carroll County ..... 104,516
Maryland, Harford County ..... 153,125
Maryland, Howard County ..... 163,767
Maryland, Queen Annes County ..... 29,465
Maryland, Baltimore City ..... 599,685
4. Boston, MA ..... 3,144,871
Massachusetts, Essex County ..... 551,793
Massachusetts, Middlesex County ..... 1,170,799
Massachusetts, Norfolk County ..... 516,160
Massachusetts, Plymouth County ..... 355,370
Massachusetts, Suffolk County ..... 550,750

## Appendix B. Definition Of 25 MSAs Selected For Small Area Estimation (continued)

1992
Population Projection
5. Chicago, IL ..... 4,981,375
Illinois, Cook County ..... 4,175,359
Illinois, Du Page County ..... 654,320
Illinois, Mchenry County ..... 151,696
6. Dallas, TX ..... 2,120,056
Texas, Collin County ..... 227,616
Texas, Dallas County ..... 1,518,374
Texas, Denton County ..... 237,971
Texas, Ellis County ..... 70,322
Texas, Kaufman County ..... 43,729
Texas, Rockwall County ..... 22,044
7. Denver, CO ..... 1,345,668
Colorado, Adams County ..... 211,897
Colorado, Arapahoe County ..... 329,437
Colorado, Denver County ..... 381,917
Colorado, Douglas County ..... 53,022
Colorado, Jefferson County ..... 369,394
8. Detroit, MI ..... 3,592,682
Michigan, Lapeer County ..... 60,050
Michigan, Livingston County ..... 96,340
Michigan, Macomb County ..... 603,448
Michigan, Monroe County ..... 107,869
Michigan, Oakland County ..... 909,637
Michigan, St Clair County ..... 119,365
Michigan, Wayne County ..... 1,695,974
9. El Paso, TX ..... 456,359
Texas, El Paso County ..... 456,359
10. Houston, TX ..... 2,661,181
Texas, Fort Bend County ..... 184,640
Texas, Harris County ..... 2,261,297
Texas, Liberty County ..... 42,903
Texas, Montgomery County ..... 152,654
Texas, Waller County ..... 19,687
11. Los Angeles, CA ..... 7,127,293
California, Los Angeles County ..... 7,127,293
12. Miami-Hialeah, FL ..... 1,600,103
Florida, Dade County ..... 1,600,103

## Appendix B. Definition Of 25 MSAs Selected For Small Area Estimation (continued)

1992
13. Minneapolis-St. Paul ..... 2,035,347
Minnesota, Anoka County ..... 198,093
Minnesota, Carver County ..... 39,020
Minnesota, Chisago County. ..... 24,780
Minnesota, Dakota County ..... 228,159
Minnesota, Hennepin County ..... 865,489
Minnesota, Isanti County ..... 20,829
Minnesota, Ramsey County ..... 398,328
Minnesota, Scott County ..... 47,001
Minnesota, Washington County ..... 118,214
Minnesota, Wright County ..... 54,470
Wisconsin, St Croix County ..... 40,963
14. Nassau-Suffolk, NY ..... 2,177,956
New York, Nassau County ..... 1,085,945
New York, Suffolk County ..... 1,092,011
15. New York, NY ..... 7,085,772
New York, Bronx County ..... 938,595
New York, Kings County ..... 1,873,534
New York, New York County ..... 1,283,134
New York, Putnam County ..... 69,880
New York, Queens County ..... 1,648,200
New York, Richmond County ..... 316,399
New York, Rockland County ..... 218,687
New York, Westchester County ..... 737,342
16. Newark, NJ ..... 1,499,843
New Jersey, Essex County ..... 628,943
New Jersey, Morris County ..... 353,820
New Jersey, Sussex County ..... 106,854
New Jersey, Union County ..... 410,225
17. Oakland, CA ..... 1,727,459
California, Alameda County ..... 1,054,766
California, Contra Costa County ..... 672,693

## Appendix B. Definition Of 25 MSAs Selected For Small Area Estimation (continued)

1992
18. Philadelphia, PA-NJ ..... 4,036,961
New Jersey, Burlington County. ..... 329,783
New Jersey, Camden County. ..... 407,164
New Jersey, Gloucester County. ..... 190,673
Pennsylvania, Bucks County ..... 456,745
Pennsylvania, Chester County ..... 320,513
Pennsylvania, Delaware County ..... 454,906
Pennsylvania, Montgomery County ..... 573,220
Pennsylvania, Philadelphia County ..... 1,303,956
19. Phoenix, AZ ..... 1,770,449
Arizona, Maricopa County ..... 1,770,449
20. San Antonio, TX ..... $.1,040,318$
Texas, Bexar County ..... 941,916
Texas, Comal County ..... 44,601
Texas, Guadalupe County ..... 53,801
21. San Bernardino, CA ..... 2,122,022
California, Riverside County ..... 978,288
California, San Bernardino County ..... 1,143,734
22. San Diego, CA ..... 2,089,322
California, San Diego County ..... 2,089,322
23. St. Louis, MO-IL ..... 2,006,385
Illinois, Clinton County ..... 28,060
Illinois, Jersey County ..... 16,844
Illinois, Madison County ..... 206,040
Illinois, Monroe County ..... 18,700
Illinois, St Clair County ..... 212,612
Missouri, Franklin County ..... 66,062
Missouri, Jefferson County ..... 139,312
Missouri, St Charles County ..... 177,308
Missouri, St Louis County ..... 826,259
Missouri, St Louis City ..... 315,187
24. Tampa-St. Petersburg, FL ..... 1,822,154
Florida, Hernando County ..... 97,648
Florida, Hillsborough County ..... 708,882
Florida, Pasco County ..... 258,574
Florida, Pinellas County ..... 757,050

## Appendix B. Definition Of 25 MSAs Selected For Small Area Estimation (continued)

1992
Population Projection
25. Washington, DC .......................................................................................................3,345,080
District of Columbia .....................................................................................................513,842
Maryland, Calvert County ..............................................................................................43,912
Maryland, Charles County..............................................................................................84,579
Maryland, Frederick County..........................................................................................127,118
Maryland, Montgomery County ....................................................................................651,746
Maryland, Prince Georges County ...............................................................................611,812
Virginia, Arlington County...........................................................................................151,317
Virginia, Fairfax County................................................................................................706,226
Virginia, Loudoun County ..............................................................................................73,193
Virginia, Prince William County..................................................................................178,043
Virginia, Stafford County ...............................................................................................51,577
Virginia, Alexandria City ...............................................................................................98,061
Virginia, Fairfax City......................................................................................................16,699
Virginia, Falls Church City...............................................................................................8,157
Virginia, Manassas City...................................................................................................23,622
Virginia, Manassas Park City ..........................................................................................5,176

## Appendix C: Fitting the Models <br> Given Variable <br> Selection

C-2

## Appendix C. Fitting the Models Given Variable Selection

As discussed in Section 2.4, the model fitting procedure was an iterative series of iterative subprocedures. The first subprocedure is based on knowing $G$, the variance-covariance matrix for the random effects. The objective of this subprocedure is to find $\beta 55^{\wedge}$ and $U 50^{\wedge}$ that maximize $L_{w}(\beta, U \mid y, G)$.

## C.1Estimating $\boldsymbol{\beta}$ and $\boldsymbol{U}$ Given $\boldsymbol{G}$

Because the natural $\log$ function is monotone increasing, finding $\beta 55^{\wedge}$ and $U 50^{\wedge}$ that maximize $L_{w}(\beta, U \mid y, G)$ is identical to finding $\beta 55^{\wedge}$ and $U 50^{\wedge}$ that maximize $\ln \left[L_{w}(\beta, U \mid y, G)\right]$. Taking the $\log$ will simplify further steps considerably. Standard results from calculus tell us that if a function of one variable has a maximum at an interior point of its domain, then the first derivative will be zero at that point and the second derivative will be negative. Similar results are available for functions of many variables. Recall that if f is a real-valued function of $x_{1}, \ldots, x_{n}$ then the transpose of the Jacobian matrix ${ }^{1}$ of $f$ is an $\mathrm{n} \times 1$ matrix defined as

$$
\frac{\partial f(x)}{\partial x}=\left[\begin{array}{c}
\frac{\partial f}{\partial x_{1}}\left(x_{1}, \ldots, x_{n}\right) \\
\operatorname{DOTSVERT} \\
\frac{\partial f}{\partial x_{n}}\left(x_{1}, \ldots, x_{n}\right)
\end{array}\right]
$$

and the Hessian of $f$ is an n x n matrix defined as

$$
\frac{\partial^{2} f(x)}{\partial x^{2}}=\left[\begin{array}{l}
\frac{\partial^{2} f}{\partial x_{1}^{2}}\left(x_{1}, \ldots, x_{n}\right) \text { DOTSAXIS } \frac{\partial^{2} f}{\partial x_{1} \partial x_{n}}\left(x_{1}, \ldots, x_{n}\right) \\
\text { DOTSVERT } \\
\frac{\partial^{2} f}{\partial x_{n} \partial x_{1}}\left(x_{1}, \ldots, x_{n}\right) \text { DOTSAXIS } \frac{\partial^{2} f}{\partial x_{n}^{2}}\left(x_{1}, \ldots, x_{n}\right)
\end{array}\right]
$$

For $f$ to have a local maximum at an interior point $x^{\star}$, it is necessary that

$$
\frac{\partial f\left(x^{*}\right)}{\partial x}=\left[\begin{array}{c}
0 \\
\operatorname{DOTSVERT} \\
0
\end{array}\right]
$$

[^12]and sufficient that this condition hold and that
$$
\frac{\partial^{2} f\left(x^{*}\right)}{\partial x^{2}}
$$
is a negative definite matrix, by which it is meant that
$$
x^{\prime} \frac{\partial^{2} f\left(x^{*}\right)}{\partial x^{2}} x<0 \quad \text { all } x \neq 0 .
$$

The transpose of the Jacobian matrix of the log of the likelihood function (with respect to the parameters - not the data) is often called the efficient score of the parameters for the data or simply the score function. In our application, we write

$$
S_{w}(\beta, U \mid y, G)=\frac{\partial \ln \left[L_{w}(\beta, U \mid y, G)\right]}{\partial(\beta, U)}
$$

We now derive this score function

Note that

$$
\ln L_{w}=\sum_{i=1}^{\text {nleft }}\left[w_{i} y_{i} \ln \left(\pi_{i}\right)+w_{i}\left(1-y_{i}\right) \ln \left(1-\pi_{i}\right)\right.
$$

Recall from our model that $\operatorname{logit}\left(\pi_{\mathrm{i}}\right)=X_{i} \beta+Z_{i} U$, where $X_{\mathrm{i}}$ is the ${ }^{\mathrm{i} \text {-th }}$ row of $X$ and $Z_{i}$ is the ${ }^{\text {i-th }}$ row of $Z$. By inverting the logit transform, we have that

$$
\pi_{i}=\frac{e^{X \beta}+Z_{i} U}{1+e^{X i} \beta+Z_{i} U}
$$

From this, it easily follows that

$$
1-\pi_{i}=\frac{1}{1+e^{X} \beta+Z_{i} U}
$$

Thus, we may write

$$
\begin{aligned}
& \ln L_{w}=\sum_{i=1}^{n}\left\{w_{i} y_{i}\left[\left(X_{i} \beta+Z_{i} U\right)-\ln \left(1+e^{X_{i} \beta+Z_{i} U}\right)\right]-w_{i}\left(1-y_{i}\right) \ln \left(1+e^{X, \beta+Z_{i} U}\right)\right\} \\
& -\frac{1}{2} U^{t} G^{-1} U-\frac{q}{2} \ln (2 \pi)-\frac{1}{2} \ln |G| \\
& =\sum_{i=1}^{n}\left\{w_{i} y_{i}\left(X_{i} \beta+Z_{i} U\right)-w_{i} \ln \left(1+e^{X, \beta+Z_{i} U}\right)\right\}-\frac{1}{2} U^{t} G^{-1} U-\frac{q}{2} \ln (2 \pi)-\frac{1}{2} \ln |G| .
\end{aligned}
$$

Taking first the derivative with respect to $\beta_{1}$, we have that

$$
\begin{aligned}
\frac{\partial}{\partial \beta_{1}} \ln \left(L_{w}\right) & =\sum_{i=1}^{n}\left[/ w_{i} y_{i} X_{i l}-\frac{w_{i} X_{i l} e^{X_{i} \beta+Z_{i} U}}{1+e^{X_{i} \beta+Z_{i} U}}\right] / \\
& =\sum_{i=1}^{n} X_{i l} w_{i}\left(y_{i}-\pi_{i}\right)
\end{aligned}
$$

where $X_{i 1}$ is the first component of the row vector $X_{i}$.

Similarly,

$$
\frac{\partial \ln }{\partial \beta_{p}}\left(L_{w}\right)=\sum_{i=1}^{n} X_{i p} w_{i}\left(y_{i}-\pi_{i}\right)
$$

Let $W$ be an nx n diagonal matrix with the sampling weights on the diagonal:

$$
W=\left[\begin{array}{ll}
w_{1} & 0 \\
\hline D O T S D I A G
\end{array} / /\right.
$$

where it is important to note that the $n$ weights were standardized to sum to $n$. Otherwise, the procedure behaves as if we have a sample as large as the U.S. population. Then

$$
\frac{\partial \ln }{\partial \beta}\left(L_{w}\right)=\left[\begin{array}{c}
\sum_{i=1}^{n} X_{i 1} w_{i}\left(y_{i}-\pi_{i}\right) \\
\operatorname{DOTSVERT} \\
\sum_{i=1}^{n} X_{i p} w_{i}\left(y_{i}-\pi_{i}\right)
\end{array} /_{/}=X^{t} W(y-\pi)\right.
$$

Note that $W(y-\pi)$ is an nx 1 matrix and that $X^{t}$ is px n so that $X^{t} W(y-\pi)$ is a px 1 matrix, as required. Having found the Jacobian of $\ln L_{w}$ with respect to $\beta$, we now need to find the Jacobian with respect to $U$. Here it is useful to note that

$$
G^{-1}=\left[\begin{array}{ll}
\frac{I_{m}}{\sigma_{1}^{2}} & O \\
& \\
O & \frac{I_{r}}{\sigma_{2}^{2}}
\end{array} /\right.
$$

So that $U^{t} G^{-1} U$ is simply

$$
\frac{1}{\sigma_{1}^{2}} \sum_{i=1}^{m} U_{i}^{2}+\frac{1}{\sigma_{2}^{2}} \sum_{i=m+1}^{m+r} U_{i}^{2}
$$

where m is the number of states and $r$ is the number of sample PSUs. Taking first the derivative with respect to $U_{1}$, we have that

$$
\begin{aligned}
& \frac{\partial}{\partial U_{1}} \ln \left(L_{w}\right)= \sum_{i=1}^{n} / / w_{i} y_{i} Z_{i l}-\frac{w_{i} Z_{i l} e^{X} \beta+Z_{i} U}{1+e^{X} X_{i} \beta+Z_{i} U} \\
& / \frac{\partial 1}{\partial U_{1} 2} \\
&\left\lceil\frac{1}{\sigma_{1}^{2}} \sum_{i=1}^{m} U_{i}^{2}+\frac{1}{\sigma_{2}^{2}} \sum_{i=m+1}^{m+r} U_{i}^{2} / /\right. \\
&=\sum_{i=1}^{n} Z_{i l} w_{i}\left(y_{i}-\pi_{i}\right)-\frac{U_{1}}{\sigma_{1}^{2}}
\end{aligned}
$$

Similarly, for the random effect corresponding to the $m^{\text {th }}$ state,

$$
\frac{\partial}{\partial U_{m}} \ln \left(L_{w}\right)=\sum_{i=1}^{n} Z_{i m} w_{i}\left(y_{i}-\pi_{i}\right)-\frac{U_{m}}{\sigma_{1}^{2}}
$$

For the $r$ random effects corresponding to the PSU-level random effects, we have

$$
\frac{\partial}{\partial U_{j}} \ln \left(L_{w}\right)=\sum_{i=1}^{n} Z_{i j} w_{i}\left(y_{i}-\pi_{i}\right)-\frac{U_{j}}{\sigma_{2}^{2}} \quad m<j \leq m+r .
$$

We can thus write

By stacking $\frac{\partial}{\partial \beta} \ln \left(L_{w}\right)$ above $\frac{\partial}{\partial U} \ln \left(L_{w}\right)$, we may write

$$
S_{W}(\beta, U \mid y, G)=\frac{\partial}{\partial(\beta, U)} \ln \left(L_{w}\right)=\left\langle\begin{array}{c}
X^{t} W(y-\pi) \\
Z^{t} W(y-\pi)-G^{-1} U
\end{array}\right]
$$

Note that this an $(\mathrm{p}+\mathrm{q}) \times 1$ matrix as required. In order to maximize $L_{w}$ for fixed $y$ and $G$, we need to find $\beta 55^{\wedge}$ and $U 50{ }^{\wedge}$ such that all $\mathrm{p}+\mathrm{g}$ rows of $S_{w}$ are identically equal to zero. Since this system of equations is nonlinear in $\beta$ and $U$, we need to use numerical methods to solve it. The method we used is called Fisher's method of scoring (or simply "the method of scoring").

To describe this method, we need to define another term. The "Fisher information matrix" (or simply "the information matrix") is the expected value of the product of the score function with its transpose with respect to the distribution of $y$. We write this as

$$
J_{w}(\beta, U \mid y, G)=E\left(S_{w} S_{w}^{t}\right),
$$

where the expected value is with respect to the modeled distribution for $y$ and $U$, ignoring the sample design and treating $G$ and $\beta$ as fixed.

In our application, note that $J_{w}$ is a $(p+q) \times(p+q)$ matrix. Deriving it for our application is made simpler if we write $S_{w}$ in terms of a transform of $y-\pi$.

$$
\varepsilon_{i}=\frac{y_{i}-\pi_{i}}{\pi_{i}\left(1-\pi_{i}\right)}
$$

Note that the expected value of $\varepsilon_{i}$ given fixed $\pi_{i}$ is $E\left(\varepsilon_{i} \mid \pi_{i}\right)=0$ since $E\left(y_{i} \mid \pi_{i}\right)=\pi_{i}$. Also note that

$$
\begin{aligned}
\operatorname{Var}\left(\varepsilon_{i} \mid \pi_{i}\right) & =\frac{\pi_{i}\left(1-\pi_{i}\right)}{\left[\pi_{i}\left(1-\pi_{i}\right)\right]^{2}} \\
& =\frac{1}{\pi_{i}\left(1-\pi_{i}\right)}
\end{aligned}
$$

and that $\operatorname{Cov}\left(\varepsilon_{i}, \varepsilon_{j} \mid \pi_{i}, \pi_{j}\right)=0$ since the individual outcomes are assumed to be independent once the random effects have been fixed. If we use $C$ to denote the n x n diagonal matrix with $\pi_{i}\left(1-\pi_{i}\right)$ sequenced down the main diagonal as

$$
\left.C=\begin{array}{l}
\pi_{11}\left(1-\pi_{1}\right) \\
\text { DOTSDIAG } \\
O \\
O \\
\pi_{n}\left(1-\pi_{n}\right)
\end{array}\right] \quad \varepsilon=\begin{gathered}
\varepsilon_{1} \\
\text { DOTSVERT }
\end{gathered} / /
$$

then we may write

$$
\varepsilon=C^{-1}(y-\pi)
$$

the covariance matrix for $\varepsilon$ as $\operatorname{Cov}(\varepsilon)=C^{-1}$, and the score function as

$$
S_{W}(\beta, U \mid \varepsilon, G)=\left[\begin{array}{l}
X^{t} W C \varepsilon \\
Z^{t} W C \varepsilon-G^{-1} U
\end{array}\right]
$$

The Fisher information matrix for $\beta$ and $U$ given $\varepsilon$ and $G$ is then

$$
\left.J_{W}(\beta, U \mid \varepsilon, G)=E\left\{\begin{array}{cc}
X^{t} W C \varepsilon & 7 /\left[\varepsilon^{t} W W X\right. \\
{\left[Z^{t} W C \varepsilon-G^{-1} U\right.}
\end{array} \quad \varepsilon^{t} C W Z-U^{t} G^{-1}\right]\right\},
$$

where we note that $C, W$, and $G^{-1}$ are all symmetric. Expanding the product, we have

## Error!

We now note that

$$
E\left(\varepsilon_{i} U_{i}\right)=E_{U_{i}}\left[E\left(\varepsilon_{i} \mid U_{i}\right)\right]=E_{U_{i}}\left[E\left(\varepsilon_{i} \mid \pi_{i}\right)\right]=E_{U_{i}}(0)=0
$$

so that $E\left(\varepsilon U^{t}\right)=E\left(U \varepsilon^{t}\right)=0$. We also note that by definition, $E\left(\varepsilon \varepsilon^{t}\right)=C^{-1}$ and $E\left(U U^{t}\right)=G$. Furthermore, since we are treating $G$ as fixed and known, we can move the expected value operator inside to just the factors involving U and $\varepsilon$. We thus have

$$
J_{w}=\sqrt{X^{t} W C W X} \quad \begin{aligned}
& X^{t} W C W Z \\
& Z^{t} W C W X
\end{aligned} Z^{t} W C W Z+G^{-1} \% .
$$

Returning to the definition of Fisher's method of scoring, this is an iterative method that starts with a guess at a solution and then improves upon the guess. The improvement equation in our application is
where the $a$ superscript indexes iterations of the cycle.

As the algorithm converges, $\beta 55^{\wedge(a+1)}-\beta 55^{\wedge(a)} \rightarrow 0, U 50^{\wedge(a=1)}-U 50^{\wedge(a)} \rightarrow 0$, $S_{w}^{(a)} \rightarrow 0, \quad$ and $J_{w}^{(a)} \rightarrow J_{w}^{(\infty)}$. We note that the matrices $X, W, Z$ and $G^{-1}$ are all constant during the convergence. Only the matrix $C$ changes in $J_{w}$. Note that if any of the $\pi_{\mathrm{i}}$ are close to 0 or to 1 , then $C$ will have a diagonal entry close to zero, thereby making $J_{w}$ ill-conditioned (i.e., difficult to invert). In such a case, convergence may be a problem. Otherwise, it may be proven that this process will converge. It is our understanding, however, that it has not been proven that there is a single solution to $S_{w}=0$. If there are multiple solutions, it may be best to start the system with several different initial guesses. See Section C. 3 for more discussion of this point.

Although we have completely specified the procedure for finding $\beta 55^{\wedge}$ and $U 50^{\wedge}$ given $G$, it is useful for discussion purposes to describe the algorithm in an equivalent but different form. To this end, we note that the score function can be rewritten as where

$$
S_{W}=\left[\begin{array}{c}
X^{t} W(y-\pi) \\
\left\langle Z^{t} W(y-\pi)-G^{-1} U\right.
\end{array}\right]=\left[/ \begin{array}{c}
X^{t} W C W(\zeta-X \beta-Z U) \\
Z^{t} W C W(\zeta-X \beta-Z U)-G^{-1} U
\end{array}\right] /
$$

$$
\zeta=\left\{\begin{array}{l}
\left.X_{1} \beta+Z_{1} U+\frac{y_{1}-\pi_{1}}{w_{1} \pi_{1}\left(1-\pi_{1}\right)}\right]_{/}^{D O T S V E R T} \\
{\left[X_{n} \beta+Z_{n} U+\frac{y_{n}-\pi_{n}}{w_{n} \pi_{n}\left(1-\pi_{n}\right)}\right.}
\end{array} / / E X \beta+Z U+W^{-1} C^{-1}(y-\pi)=X \beta+Z U+W^{-1} \varepsilon\right.
$$

Continuing to transform $S_{w}$, we have

$$
\begin{aligned}
& S_{W}= {\left[\begin{array}{c}
X^{t} W C W \zeta \\
Z^{t} W C W \zeta
\end{array}\right]-\left[\begin{array}{c}
X^{t} W C W X \beta \\
Z^{t} W C W X \beta
\end{array}\right]-\left[\begin{array}{c}
X^{t} W C W Z U \\
Z^{t} W C W Z U+G^{-1} U
\end{array}\right] } \\
&= {\left[\begin{array}{c}
X^{t} W C W \zeta \\
Z^{t} W C W \zeta
\end{array}\right]-\left[\begin{array}{c}
X^{t} W C W X \\
Z^{t} W C W X
\end{array}\right] \beta-\left[\begin{array}{c}
X^{t} W C W Z \\
Z^{t} W C W Z+G^{-1}
\end{array}\right] U } \\
&= {\left[\begin{array}{c}
X^{t} W C W \zeta \\
X^{t} W C W \zeta
\end{array}\right]-\left[\begin{array}{c}
X^{t} W C W X \\
Z^{t} W C W X \\
X^{t} W C W Z \\
Z^{t} W C W Z+G^{-1}
\end{array}\right]\left[\begin{array}{l}
\beta \\
U
\end{array}\right] } \\
&=\left[\begin{array}{c}
X^{t} W C W \zeta \\
Z^{t} W C W \zeta
\end{array}\right]-J_{w}\left[\begin{array}{c}
\beta \\
U
\end{array}\right]
\end{aligned}
$$

So if we had the final version of $C$ available, we could solve $S_{w}=0$ by just setting This is a nice form since it corresponds to the form that would be used if $\zeta$ were the observed

$$
\left[\begin{array}{c}
\beta \\
U
\end{array}\right]=J_{w}^{1}\left[\begin{array}{l}
X^{t} W C W \zeta \\
Z^{t} W C W \zeta
\end{array}\right] .
$$

random variable instead of $y$ and if $\zeta$ were a normal random variable. For this reason, we have sometimes referred to $\zeta$ as the working linear variable since it allows us to express the solution for $\beta$ and $U$ as a linear function of the "data." Of course, iteration is still required for the solution in this form since one must have preliminary values of $\beta$ and $U$ in order to calculate $\zeta, C$, and $J_{w}$.

We give the form of $J_{W}^{-1}$ below and prove that the form is correct, but some additional notation and a lemma are first required. Let $R=(W C W)^{-1}$ and $V=R+Z G Z^{t}$. Also, let $P=V^{-1}-V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}$. This matrix has several useful properties that we prove as needed throughout the appendix. The properties that we need to find $J_{w}^{-1}$ are that P is symmetric and that $P$ is orthogonal to $X$, meaning that $P X=0$.

## Lemma C.1: $\quad P X=0$

Proof:

$$
\begin{gathered}
P X=\left[V^{-1}-V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\right] X \\
=V^{-1}\left[X-X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} X\right] \\
=V^{-1}[X-X I] \\
=V^{-1} 0 \\
=0 .
\end{gathered}
$$

We are now ready to prove that

$$
J_{w}^{-1}=\left[\begin{array}{cc}
\left(X^{t} V^{-1} X\right)^{-1} & -\left(X^{t} V^{-1} X\right)^{-1}\left(X^{t} V^{-1} Z\right) G 7 \\
-G\left(Z^{t} V^{-1} X\right)\left(X^{t} V^{-1} X\right)^{-1} & G-G Z^{t} P Z G
\end{array}\right]
$$

We will prove this by demonstrating that $J_{w} J_{w}^{-1}=I$. A similar argument would demonstrate that $J_{w}^{-1} J_{w}=I, \quad$ as required. There are four steps to the proof. Using the new notation, we have that

$$
J_{W}=\left[\begin{array}{cc}
X^{t} R^{-1} X & X^{t} R^{-1} Z \\
Z^{t} R^{-1} X & Z^{t} R^{-1} Z+G^{-1}
\end{array}\right]
$$

We must show that

$$
\begin{gathered}
X^{t} R^{-1} X\left(X^{t} V^{-1} X\right)^{-1}-X^{t} R^{-1} Z G\left(Z^{t} V^{-1} X\right)\left(X^{t} V^{-1} X\right)^{-1}=I_{p \times p}, \\
-X^{t} R^{-1} X\left(X^{t} V^{-1} X\right)^{-1}\left(X^{t} V^{-1} Z\right) G+X^{t} R^{-1} Z\left(G-G Z^{t} P Z G\right)=0_{p x q^{\prime}} \\
Z^{t} R^{-1} X\left(X^{t} V^{-1} X\right)^{-1}-\left(Z^{t} R^{-1} Z+G^{-1}\right) G\left(Z^{t} V^{-1} X\right)\left(X^{t} V^{-1} X\right)^{-1}=0_{q \times p} \\
-Z^{t} R^{-1} X\left(X^{t} V^{-1} X\right)^{-1}\left(X^{t} V^{-1} Z\right) G+\left(Z^{t} R^{-1} Z+G^{-1}\right)\left(G-G Z^{t} P Z G\right)=I_{q \times q} .
\end{gathered}
$$

Proving the first condition, we have that

$$
\begin{gathered}
X^{t} R^{-1} X\left(X^{t} V^{-1} X\right)^{-1}-X^{t} R^{-1} Z G\left(Z^{t} V^{-1} X\right)\left(X^{t} V^{-1} X\right)^{-1} \\
=X^{t} R^{-1}\left[I-Z G Z^{t} V^{-1}\right] X\left(X^{t} V^{-1} X\right)^{-1} \\
=X^{t} R^{-1}\left[V-Z G Z^{t}\right] V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} \\
=X^{t} R^{-1} R V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} \\
=X^{t} V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} \\
=I_{p x p},
\end{gathered}
$$

as required. Proving the second condition, we have that

$$
\begin{aligned}
& -X^{t} R^{-1} X\left(X^{t} V^{-1} X\right)^{-1}\left(X^{t} V^{-1} Z\right) G+\left(X^{t} R^{-1} Z\right)\left(G-G Z^{t} P Z G\right) \\
& =X^{t} R^{-1}\left[-X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} Z+Z\left(I-G Z^{t} P Z\right)\right] G \\
& =X^{t} R^{-1}\left[-X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}+\left(I-Z G Z^{t} P\right)\right] Z G \\
& =X^{t} R^{-1} V\left[-V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}+V^{-1}\left(I-Z G Z^{t} P\right)\right] Z G \\
& =X^{t} R^{-1} V\left[V^{-1}-V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}-V^{-1} Z G Z^{t} P\right] Z G \\
& =X^{t} R^{-1} V\left[P-V^{-1} Z G Z^{t} P\right] Z G \quad \text { by definition of } P \\
& =X^{t} R^{-1} V\left[I-V^{-1} Z G Z^{t}\right] P Z G \\
& =X^{t} R^{-1}\left[V-Z G Z^{t}\right] P Z G \\
& =X^{t} R^{-1} R P Z G \\
& =\left(X^{t} P\right) Z G \\
& =0 Z G \quad \text { since } P X=0 \quad X^{t} P=(P X)^{t}=0^{t}=0 \\
& =0_{p \times q}
\end{aligned}
$$

as required.

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Proving the third condition, we have that

$$
\begin{gathered}
Z^{t} R^{-1} X\left(X^{t} V^{-1} X\right)^{-1}-\left(Z^{t} R^{-1} Z+G^{-1}\right) G\left(Z^{t} V^{-1} X\right)\left(X^{t} V^{-1} X\right)^{-1} \\
=\left[Z^{t} R^{-1} X-\left(Z^{t} R^{-1} Z+G^{-1}\right) G Z^{t} V^{-1} X\right]\left(X^{t} V^{-1} X\right)^{-1} \\
=\left[Z^{t} R^{-1}-\left(Z^{t} R^{-1} Z+G^{-1}\right) G Z^{t} V^{-1}\right] X\left(X^{t} V^{-1} X\right)^{-1} \\
=\left[Z^{t} R^{-1} V-\left(Z^{t} R^{-1} Z+G^{-1}\right) G Z^{t}\right] V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} \\
=\left[Z^{t} R^{-1} V-\left(Z^{t} R^{-1} Z G Z^{t}+Z^{t}\right)\right] V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} \\
=\left[Z^{t} R^{-1} V-Z^{t} R^{-1}\left(Z G Z^{t}+R\right)\right] V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} \\
=\left[Z^{t} R^{-1} V-Z^{t} R^{-1} V\right] V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} \\
=0 V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} \\
=0_{q x p},
\end{gathered}
$$

as required.

Proving the fourth condition, we have that

$$
\begin{gathered}
-Z^{t} R^{-1} X\left(X^{t} V^{-1} X\right)^{-1}\left(X^{t} V^{-1} Z\right) G+\left(Z^{t} R^{-1} Z+G^{-1}\right)\left(G-G Z^{t} P Z G\right) \\
=\left[-Z^{t} R^{-1} V V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} Z+\left(Z^{t} R^{-1} Z+G^{-1}\right)\left(I-G Z^{t} P Z\right)\right] G \\
=\left[-Z^{t} R^{-1} V\left(V^{-1}-P\right) Z+\left(Z^{t} R^{-1} Z+G^{-1}\right)\left(I-G Z^{t} P Z\right)\right] G \quad \text { definition of } P \\
=\left[-Z^{t} R^{-1} Z+Z^{t} R^{-1} V P Z+Z^{t} R^{-1} Z-Z^{t} R^{-1} Z G Z^{t} P Z+G^{-1}-Z^{t} P Z\right] G \\
=\left[Z^{t} R^{-1} V P Z-Z^{t} R^{-1}(V-R) P Z+G^{-1}-Z^{t} P Z\right] G \\
=\left[Z^{t} R^{-1} V P Z-Z^{t} R^{-1} V P Z+Z^{t} P Z+G^{-1}-Z^{t} P Z\right] G \\
=G^{-1} G \\
= \\
=I_{q X q^{\prime}}
\end{gathered}
$$

as required. This completes the proof that $\mathcal{J}_{w}^{-1}$ has the form claimed. Going back to the solution for ( $\beta 55^{\wedge}, U 50^{\wedge}$ ) in terms of $J_{w}^{-1}$ and $\zeta$, we have that

$$
\begin{aligned}
& =\left[\begin{array}{ccc}
\left(X^{t} V^{-1} X\right)^{-1} & -\left(X^{t} V^{-1} X\right)^{-1}\left(X^{t} V^{-1} Z\right) G \\
& -G\left(Z^{t} V^{-1} X\right)\left(X^{t} V^{-1} X\right)^{-1} & G-G Z^{t} P Z G
\end{array}\right]\left[\begin{array}{l} 
\\
X^{t} R^{-1} \zeta \\
Z^{t} R^{-1} \zeta \\
\zeta
\end{array}\right]
\end{aligned}
$$

$$
\begin{aligned}
& =\left[/\left[\begin{array}{c}
\left(X^{t} V^{-1} X\right)^{-1}\left(X^{t}-X^{t} V^{-1} Z G Z^{t}\right) \\
{\left[-V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t}+I-P Z G Z^{t}\right]}
\end{array} R^{-1} \zeta\right.\right. \\
& =\left[/ / G Z^{t}\left[-V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}+V^{-1}-P Z G Z^{t} V^{-1}\right] V / V^{-1} \zeta\right. \\
& \left.=\left[/ /\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} R \quad 7 / P-P Z G Z^{t} V^{-1}\right] V\right] / R^{-1} \zeta \\
& =\left[/ \begin{array}{c}
\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} \\
G Z^{t}\left[P-P Z G Z^{V} V^{-1}\right] V R^{-1}
\end{array}\right] / / \\
& =\sqrt{\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}} / G Z^{t} P\left(V-Z G Z^{t}\right) R^{-1} / / 5 \\
& =\left[/\left[\begin{array}{c}
\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} \\
G Z^{t} P
\end{array}\right] / / 5\right.
\end{aligned}
$$

In other words, given preliminary estimates of $\pi$, we may compute $\zeta, C, R, V$, and $P$ and then obtained improved estimates of $\beta$ and $U$ as

$$
\beta 55^{\wedge}=\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} \zeta
$$

and

$$
U 50^{\wedge}=G Z^{t} P \zeta .
$$

Given improved estimates of $\beta$ and $U$, we can get an improved estimate of $\pi$ by

$$
\mathrm{C}-13
$$

$$
\pi 50^{\wedge}=\frac{e^{X \beta 50^{\wedge}+Z U 50^{\wedge}}}{1+e^{X \beta} 50^{\wedge}+Z U 50^{\wedge}}
$$

We iterate back and forth, first improving $\beta 55^{\wedge}$ and $U 50^{\wedge}$ and then improving $\pi 50^{\wedge}$ until the process converges.

Recall, however, that this is all conditional on knowing $G$, which we don't. In the next section, we describe the estimation process for $G$.

## C.2Estimating $G$ Given $\beta U$

Staying within the Bayes approach, the ideal procedure would be to derive the posterior distribution of $G$ given $y, \beta$, and $U$, and then to find the mean of that posterior distribution or perhaps its mode. Unfortunately, this approach is not tractable. This would require integration of $L_{W}$ not just with respect to $U$, but also with respect to $\beta$. As discussed in Section C.1, the integration of $\mathrm{L}_{\mathrm{W}}$ with respect to just U was deemed too numerically intensive. Integrating with respect to the $p$ components of $\beta$ would raise the amount of required computer time to even higher levels.

In order to get some sort of estimate of $G$, we followed the approach used by Stiratelli et al (1984), Schall (1991), and Breslow and Clayton (1993). This approach works by adapting a method that has favorable properties when the outcome variable $y$ has a multivariate normal distribution.

Specifically, consider the linear model

$$
\zeta=X \beta+Z U+e,
$$

where $X, \beta, Z$, and $U$ are defined the same as in our model, $\operatorname{Cov}(U, e)=0$, and $\mathrm{e} \sim \mathrm{N}_{n}(0, R)$. For this linear model, there are several alternate methods for estimating $G$. The maximum likelihood method finds the maximum of the likelihood of $G$ given $\zeta$. This means finding the value of $G$ that maximizes

$$
\ln L_{1}^{*}(G \mid \beta, \zeta)=-\frac{1}{2} \ln \left|R+Z G Z^{t}\right|-\frac{1}{2}(\zeta-X \beta)^{t}\left(R+Z G Z^{t}\right)^{-1}(\zeta-X \beta)
$$

This method is favored by some statisticians, but others are displeased by the fact that $G$ obtained by this method is different from the classical estimates for balanced ANOVAs and that the maximum likelihood estimate of $G$ is seriously negatively biased when the number of fixed effects is large relative to the number of observations.

Because of these concerns, an alternative method of estimating $G$ in linear models was developed. This method is called restricted maximum likelihood (REML). For this method, $G$ is estimated by finding the value of $G$ that maximizes

$$
\begin{gathered}
\ln L_{1} \quad(G \mid \beta, \zeta)=\frac{1}{2} \ln \left|R+Z G Z^{t}\right|-\frac{1}{2} \ln \left|X^{T}\left(R+Z G Z^{t}\right)^{-1} X\right|+ \\
-\frac{1}{2}(\zeta-X \beta)^{t}\left(R+Z G Z^{t}\right)^{-1}(\zeta-X \beta),
\end{gathered}
$$

where it is assumed that $X^{t} X$ is of rank $p$ so that the determinate in the second term is nonzero. The REML estimate $G$ does agree with the classical $G$ for balanced designs and it is not as biased when $p$ is large relative to $n$. Further arguing in favor of the REML estimate of $G$, Harville (1977) noted that in Harville (1974) he had demonstrated that with a noninformative prior on $(\beta, G)$, the REML estimate of $G$ maximizes the marginal posterior distribution of $G$, while the ML estimate of $G$ is merely the value of $G$ that together with some value of $\beta$ maximizes the joint posterior distribution of $\beta$ and $G$. For more information on REML methods, see Patterson and Thompson (1971) and Cox and Reid (1987).

We chose the REML estimator for this project because we believed that it might be more robust to the nonnormality of $\zeta$ in our application and because Breslow and Clayton conducted some simulations of it which appeared encouraging.

Further justifying the use of this approach, we note that although $\zeta$ as defined in Section C. 1 is far from multivariate normal, it does have the correct mean and covariance matrix. Furthermore, if we equate $W^{-1} \varepsilon$ from our model with $e$ in the linear model, we have that $\operatorname{Cov}\left(U, W^{-1} \varepsilon\right)=0$ as required and that $\operatorname{Cov}\left(W^{-1} \varepsilon\right)=R=(W C W)^{-1}$.

Without further reference to nonnormality of $W^{-1} \varepsilon$, we describe the algorithm we used to obtain the REML estimate of $G$. The method was iterative, as for the estimation of $(\beta, V)$. In fact, we again used Fisher's method of scoring as defined in Section C.1.

$$
\mathrm{C}-15
$$

The score function for $G$ using the REML approach is

$$
S_{1}(G \mid \beta, \zeta)=\frac{\partial}{\partial G} \ln L_{1}(G \mid \beta, \zeta)
$$

Here we note that $G$ has a very simple structure as specified in Section C.1. So we will define the score function as the derivative of $\ln L_{1}$, with respect to $\left(\sigma_{1}, \sigma_{2}\right)$. By finding the values of $\sigma_{1}$ and $\sigma_{2}$ (positive or negative) that maximize $L_{1}$, we will be able to estimate $\sigma_{1}^{2}$ by $\left(\sigma_{1}\right)^{2}$ and $\sigma_{2}^{2}$ by $\left(\sigma_{2}\right)^{2}$, thereby avoiding difficulties with negative estimates of variance components.

Starting with the first partial derivative with respect to $\sigma_{1}$, we have

$$
\begin{gathered}
\qquad\left(\sigma_{1}\right)=\frac{\partial}{\partial \sigma_{1}} \ln L_{1} \\
=\frac{\partial}{\partial \sigma_{1}}\left\{\frac{1}{2} \ln \left|R+Z G Z^{t}\right|-\frac{1}{2} \ln \left|X^{t}\left(R+Z G Z^{t}\right)^{-1} X\right|-\frac{1}{2}(\zeta-X \beta)^{t}\left(R+Z G Z^{t}\right)(\zeta-X \beta)\right\} \\
=\frac{\partial}{\partial \sigma_{1}}\left\{\frac{1}{2} \ln |V|-\frac{1}{2} \ln \left|X^{t} V^{-1} X\right|-\frac{1}{2}(\zeta-X \beta)^{t} V^{-1}(\zeta-X \beta)\right.
\end{gathered}
$$

To derive this partial derivative, we need some results from stochastic linear algebra.

Lemma C.2: Let $A$ be a symmetric nonsingular $n x n$ matrix whose elements are functions of variables $x_{1}, \ldots, x_{t}$. Then

$$
\frac{\partial}{\partial x_{i}} \ln |A|=\operatorname{trace}\left(A^{-1} \frac{\partial A}{\partial x_{i}}\right)
$$

where

$$
\mathrm{C}-16
$$

$$
\frac{\partial A}{\partial x_{i}}=\left(\begin{array}{l}
\frac{\partial a_{11}}{\partial x_{i}} \text { DOTSLOW } \\
\frac{\partial a_{1 n}}{\partial x_{i}} \\
\text { DOTSVERT } \\
\frac{a_{n 1}}{\partial x_{i}} \text { DOTSLOW } \frac{\partial a_{n n}}{\partial x_{i}}
\end{array}\right)
$$

recalling that the trace of a matrix is the sum of the elements on its main diagonal. For the proof of Lemma C.2, see Graybill (1969), section 10.8.

## Lemma C.3:

Let A and B be conformable matrices so that AB is defined. Then

$$
\frac{\partial A B}{\partial \theta}=\frac{\partial A}{\partial \theta} B+A \frac{\partial B}{\partial \theta} .
$$

Again, see Graybill for a proof.

## Lemma C.4:

Let A be a square nonsingular matrix. Then $\frac{\partial A^{-1}}{\partial \theta}=-A^{-1} \frac{\partial A}{\partial \theta} A^{-1}$.

Proof:

Since $A A^{-1}=I$ and $\frac{\partial I}{\partial \theta}=0$, we have

$$
0=\frac{\partial A}{\partial \theta} A^{-1}+A \frac{\partial A^{-1}}{\partial \theta}, \text { by Lemma C. } 4
$$

leading to

$$
-\frac{\partial A}{\partial \theta} A^{-1}=A \frac{\partial A^{-1}}{\partial \theta} \quad \text { and }
$$

$-A^{-1} \frac{\partial A}{\partial \theta} A^{-1}=\frac{\partial A^{-1}}{\partial \theta}$,
as required.

## Lemma C.5:

Let $A$ and $B$ be conformable matrices so that $A B$ and $B A$ are defined. Then $\operatorname{tr}(A B)=\operatorname{tr}(B A)$. (See any linear algebra textbook for proof.)

This means that even though matrix multiplication is not commutative, it is possible to commute the order of multiplication inside the trace operator.

## Lemma C.6:

Let $x$ be a matrix such that $x^{t} A x$ is defined and $x$ does not depend on $\theta$. Then

$$
\frac{\partial\left(x^{t} A x\right)}{\partial \theta}=x^{t} \frac{\partial A}{\partial \theta} x .
$$

(Again, see Graybill for proof).

## Lemma C.7:

$$
V^{-1}(\zeta-X \beta)=P \zeta
$$

Proof:

$$
\begin{aligned}
V^{-1}(\zeta-X \beta) & \left.=V^{-1}\left(\zeta-X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\right) \zeta\right) \\
& =V^{-1}\left(I-X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\right) \zeta \\
& =P \zeta
\end{aligned}
$$

Lemma C.8: If $y$ is a random vector such that $\mathrm{E} y=0$ with covariance matrix $V$ and $A$ is a fixed square conformable matrix, then

$$
\mathrm{C}-18
$$

$\mathrm{E}\left(y^{t} A y\right)=\operatorname{trace}(A V)$

Since this lemma is simple to prove, the proof is not given here.

## Lemma C.9:

$$
\frac{\partial P}{\partial \sigma_{i}}=-P \frac{\partial V}{\partial \sigma_{i}} P
$$

Proof:

$$
\begin{aligned}
\frac{\partial P}{\partial \sigma_{i}} & =\frac{\partial}{\partial \sigma_{i}}\left(V^{-1}-V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\right) \\
& =\frac{\partial V^{-1}}{\partial \sigma_{i}}\left(I-X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\right)+V^{-1} \frac{\partial}{\partial \sigma_{i}}\left(I-X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\right) \\
& =-V^{-1}\left(\frac{\partial V}{\partial \sigma_{i}}\right) V^{-1}\left(I-X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\right)-V^{-1} \frac{\partial}{\partial \sigma_{i}}\left(X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\right) \\
& \left.=-V^{-1}\left(\frac{\partial V}{\partial \sigma_{i}}\right) P-V^{-1} 乡 X\left[\frac{\partial}{\partial \sigma_{i}}\left(X^{t} V^{-1} X\right)^{-1}\right] X^{t} V^{-1}+X\left(X^{t} V^{-1} X\right)^{-1} X^{t}\left(\frac{\partial V^{-1}}{\partial \sigma_{i}}\right)\right]
\end{aligned}
$$

$$
=-V^{-1}\left(\frac{\partial V}{\partial \sigma_{i}}\right) P+
$$

$$
-V^{-1}\left\{,-X\left(X^{t} V^{-1} X\right)^{-1} \frac{\partial\left(X^{t} V^{-1} X\right)}{\partial \sigma_{i}}\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}-X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\left(\frac{\partial V}{\partial \sigma_{i}}\right) V^{-1}\right\}_{\}}
$$

$$
\begin{aligned}
& =-V^{-1}\left(\frac{\partial V}{\partial \sigma_{i}}\right) P+ \\
& -V^{-1} /+X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\left(\frac{\partial V^{-1}}{\partial \sigma_{i}}\right) V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}-X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\left(\frac{\partial V}{\partial \sigma_{i}}\right) V^{-1} \\
& =-V^{-1}\left(\frac{\partial V}{\partial \sigma_{i}}\right) P-V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\left(\frac{\partial V}{\partial \sigma_{i}}\right)\left[V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}-V^{-1}\right] \\
& \quad=-V^{-1}\left(\frac{\partial V}{\partial \sigma_{i}}\right) P+\left(P-V^{-1}\right)\left(\frac{\partial V}{\partial \sigma_{i}}\right)(-P) \\
& \quad=-V^{-1}\left(\frac{\partial V}{\partial \sigma_{i}}\right) P-P\left(\frac{\partial V}{\partial \sigma_{i}}\right) P+V^{-1}\left(\frac{\partial V}{\partial \sigma_{i}}\right) P \\
& \quad=-P\left(\frac{\partial V}{\partial \sigma_{i}}\right) P
\end{aligned}
$$

Returning now to the derivation of $S\left(\sigma_{1}\right)$, we have by Lemma C. 2 that

$$
\frac{\partial}{\partial \sigma_{1}} \ln |V|=\operatorname{trace}\left[V^{-1} \frac{\partial V}{\partial \sigma_{1}}\right]
$$

For the second term of $S\left(\sigma_{1}\right)$, we have that

$$
\frac{\partial \ln }{\partial \sigma_{1}}\left|X^{t} V^{-1} X\right|
$$

$$
\begin{aligned}
& =\text { trace }\left[\left(X^{t} V^{-1} X\right)^{-1} \frac{\partial\left(X^{t} V^{-1} X\right)}{\partial \sigma_{1}}\right] \quad \text { by Lemma C. } 2 \\
& =\text { trace }\left[\left(X^{t} V^{-1} X\right)^{-1} X^{t} \frac{\partial V^{-1}}{\partial \sigma_{1}} X\right] \quad \text { by Lemma C. } 6 \\
& =\text {-trace }\left[\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} \frac{\partial V}{\partial \sigma_{1}} V^{-1} X\right] \quad \text { by Lemma C. } 4 \\
& =-\operatorname{trace}\left[V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} \frac{\partial V}{\partial \sigma_{1}}\right] \quad \text { by Lemma C. } 5
\end{aligned}
$$

Adding this result to the result for $\frac{\partial}{\partial \sigma_{1}} \ln |V|$, we have that

$$
\begin{gathered}
\frac{\partial}{\partial \sigma_{1}}\left[\ln |V|+\ln \left|X^{t} V^{-1} X\right|\right]=\operatorname{trace}\left[V^{-1} \frac{\partial V}{\partial \sigma_{1}}\right]-\operatorname{trace}\left[V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} \frac{\partial V}{\partial \sigma_{1}}\right] \\
=\operatorname{trace}\left[V^{1} \frac{\partial V}{\partial \sigma_{1}}-V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} \frac{\partial V}{\partial \sigma_{1}}\right] \\
=\operatorname{trace}\left\{\left[V^{-1}-V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\right] \frac{\partial V}{\partial \sigma_{1}}\right\}_{y} \\
=\operatorname{trace}\left(P \frac{\partial V}{\partial \sigma_{1}}\right) \\
\begin{aligned}
& \mathrm{C}-21
\end{aligned}
\end{gathered}
$$

This is the general result given by Harville. Applying this general result to our particular application results in further simplification:

$$
\begin{aligned}
& =\operatorname{trace}\left[P \frac{\partial}{\partial \sigma_{1}}\left(R+Z G Z^{t}\right)\right] \quad \text { by definition of } \mathrm{V} \\
& =\operatorname{trace}\left[\begin{array}{ll}
P & Z \frac{\partial G}{\partial \sigma_{1}} Z^{t}
\end{array}\right]
\end{aligned}
$$

## Error!

$=\operatorname{trace}\left\{, P Z\left[\begin{array}{cc}2 \sigma_{1} & 0 \\ 0 & 0\end{array}\right] Z^{t}\right\}$
$=\operatorname{trace}\left\{, P\left[\begin{array}{ll}Z & 50 \sim_{1} \\ Z & 50 \sim_{2}\end{array}\right]\left[\begin{array}{cc}2 \sigma_{1} I_{m} 0 \\ 0 & 0\end{array}\right]\left[\begin{array}{ll}Z_{1} & 80 \sim^{t} \\ Z_{2} & 80 \sim^{t}\end{array}\right] /\right\}$
$=2 \sigma_{1} \operatorname{trace}\left\{, P\left[\begin{array}{lll}Z & 50 \sim_{1} & Z \\ 50 \sim_{2}\end{array}\right]\left[\begin{array}{cc}Z & 50 \sim_{1}^{t} \\ 0\end{array}\right]\right\}$
$=2 \sigma_{1} \operatorname{trace}\left(P Z 55 \sim_{1} Z 55 \sim_{1}^{t}\right)$

$$
\mathrm{C}-22
$$

$$
=2 \sigma_{1} \operatorname{trace}\left(Z 50 \sim_{1}^{t} P Z 50 \sim_{1}\right)
$$

where $\quad Z 55 \sim_{1}$ consists of the first $m$ columns of $Z$ and $\quad Z 55 \sim_{2}$ consists of the remaining $r$ columns of $Z$.

Working on the third term of $S\left(\sigma_{1}\right)$, we have that

$$
\frac{\partial}{\partial \sigma_{1}}\left[(\zeta-X \beta)^{t} V^{-1}(\zeta-X \text { betahat })\right]
$$

$\left.=\frac{\partial}{\partial \sigma_{1}}[\zeta-X \beta]^{t} P \zeta\right)$ by lemma C. 7
$=\frac{\partial}{\partial \sigma_{1}}\left[\zeta^{t} P \zeta\right]$ since $X^{t} P=0$ by lemma C. 1
$=\zeta^{t}\left(\frac{\partial P}{\partial \sigma_{1}}\right) \zeta$
$=-\zeta^{t} P\left(\frac{\partial V}{\partial \sigma_{1}}\right) P \zeta \quad$ by lemma C.9.
$=-(\zeta-X \beta)^{t} V^{-1}\left(\frac{\partial V}{\partial \sigma_{1}}\right) V^{-1}(\zeta-X \beta) \quad$ by lemma C. 7

This is the general result given by Harville. Applying this general result to our particular application results in further simplification.

As demonstrated in the derivation of the second term of $S\left(\sigma_{1}\right)$, we know that in this application,

$$
\frac{\partial V}{\partial \sigma_{1}}=2 \sigma_{1} Z 55 \sim_{1} Z 55 \sim_{1}^{t} .
$$

So

$$
\begin{aligned}
\frac{\partial}{\partial \sigma_{1}} & {\left[(\zeta-X \beta)^{t} V^{-1}(\zeta-X \beta)\right] } \\
& =-2 \sigma_{1}(\zeta-X \beta)^{t} V^{-1} Z 55 \sim{ }_{1} Z 55 \sim_{1}^{t} V^{-1}(\zeta-X \beta) \\
& =-2 \sigma_{1}\left[Z 55 \sim_{1}^{t} V^{-1}(\zeta-X \beta)\right]^{t}\left[Z 55 \sim_{1}^{t} V^{-1}(\zeta-X \beta)\right] \\
& =-2 \sigma_{1} \xi_{1}^{t} \xi_{1},
\end{aligned}
$$

where $\xi_{1}=Z 55{ }_{1}^{t} V^{-1}(\zeta-X \beta)$

Finally, we can write out a complete expression for the score function for $\sigma_{1}$ using Harville's general form as

$$
\begin{gathered}
S\left(\sigma_{1}\right)=\frac{\partial \ln L_{1}}{\partial \sigma_{1}}=\frac{\partial}{\partial \sigma_{1}}\left\{-\frac{1}{2} \ln |V|-\frac{1}{2} \ln \left|X^{t} V^{-1} X\right|-\frac{1}{2}(\zeta-X \beta)^{t} V^{-1}(\zeta-X \beta)\right\} \\
=-\frac{1}{2} \operatorname{trace}\left(P \frac{\partial V}{\partial \sigma_{1}}\right)+\frac{1}{2}(\zeta-X \beta)^{t} V^{-1} \frac{\partial V}{\partial \sigma_{1}} V^{-1}(\zeta-X \beta)
\end{gathered}
$$

Equivalently for our application, we may write

$$
S\left(\sigma_{1}\right)=-\sigma_{1} \operatorname{trace}\left(Z 55 \sim_{1}^{t} P Z 55 \sim_{1}\right)+\sigma_{1} \xi 50_{1}^{\wedge} \xi 50_{1}^{\wedge}
$$

Going through similar algebra, we get the score function for $\sigma_{2}$ as

$$
\mathrm{C}-24
$$

$$
S\left(\sigma_{2}\right)=\frac{\partial \ln L_{1}}{\partial \sigma_{2}}=-\sigma_{2} \operatorname{trace}\left(Z 55 \sim_{2}^{t} P Z 55 \sim \operatorname{sub} 2\right)+\sigma_{2} \xi 50_{2}^{\wedge_{2}^{t} \xi 50^{\wedge}{ }_{2}}
$$

Just as in the estimation of $(\beta, U)$, we want to find $\left(\sigma_{1}, \sigma_{2}\right)$ such that simultaneously solves the system $\mathrm{S}\left(\sigma_{1}\right)=0$ and $\mathrm{S}\left(\sigma_{2}\right)=0$. Clearly, $\left(\sigma 50^{\wedge}, \sigma 50^{\wedge}{ }_{2}\right)=(0,0) \quad$ is a root of the score function that does not interest us. It is interesting to note the lemmas C.5, C. 7 and C. 8 can be used to demonstrate that $E\left(\xi 50{ }_{i}^{t} \xi 50 \wedge{ }_{i}\right)=\left(Z 50 \sim_{i}^{t} P Z 50 \sim_{i}\right)$ for $\sigma_{1}$ and $\sigma_{2}$ that solve the system. This means that finding the REML estimates of $\sigma_{1}$ and $\sigma_{2}$ is equivalent to setting $\xi 50^{\wedge}{ }_{i} \xi 50 \wedge{ }_{i}$ equal to its own expected value.

Solving the system requires an iterative approach. We did this using Fisher's method of scoring again. However, rather than computing the Fisher information matrix as
${ }^{E}\left\{_{\mathcal{L}}\left[\begin{array}{c}S\left(\sigma_{1}\right) \\ S\left(\sigma_{2}\right)\end{array}\right]\left[\begin{array}{l}S\left(, \sigma_{1}\right) \\ S\left(, \sigma_{2},\right)\end{array}\right]\right\}_{\rho}$ we used a theorem from advanced probability theory.

This theorem states that given suitable regularity conditions, ${ }^{2} \mathrm{E}\left(S S^{t}\right)=-\mathrm{E}\left[\frac{\partial S}{\partial \theta}\right]$, where

$$
\frac{\partial S}{\partial \theta}=\left(\begin{array}{cc}
\frac{\partial^{2} \ln f}{\partial \theta_{1}^{2}} & \text { DOTSLOW } \\
\frac{\partial^{2} \ln f}{\partial \theta_{1} \partial \theta_{n}} \\
D O T S V E R T & \text { DOTSVERT } \\
\frac{\partial^{2} \ln f}{\partial \theta_{1} \partial \theta_{n}} \text { DOTSLOW } \frac{\partial^{2} \ln f}{\partial \theta_{n}^{2}}
\end{array}\right)
$$

[^13]is the Hessian of $\ln f$ with respect to $\theta$.

For this particular application, it is easier to find the second partial derivatives of $\ln L_{1}$ and then to find the expected value of those second partial derivatives than to try to find the expected value of the product of the score function with its transpose. The reason for this is the difficulty of integrating products of traces. To find the second partial derivatives of $\ln L_{l}$, we go back to the equations for $S\left(\sigma_{i}\right)$ in terms of $V$ to allow easier comparison with Harville (1977).

Focusing first on the first two components of $\ln L_{l}$, we have that

$$
\begin{aligned}
& \frac{\partial^{2}}{\partial \sigma_{i} \partial \sigma_{1}}\left[\ln |V|+\ln \left|X^{t} V^{-1} X\right|\right]=\frac{\partial}{\partial \sigma_{i}} \operatorname{trace}\left(P \frac{\partial V}{\partial \sigma_{j}}\right) \\
& =\operatorname{trace}\left[\frac{\partial}{\partial \sigma_{i}}\left(P\left(\frac{\partial V}{\partial \sigma_{j}}\right)\right)\right] \text { since the trace is a linear function of the elements of a matrix } \\
& =\operatorname{trace}\left[\left(\frac{\partial P}{\partial \sigma_{i}}\right)\left(\frac{\partial V}{\partial \sigma_{j}}\right)+P\left(\frac{\partial^{2} V}{\partial \sigma_{i} \partial \sigma_{j}}\right)\right] \\
& =\operatorname{trace}\left[-P\left(\frac{\partial V}{\partial \sigma_{i}}\right) P\left(\frac{\partial V}{\partial \sigma_{j}}\right)+P\left(\frac{\partial^{2} V}{\partial \sigma_{i} \partial \sigma_{j}}\right)\right] \\
& =\operatorname{trace}\left[P\left(\frac{\partial^{2} V}{\partial \sigma_{i} \partial \sigma_{j}}\right)-P\left(\frac{\partial V}{\partial \sigma_{i}}\right) P\left(\frac{\partial V}{\partial \sigma_{j}}\right)\right] \\
& =\operatorname{trace}\left[P Z\left(\frac{\partial^{2} G}{\partial \sigma_{i} \partial \sigma_{j}}\right) Z^{t}-P Z\left(\frac{\partial G}{\partial \sigma_{i}}\right) Z^{t} P Z\left(\frac{\partial G}{\partial \sigma_{j}}\right) Z^{t}\right]
\end{aligned}
$$

For $i=j$, this expression will equal

$$
\mathrm{C}-26
$$

$$
\text { trace }\left[2 P Z 55 \sim_{i} Z 55 \sim_{i}^{t}-4 \text { sigmasubi}{ }^{2} P Z 55 \sim_{i} Z 55 \sim_{i}^{t} P Z 55 \sim_{i} Z 55 \sim_{i}^{t}\right]
$$

For $i \neq j$, this expression will equal

$$
\text { -trace }\left[4 \sigma_{i} \sigma_{j} P Z 55 \sim_{i} Z 55 \sim_{i}^{t} P Z 55 \sim_{j} Z 55 \sim_{j}^{t}\right]
$$

since $\frac{\partial^{2} G}{\partial \sigma_{i} \partial \sigma_{j}}=0$ for $i \neq j$.

Focusing now on the third component of $\ln L_{l}$, we have that

$$
\frac{\partial^{2}}{\partial \sigma_{i} \partial \sigma_{j}}(\zeta-X \beta)^{t} V^{-1}(\zeta-X \beta)
$$

$$
=-\frac{\partial}{\partial \sigma_{i}}\left\{(\zeta-X \beta)^{t} V^{-1}\left(\frac{\partial V}{\partial \sigma_{j}}\right) V^{-1}(\zeta-X \beta) l_{\zeta}\right.
$$

$$
=-\frac{\partial}{\partial \sigma_{i}}\left[\zeta^{t} P\left(\frac{\partial V}{\partial \text { sigmasubi }}\right) P \zeta\right]
$$

$$
=-\zeta^{t}\left[\left(\frac{\partial P}{\partial \sigma_{i}}\right)\left(\frac{\partial V}{\partial \sigma_{j}}\right) P+P\left[\left(\frac{\partial^{2} V}{\partial \sigma_{i} \partial \sigma_{j}}\right) P+\left(\frac{\partial V}{\partial \sigma_{j}}\right)\left(\frac{\partial P}{\partial \sigma_{i}}\right)\right]\right] \zeta
$$

$$
\begin{aligned}
& =-\zeta^{t}\left[-P\left(\frac{\partial V}{\partial \sigma_{i}}\right) P\left(\frac{\partial V}{\partial \sigma_{j}}\right) P+P\left(\frac{\partial^{2} V}{\partial \sigma_{i} \partial \sigma_{j}}\right) P-P\left(\frac{\partial V}{\partial \sigma_{j}}\right) P\left(\frac{\partial V}{\partial \sigma_{i}}\right) P\right] \zeta \\
& =-\zeta^{t} P\left[-\left(\frac{\partial V}{\partial \sigma_{i}}\right) P\left(\frac{\partial V}{\partial \sigma_{j}}\right)+\left(\frac{\partial^{2} V}{\partial \sigma_{i} \partial \sigma_{j}}\right)-\left(\frac{\partial V}{\partial \sigma_{j}}\right) P\left(\frac{\partial V}{\partial \sigma_{i}}\right)\right] P \zeta \\
& =-\left(\zeta^{t}-X \beta\right) V^{-1}\left[\frac{\partial^{2} V}{\partial \sigma_{i} \partial \sigma_{j}}-2\left(\frac{\partial V}{\partial \sigma_{j}}\right) P\left(\frac{\partial V}{\partial \sigma_{i}}\right)\right] V^{-1}(\zeta-X \beta)
\end{aligned}
$$

(The last equality holds since $\frac{\partial^{2} A}{\partial \sigma_{j} \partial \sigma_{i}}=\frac{\partial^{2} A}{\partial \sigma_{j} \partial \sigma_{i}}$ for any twice differential matrix A.)

We have now reconfirmed the formula $\frac{\partial^{2} \ln L_{1}}{\partial \sigma_{j} \partial \sigma_{i}}$ given by Harville (1977):

## Error!

Having found the Hessian of $\ln L_{l}$, we now need to find the expected value of this Hessian with respect to the distribution of $\zeta$ in order to get the Fisher information matrix for G. We first prove several lemmas.

Lemma C.10: $\operatorname{Cov}(\zeta)=V$
Proof:
Lemma C.11: $V$ is a generalized inverse of $P$, meaning that $P V P=P$

$$
\begin{gathered}
\operatorname{Cov} \zeta=\operatorname{Cov}\left(X \beta+Z U+W^{-1} C^{-1}(y-\pi)\right) \\
=\operatorname{Cov}(Z U)+\operatorname{Cov}\left(W^{-1} \varepsilon\right) \quad U \varepsilon \\
=Z(\operatorname{Cov} U) Z^{t}+W^{-1} 1(\operatorname{Cov} \varepsilon) W^{-1} \quad(W \text { is diagonal hence symmetric }) \\
=Z G Z^{t}+W^{-1} C^{-1} W^{-1} \\
=Z G Z^{t}+(W C W)^{-1} \\
=Z G Z^{t}+R \\
=V .
\end{gathered}
$$

Proof:

$$
\begin{gathered}
P V P=\left[V^{-1}-V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} V^{-1}\right] V\left[V^{-1}-V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\right] \\
=V^{-1}\left[I-X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\right]\left[I-X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\right] \\
=V^{1}\left[I-2 X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}+X\left(X^{t} V^{1} X\right)^{-1} X^{t} V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\right] \\
=V^{-1}\left[I-2 X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}+X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\right] \\
=V^{-1}\left[I-X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\right] \\
=V^{-1}-V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} \\
=P .
\end{gathered}
$$

Lemma C.12: $\operatorname{Cov}(A y)=A \operatorname{Cov}(y) A^{t}$

The proof for Lemma C. 12 is not given here but is elementary.

Continuing with the task of finding the expected value of the Hessian of $\ln L_{1}$, we note that the
first term of $\frac{\partial^{2} \ln L_{1}}{\partial \sigma_{j} \partial \sigma_{i}}$ is a constant and that the second term may be written as $\frac{1}{2} b^{t} A b$,
where $\mathrm{b}=\mathrm{P} \zeta=V^{-1}(\zeta-X \beta)$ is a
random variable with expected value 0 , and

$$
A=\frac{\partial^{2} V}{\partial \sigma_{j} \partial \sigma_{i}}-2\left(\frac{\partial V}{\partial \sigma_{i}}\right) P\left(\frac{\partial V}{\partial \sigma_{j}}\right) .
$$

Using lemma C.8, we have that

$$
E\left(b^{t} A b\right)=\operatorname{trace}(A \operatorname{Cov}(b))=\operatorname{trace}((\operatorname{Cov}(b)) A)
$$

The covariance matrix for $b$ is

$$
\begin{aligned}
\operatorname{Cov} b & =\operatorname{Cov}(P \zeta) \\
& =P \operatorname{Cov}(\zeta) P \text { by lemma C. } 12 \text { since } P^{t}=P \\
& =P V P \text { by lemma C. } 10 \\
& =P \text { by lemma C. } 11
\end{aligned}
$$

Thus

$$
\begin{gathered}
\mathrm{E}_{\zeta}\left(\frac{\partial^{2} L_{1}}{\partial \sigma_{i} \partial \sigma_{j}}\right) \\
=-\frac{1}{2} \operatorname{trace}\left\{P\left[\left(\frac{\partial^{2} V}{\partial \sigma_{i} \partial \sigma_{j}}\right)-\left(\frac{\partial V}{\partial \sigma_{i}}\right) P\left(\frac{\partial V}{\partial \sigma_{j}}\right)\right]\right\}_{j} \\
+\frac{1}{2} \operatorname{trace}\left\{P\left[\left(\frac{\partial^{2} V}{\partial \sigma_{i} \partial \sigma_{j}}\right)-2\left(\frac{\partial V}{\partial \sigma_{i}}\right) P\left(\frac{\partial V}{\partial \sigma_{j}}\right)\right]\right\}_{j} \\
=-\frac{1}{2} \operatorname{trace}\left[P\left(\frac{\partial V}{\partial \sigma_{i}}\right) P\left(\frac{\partial V}{\partial \sigma_{i}}\right)\right],
\end{gathered}
$$

as claimed by Harville.

Applying this general formula to our application, we have that

$$
\begin{aligned}
E_{\zeta}\left(\frac{\partial^{2} L_{1}}{\partial \sigma_{i} \partial \sigma_{j}}\right) & =-\frac{1}{2} \operatorname{trace}\left[P Z \frac{\partial G}{\partial \sigma_{i}} Z^{t} P Z \frac{\partial G}{\partial \sigma_{j}} Z^{t}\right] \\
& =-2 \sigma_{i} \sigma_{j} \operatorname{trace}\left[P Z 55 \sim_{i} Z 55 \sim_{i}^{t} P Z 55 \sim_{j} Z 55 \sim_{j}^{t}\right]
\end{aligned}
$$

Thus, Fisher's information matrix is

## Error!

Alternatively using lemma C.5, we can specify the $(i, j)$-th element of $J_{\mathrm{G}}$ as

$$
J_{G}(i, j)=2 \sigma_{i} \sigma_{j}\left[\left(Z 55 \sim_{i}^{t} P Z 55 \sim_{j}\right)\left(Z 55 \sim_{i}^{t} P Z 55 \sim_{j}\right)^{t}\right]
$$

This alternative formula is computationally useful since for an arbitrary matrix $A$, the trace of $A A^{\mathrm{t}}$ can be computed as the sum of the squared elements of $A$.

We now have all the information needed to write out our iterative cycle for estimating $\left(\sigma_{1}, \sigma_{2}\right)$ using Fisher's method of scoring and the REML form of the log likelihood function.

Given initial estimates $\sigma_{1}^{(0)} \sigma_{2}^{(0)}$, we calculated an initial value for $G$ and hence $V$ and $P$. We already had values for $\beta$ to calculate $\xi 50^{\wedge}$. We then used these to obtain an initial value for the score function

## Error!

and an initial value for Fisher's information matrix

## Error!

Improved estimates of $\sigma_{1}$ and $\sigma_{2}$ were then obtained as

$$
\binom{\sigma_{1}^{(1)}}{\sigma_{2}^{(1)}}=\left(\begin{array}{c}
\sigma_{1}^{(0)} \\
\\
\sigma_{2}^{(0)}
\end{array}\right)+\left(J_{G}^{(0)}\right)^{-1} S_{G}^{(0)}
$$

This process is then allowed to iterate until convergence is obtained.

## C. 3 Joint Estimation of $\beta, U, G$

In Section C.1, an iterative method was described for estimating $\beta$ and $U$, given $G$. In section C.2, another iterative method was described for estimating $G$ given $\beta U$. These algorithms were run simultaneously with interchange of estimates back and forth to jointly estimate $\beta, U, G$.

We experimented with different ways of running the algorithms. The method that we chose as providing the fastest convergence was to iterate the first algorithm a single step, then to iterate the second algorithm a single step, then return to the first for one more step, then return to the second for one more step, and so on.

The main alternative we considered was to allow the first algorithm to converge, then to allow the second to converge, return to the first for another full convergence, and so on. This alternative proved to be slower. Other alternatives are possible such as allowing the second algorithm two steps for every one step of the first, but interchange after a single step of each algorithm appeared to be a good choice.

Even so, the computational burden was such that the full model (with state and PSU random effects) could not be run on a Pentium in a reasonable time. We ran the reduced models (with only state effects) on several Pentiums and the full models on a separate VAX server. For future applications, we would recommend the use of a dedicated VAX server or one or more fast UNIX workstations. For some states and variables, we could not get the full model to converge. When this occurred, we dropped back to the reduced model.

With an iterative procedure of this complexity, there is always the possibility of convergence to local maxima rather than global maxima. There is also the possibility of convergence to saddlepoints (where even though the score function is zero, the derivative of the score function is indeterminate, meaning that there are directions for change in the log likelihood that are both positive and negative). If the method were strict maximum likelihood, then there are theorems to indicate when the score function has a unique solution and that thus there were no saddlepoints and the only local maximum was also a global maximum. However, our method only approximates maximum likelihood and the method used to force $\sigma_{1}^{2}>0 \sigma_{2}^{2}>0$ does create saddlepoints since $\mathrm{S}\left(\sigma_{1}, \sigma_{2}\right)=0$ for $\left(\sigma_{1}^{2}, \sigma_{1}^{2}\right)=(0,0) \quad$, which is clearly not an optimum estimate. Thus, the ideal procedure would have been to choose multiple starting points for the algorithm and to compare the results of starting it from those various points. However, the CPU time and VAX charges were higher per run than our time schedule and budget could support for multiple runs. We, therefore, ran each model only once, choosing the starting values carefully.

The starting values for $\beta$ were taken from the ordinary logistic regressions for y or X without random effects. The starting values for $U$ were taken to be zero, a reasonable procedure since the unconditional expectation of $U$ is zero. The starting values for $G$ were taken from by guessing at how much shrinkage should occur. See Section C. 5 for a description of how shrinkage relates to the components of variance.

## C. 4 Asymptotic Properties of the Estimators

A sequence of random variables $\left\{Y_{\mathrm{i}}\right\}$ is said to be consistent for a parameter $\theta$ if

$$
\lim _{i \rightarrow \infty} \operatorname{Pr}\left(\left|Y_{i}-\theta\right|>\varepsilon\right)=0 \text { for every } \varepsilon>0
$$

Similarly, two sequences $\left\{Y_{i}\right\}$ and $\left\{X_{i}\right\}$ are said to be asymptotically equivalent if $\lim _{i \rightarrow \infty} \operatorname{Pr}\left(\left|Y_{i}-X_{i}\right|>\varepsilon\right)=0$ for every $\varepsilon>0$. We claimed in Section 1.4.6 and again in Section 2.1.2
that

$$
\lim _{n_{i} \rightarrow N_{i}} \frac{\pi 50_{i}^{\wedge}}{\pi 50_{i}^{\wedge}}=1,
$$

where $i$ indexes the target small areas. By this rather loose statement, we meant that $\pi 50{ }_{i}{ }_{i}^{w}$ and $\pi 50_{i}{ }_{i}^{D}$ are asymptotically equivalent as defined above. This claim has actually not yet been rigorously proven, but we do discuss our reasoning in this section for believing this assertion to be true. A rigorous proof might also require that $N_{i}$ tend to infinity. Letting both $n_{i}$ and $N_{i}$ tend to infinity requires some care in specifying the stratification and clustering of the population as it grows larger that we do not attempt to address here.

We base our belief that $\pi 50 \wedge_{i}^{w}$ and $\pi 50^{\wedge^{D}}$ are asymptotically equivalent upon the observation that if the scaled residual error $\varepsilon$ was normally distributed such that its covariance matrix did not depend on $\beta$, then the desired asymptotic equivalency can be proven. Recall from Section C. 1 that we defined $\varepsilon=C^{-1}(y-\pi)$ and that we defined $\zeta=X \beta+Z U+W^{-1} \varepsilon$ with $\operatorname{Cov}(U)=\mathrm{G}$. If $\varepsilon$ were multivariate with covariance matrix $C^{-1}=\sigma_{e}^{2} I$, then our score function for $\beta$ and $U$ would have the same form as in Section C.1, but since the conditional covariance matrix for $\zeta$ given $U$ would not depend on $\beta$ or $U$, it would be possible to get an explicit formula for the root of the score function instead of having to use an iterative method to find the root. Note that these conditions hold for the standard linear mixed model where $y=X \beta+Z U+\varepsilon, \operatorname{Cov}(\mathrm{U})=G$, $\varepsilon \sim N_{n}\left(O, I \sigma_{e}^{2}\right) \quad, U$ and $\varepsilon$ are independent and $\zeta$ is still defined as $\zeta=X \beta+Z U+W^{-1} \varepsilon$. In this case the conditional covariance matrix for $\zeta$ given $U$ is $R=W^{1} C^{-1} W^{1}$.

Recall that the score function for $\beta$ and $U$ given $C, G$ and $\zeta$ is

$$
\mathrm{C}-34
$$

$$
S(\beta, U \mid C, G, \zeta)=/\left(\begin{array}{c}
X^{t} W C W(\zeta-X \beta-Z U)
\end{array}\right) \%
$$

Given a large enough sample size, we can assume that the method used to estimate $C$ and $G$ is accurate enough to treat $C=C$ and $G=G$ as fixed and known.

To keep discussion simple assume that there is only one level of random effects so that $G=\sigma_{u}^{2} I_{q}$. ( $I_{q}$ is the $q \times q$ identity matrix, where $\mathrm{m}=\mathrm{q}$ is the number of states in the model.)

Since $S\left(\beta 55^{\wedge}, U 50^{\wedge} \mid C, G, \zeta\right)=0$,
we know from looking at the bottom half of the score function that $Z^{t} W C W\left(\zeta-X \beta 55^{\wedge}-Z U 50^{\wedge}\right)=G^{-1} U 50^{\wedge}$ so

$$
Z^{t} \frac{W W}{\sigma_{e}^{2}}\left(\zeta-X \beta 55^{\wedge}-Z U 55^{\wedge}\right)=\frac{U 55^{\wedge}}{\sigma_{u}^{2}}
$$

By the definitions of $y, \zeta$ and $\varepsilon$, we know that $\varepsilon=W\left(\zeta-X \beta 55^{\wedge}-Z U 50^{\wedge}\right)$ and that $\varepsilon=y-X \beta 55^{\wedge}-Z U 50^{\wedge}$. By equating these two expressions for $\varepsilon$, we have that

$$
W\left(\zeta-X \beta 55^{\wedge}-Z U 50^{\wedge}\right)=y-X \beta 55^{\wedge}-Z U 50^{\wedge} .
$$

Substituting this result into the earlier equation, we have that

$$
\frac{Z^{t} W\left(y-X \beta 55^{\wedge}-Z U 50^{\wedge}\right)}{\sigma_{e}^{2}}=\frac{U 50^{\wedge}}{\sigma_{u}^{2}}
$$

Collecting all the terms involving $U 50^{\wedge}$, we have that

$$
\left\lceil\frac{I}{\sigma_{u}^{2}}+\frac{Z^{t} W Z}{\sigma_{e}^{2}}\right\rceil / U 55^{\wedge}=\frac{Z^{t} W\left(y-X \beta 55^{\wedge}\right)}{\sigma_{e}^{2}}
$$

So

$$
U 55^{\wedge}=\frac{\Pi_{\sigma_{e}^{2}}^{2}}{\left\langle\underline{\sigma_{e}^{2}} I+Z^{t} W Z \text { right }\right]^{-1} Z^{t} W\left(y-X \beta 55^{\wedge}\right)}
$$

Note further that

$$
Z^{t} W Z=\left[\begin{array}{lll}
n_{1} W_{1} & 0 \\
& n_{2} w_{2} & \\
1 & \text { DOTSDIAG } \\
0 & n_{m} w_{m}
\end{array} / /\right.
$$

where $n_{i}$ is the number of sample persons in the i-th state and $w_{i}$ is the average sampling weight in the i-th state.

Thus,

$$
\begin{aligned}
& =\left[\begin{array}{cc}
\frac{\gamma_{1}}{n_{1} w_{1}} & 0 \\
\text { DOTSDIAG }
\end{array} / /,\right. \\
& \text { C-36 }
\end{aligned}
$$

where
$\gamma_{i}=\frac{\sigma_{u}^{2}}{\sigma_{u}^{2}+\frac{\sigma_{e}^{2}}{n_{i} w_{i}}}$
is the shrinkage factor for the i-th state.

Since the weights were scaled, $w_{i} \geq 1$. So $\gamma_{i}$ is the proportion of the total variance on the logit scale that is due to true differences among the states rather than measurement variance. For $N_{\mathrm{i}}$ sufficiently large,

$$
\lim _{n_{i} \rightarrow N_{i}} \gamma_{i-} 1 .
$$

Focusing on $U 50^{\wedge}$ ifor an individual state, we note that the i-th row of $Z^{t} W(y-X \beta)$ has the form

$$
\left.\sum_{j=1}^{n_{i}} w_{i j}\left(y_{i j}-X_{i j} \beta 55^{\wedge}\right)=n_{i} w_{i}\left(y_{D i}-X_{D i} \beta 50^{\wedge}\right\}\right)
$$

where $y_{D i}=\sum_{j=1}^{n_{i}} \frac{w_{i j}}{n_{i} w_{i}} y_{i j}$ is the design-consistent estimator of the mean of y in the i-th state, and $X_{D i}$ is defined similarly. Combining these results leads to the explicit solution for $U 50{ }^{\wedge}$ of

$$
\left.\left.U 50^{\wedge}\right\}_{i}=\gamma_{i}\left(y_{D i}-X_{D i} \beta 50^{\wedge}\right\}\right)
$$

Given this solution for $U 50^{\wedge}$, the empirical Bayes estimator $\pi_{i}^{w}$ for small area-i becomes

$$
\left.\left.\left.\pi 50^{\wedge}\right\}_{i}^{w}=\frac{1}{N_{i j}} \sum_{i=1}^{N_{i}}\left(X_{i j} \beta 50^{\wedge}\right\}+U 50^{\wedge}\right\}_{i}\right)
$$

$$
=X_{\Omega i} \beta 50_{i}^{\wedge}+U 50_{i}{ }_{i}
$$

where $X_{\Omega i}$ depicts the population mean of the $X_{\mathrm{ij}}$ vectors. Substituting in the explicit solution for $U_{i}$ leads to

$$
\begin{gathered}
\pi_{i}^{w}=X_{\Omega i} \beta+\gamma_{i}\left(y_{D i}-X_{D i} \beta\right) \\
=\left(1-\gamma_{i}\right) X_{\Omega i} \beta+\gamma_{i}\left[y_{D i}-\left(X_{D i}-X_{\Omega i} \beta\right)\right]
\end{gathered}
$$

Note that $y_{D i}$ is the traditional Horvitz-Thompsen estimator and $y_{D i}-\left(X_{D I}-X_{\Omega i}\right) \beta$ is design consistent for the mean of $y$ in state $i$ since $X_{D i}$ is a design consistent estimator of $X_{\Omega i}$. Therefore with $\pi_{i}^{D}=y_{D i}$ for this linear mixed model case

$$
\lim _{n_{i} \rightarrow N_{i}}\left(\pi_{i}^{w} \div \pi_{i}^{D}\right)=1
$$

since $X_{D i}$ is a design consistent estimator of $X_{\Omega i}$. This establishes the desired result.

As mentioned earlier, the corresponding result for applying the method to binary variables has not yet been proven. The discreteness of the distribution for binary variables is not the primary difficulty in attempting a proof since with large enough $n$, the binary variables could be grouped into sets of binomial variables which would have approximately normal distributions by the Central Limit Theorem. The main difficulty in attempting a proof is that the matrix R is a function of $\beta$. The variance of a normal variable is usually not related to its mean. When there is a relationship, the method of proof given here fails.

## Model Consistency

In addition to the question of design consistency, there is the issue of model consistency. Under fairly general conditions, maximum likelihood estimates are consistent for the parameters they are estimating. Less is known about the asymptotic properties of REML estimates, even for normally distributed errors. The model-based asymptotic characteristics of the approximations used here to estimate $G$ are unknown, even when $\beta$ is known. Given that in the procedure used

$$
\mathrm{C}-38
$$

here, there is a pattern of alternating iterations between an approximate maximum likelihood estimate for $(\beta, U)$ and an approximate restricted maximum likelihood estimate for $G$, the asymptotic frequentist properties of the method will be difficult to ever determine.

In a sense, however, the asymptotic design-based and model-based frequentist properties of the estimator are of only limited interest since the sample sizes available for a small area are small. Mean square error of the point estimates of $\pi$ is of greater interest, along with the coverage properties of the confidence intervals. Simulation studies will probably be the only fruitful approach to studying these issues. Breslow and Clayton (1993) had some small simulation studies, but more are needed.

## C. 5 Computational Tricks and the Relationship of the Survey-Weighted Empirical Bayes Estimate to Composite Estimation

In this section, we show versions of the equations from Section C. 1 that are faster to calculate than the forms given in that section. First, a useful lemma is reproduced from Robinson (1991).

Lemma C.13: $\quad$ Let $A, U, B$, and $V$ be matrices such that $A+U B V$ is well defined and invertible and such that $A^{-1}$ exists. Then

$$
(A+U B V)^{-1}=A^{-1}-A^{-1} U\left(I+B V A^{-1} U\right)^{-1} B V A^{-1} .
$$

Proof: We demonstrate below that the right-hand form of the equation is the inverse of $A+U B V$ by multiplying it by $A+U B V$ showing that the product is the identity matrix. Since matrix multiplication is not commutative, a full-proof would require evaluating the results of left-hand and right-hand multiplication, but we leave the other side of the proof to the interested reader.

$$
\begin{gathered}
(A+U B V)\left[A^{-1}-A^{-1} U\left(I+B V A^{-1} U\right)^{-1} B V A^{-1}\right] \\
=(A+U B V) A^{-1}\left[I-U\left(I+B V A^{-1} U\right)^{-1} B V A^{-1}\right] \\
=\left(I+U B V A^{-1}\right)\left[I-U\left(I+B V A^{-1} U\right)^{-1} B V A^{-1}\right] \\
=I-U\left(I+B V A^{-1} U\right)^{-1} B V A^{-1}+U B V A^{-1}-U B V A^{-1} U\left(I+B V A^{-1} U\right)^{-1} B V A^{-1} \\
=I-U\left[\left(I+B V A^{-1} U\right)^{-1}-I+B V A^{-1} U\left(I+B V A^{-1} U\right)^{-1}\right] B V A^{-1} \\
=I-U\left[-I+\left(I+B V A^{-1} U\right)\left(I+B V A^{-1} U\right)^{-1}\right] B V A^{-1} \\
=I-U[-I+I] B V A^{-1} \\
=I .
\end{gathered}
$$

Applying lemma C. 13 to V , we have that since $V=R+Z G Z^{t}$, its inverse may be written as

$$
V^{1}=R^{-1}-R^{-1} Z\left(I+G Z^{t} R^{-1} Z\right)^{-1} G Z^{t} R^{-1} .
$$

Since $R$ is a diagonal matrix, it is quite easy to find its inverse. Also $I+G Z^{t} R^{-1} Z$ is of dimension qxq, so it is much easier to find its inverse than to find the inverse of $V$ directly since $V$ is nxn. Because the matrix $I+G Z^{t} R^{-1} Z$ needs to be inverted very often in the iterative procedure, we developed a closed-form expression for the inverse rather than relying on numerical methods to invert the matrix repeatedly.

Once this matrix has been inverted, simplifications in the formulas for the random effects can be achieved that also help the intuitive understanding of the nature of these effects. First, we use lemma C. 13 to derive an expression for estimating the random effects that is fast to calculate. From Section C.1, we have that

## Error!

We will make this general matrix equation more specific to our application and even faster to compute by actually finding a closed form expression for the inverse of $I+G Z^{t} R^{-1} Z$. To find such an expression is messy, but the computing rewards are strong. We now need to consider that for some characteristics and age ranges, we were unable to get the full model with state and PSU random effects to converge. Where we were unable to obtain convergence, we simply dropped the PSU random effects from the model. The matrix inversion is considerably simpler for this simpler model and so we go through the steps for it first. If there is only a state effect, then the columns of Z are mutually orthogonal so $G Z^{t} R^{-1} Z$ is diagonal with $I$-th diagonal element

$$
\sigma_{1}^{2} \sum_{j=1}^{r_{i}} \sum_{k=1}^{n_{i j}} w_{i j k}^{2} \pi_{i j k}\left(1-\pi_{i j k}\right)
$$

We will simplify notation considerably by defining

$$
\alpha_{i j k}=w_{i j k}^{2} \pi_{i j k}\left(1-\pi_{i j k}\right)
$$

and

$$
\alpha_{i++}=\sum_{j=1}^{r_{i}} \sum_{k=1}^{n_{i j}} \alpha_{i j k}
$$

and then using these $\alpha$ factors as weights to get weighted averages of the $\zeta$ and $X$ variables:

Then $U_{i}=\frac{1}{1+\sigma_{1 j}^{2} \sum_{i j}^{2} \pi_{i j}\left(1-\pi_{i j}\right)} \sigma_{1} \sup 2 \sum_{j}^{n_{i}} w_{i j}^{2} \pi_{i j}\left(1-\pi_{i j}\right)\left(\zeta_{i j}-X_{i j} \beta 55^{\wedge}\right)$

$$
\begin{aligned}
& =\frac{\sigma_{1}^{2} \alpha_{i++}}{1+\sigma_{1}^{2} \alpha_{i++}} \sum_{j}^{r_{i} n_{i j}}\left(\frac{\alpha_{i j k}}{\alpha_{i++}}\right)\left(\zeta_{i j}-X_{i j} \beta 55^{\wedge}\right) \\
& =\frac{\sigma_{1}^{2}}{\frac{1}{\alpha_{i++}}+\sigma_{1}^{2}}\left(\zeta_{i}-X_{i} \beta 55^{\wedge}\right) \\
& = \\
& \gamma_{i}\left(\zeta_{i}-X_{i} \beta 55^{\wedge}\right)
\end{aligned}
$$

where

$$
\gamma_{i}=\frac{\sigma_{1}^{2}}{\frac{1}{\alpha_{i++}}+\sigma_{1}^{2}}
$$

Note that since the weights were standardized to sum to the national sample size, $\alpha_{i++}$ is approximately equal to the sample size for the state multiplied by $\pi(1-\pi)$ where $\pi$ is the true national average propensity. Thus,

$$
\gamma_{i-} \frac{\sigma_{1}^{2}}{\frac{1}{n_{i} \pi(1-\pi)}+\sigma_{1}^{2}}
$$

This form of the state random effect allows us to demonstrate a linkage between this estimation
system and composite estimation. Recall that $\lambda_{i j k}=\ln \left(\frac{\pi_{i j k}}{1-\pi_{i j k}}\right)$ is the estimated logit
propensity to engage in the behavior of interest. If we think of averaging the estimated logit propensities across the entire population in the i-th state, we obtain

## Error!

This equation looks just like a classical composite estimator with the design-weighted sample data in the second term and the model-based prediction in the first term. Because of this similarity, we refer to the factor $\gamma_{i}$ as the shrinkage factor for the $i$-th state. If $\gamma_{i}$ is close to 1 , then the sample data from the state predominate the estimated logit propensity for the state. On the other hand, if $\gamma_{i}$ is close to zero, then national data predominate the estimated logit propensity for the state through the model. However, it is probably not appropriate to push this analogy too hard since $\zeta_{i}$ is a complex function of the sample data in the state and the true propensities in the state:

$$
\begin{gathered}
\zeta_{i}=\frac{\sum_{j k} \alpha_{i j k} \zeta_{i j k}}{\alpha_{i++}} \\
=\frac{\sum_{j k} \sum_{k} \alpha_{i j k}\left[X_{i j k}+U_{i}+\frac{y_{i j k}-\pi_{i j k}}{w_{i j k} \pi_{i j k}\left(1-\pi_{i j k}\right)}\right]}{\alpha_{i++}} \\
=X_{i} \beta+U_{i}+\frac{\sum_{j} \sum_{k} w_{i j k}\left(y_{i j k}-\pi_{i j k}\right)}{\alpha_{i++}} \\
=\frac{\sum_{j k} \sum_{i j k} \operatorname{logit}\left(\pi_{i j k}\right)}{\alpha_{i++}}+\frac{\sum_{j k} \sum_{i j k}\left(y_{i j k}-\pi_{i j k}\right)}{\alpha_{i++}}
\end{gathered}
$$

Also note that the composting takes place on the logit transform of the estimated propensity.

That completes the discussion of the simplified model with only state-level random effects. We now tackle the more difficult analogous equations for the full model with state-level and PSU-level random effects. With 2 levels of random effects,

$$
\mathrm{C}-42
$$

$$
I+G Z^{t} R^{-1} Z=\left[\begin{array}{cc}
I+\sigma_{i}^{2} Z_{1}^{t} R^{-1} Z_{1} & \sigma_{1}^{2} Z_{1}^{t} R^{-1} Z_{2} \\
\sigma_{2}^{2} Z_{2}^{t} R^{-1} Z_{1} & I+\sigma_{2}^{2} Z_{2}^{t} R^{-1} Z_{2}
\end{array}\right]
$$

where Z 1 and Z 2 were defined in Section C.2. The columns of $Z_{1}$ are mutually orthogonal as are the columns of $Z_{2}$, making this matrix easier to invert, but $Z_{1}$ and $Z_{2}$, are not orthogonal to each other. We know that all columns involving different states are orthogonal. So we can re-order the random effects in the order $U_{1}, U_{1 l}, \ldots, U_{1 r_{1}}, \ldots \ldots, U_{m}, U_{m l}, \ldots U_{m r_{m}}$ and reorder the columns of $Z$ accordingly. Let each block of columns corresponding to a state be written $B_{\mathrm{i}}$ so that $Z=\left[B_{1}\right.$ DOTSAXISB $\left._{m}\right]$.

Also let

$$
Q_{i}=\left[\begin{array}{cc}
\sigma_{1}^{2} & 0 \\
0 & \sigma_{2}^{2} I_{r_{i}}
\end{array}\right],
$$

where $r_{\mathrm{i}}$ is number of sample PSUs in $i$-th state. Then

$$
I+G Z^{t} R^{-1} Z=\left[\begin{array}{cc}
I+Q_{i} B_{1}^{t} R^{-1} B_{1} & 0 \\
0 & \text { DOTSDIAG } \\
0 & \\
& I+Q_{m} B_{m}^{t} R^{-1} B_{m}
\end{array}\right]
$$

where the I-th block on the main diagonal is $\left(1+r_{i}\right) x\left(1+r_{i}\right)$ in dimension. To invert this matrix, we need only invert each block. Taking the first block as an example, it has the form

$$
I+Q_{1} B_{1}^{t} R^{-1} B_{1}=/_{/}^{1+\sigma_{1}^{2} \alpha_{1++} \sigma_{1}^{2} \alpha_{11+} \quad \text { DOTSLOW } \sigma_{1}^{2} \alpha_{1 r_{1}+}} / \begin{gathered}
\sigma_{2}^{2} \alpha_{11+} \\
1+\sigma_{2}^{2} \alpha_{11+} \\
\text { DOTSDIAG } \\
\sigma_{2}^{2} \alpha_{1 r_{1}+} \\
0
\end{gathered} \quad 1+\sigma_{2}^{2} \alpha_{1 r_{1}+} \quad / . /
$$

where $\alpha_{i j k}=w_{i j k}^{2} \pi_{i j k}\left(1-\pi_{i j k}\right)$ and " + " denotes summation on a subscript.

Some grinding but routine linear algebra yields a closed-form expression for the inverse of this matrix. We don't give the derivation here, but merely the result.

$$
\text { Let } h=1+\sigma_{1}^{2} \alpha_{1++}-\sum_{i=1}^{r_{1}} \frac{\sigma_{1}^{2} \sigma_{2}^{2} \alpha_{1 i+}^{2}}{1+\sigma_{2}^{2} \alpha_{1 i+}} .
$$

Then $\left(I+Q_{1} B_{1}^{t} R^{-1} B_{1}\right)^{-1}$ has the general form

$$
\left.\frac{1}{h} / 1 \quad-\sigma_{1}^{2} A \quad A A^{t}+h H\right) / j
$$

where

$$
A^{t}=\left\lceil\frac{\alpha_{11+}}{\left[1+\sigma_{2}^{2} \alpha_{11+}\right.} \text { DOTSLOW } \frac{\alpha_{1 r_{i}^{+}}}{1+\sigma_{2}^{2} \alpha_{1 r_{i}+}}\right\rceil
$$

and

$$
H=\left[\begin{array}{cc}
\frac{1}{1+\sigma_{2}^{2} \alpha_{11+}} & 0 \\
\text { DOTSDIAG } \\
0 & \frac{1}{1+\sigma_{2}^{2} \alpha_{1 r_{i}+}}
\end{array}\right],
$$

This means that the random effect for the first state is given by the first row of

$$
\left(I+Q_{1} B_{1}^{t} R^{-1} B_{1}\right)^{-1} Q_{1} B_{1}^{t} R^{-1}\left(\zeta-X \beta 55^{\wedge}\right)
$$

The random effects for the sample PSUs in that state are given by the remaining rows. Concentrating on the first row, we have that

$$
U_{1}=\frac{\sigma_{1}^{2}}{h} \sum_{j} \sum_{k} \alpha_{1 j k}\left(\zeta_{1 j k}-X_{1 j k} \beta 55^{\wedge}\right)-\frac{\sigma_{1}^{2} \sigma_{2}^{2}}{h} \sum_{j} \frac{\alpha_{1 j+}}{1+\sigma_{2}^{2} \alpha_{1 j+}} \sum_{k} \alpha_{1 j k}\left(\zeta_{1 j k}-X_{1 j k} \beta 55^{\wedge}\right) .
$$

If we let $\zeta_{i j}=\sum_{k} \frac{\alpha_{i j k}}{\alpha_{i j+}} \zeta_{i j k} \zeta 60={ }_{i}=\frac{\sum_{j} \frac{\alpha_{i j+}}{\alpha_{i j+} \sigma_{2}^{2}+1} \zeta_{i j}}{\sum_{j} \frac{\alpha_{i j+}}{\alpha_{i j+} \sigma_{2}^{2}+1}}$
and define $X_{i j} \times 60={ }_{i}$ similarly, then we have that

$$
\begin{gathered}
U_{1}=\frac{\sigma_{1}^{2}}{h} \sum_{j} \sum_{k}\left[\left(1-\frac{\sigma_{2}^{2} \alpha_{1 j+}}{1+\sigma_{2}^{2} \alpha_{1 j+}}\right) \alpha_{1 j k}\left(\zeta_{1 j k}-X_{1 j k} \beta 55^{\wedge}\right)\right] \\
=\frac{\sigma_{1}^{2}}{h} \sum_{j} \sum_{k} \frac{1}{1+\sigma_{2}^{2} \alpha_{1 j+}} \alpha_{1 j k}\left(\zeta_{1 j k}-45\right.
\end{gathered}
$$

$$
\begin{aligned}
& =\frac{\sigma_{1}^{2}}{h} \sum_{j} \frac{\alpha_{1 j+}}{1+\sigma_{2}^{2} \alpha_{1 j+}} \sum_{k} \frac{\alpha_{1 j k}}{\alpha_{1 j+}}\left(\zeta_{1 j k}-X_{1 j k} \beta 55^{\wedge}\right) \\
& =\frac{\sigma_{1}^{2}}{h} \sum_{j} \frac{\alpha_{1 j+}}{1+\sigma_{2}^{2} \alpha_{1 j+}}\left(\zeta_{1 j}-X_{1 j} \beta 55^{\wedge}\right) \\
& =\frac{\sigma_{1}^{2}}{h}\left(\sum_{j} \frac{\alpha_{1 j+}}{\sigma_{2}^{2} \alpha_{1 j+}+1}\right)\left(\zeta 60={ }_{1}-X 60={ }_{1} \beta 55^{\wedge}\right) \\
& =\frac{\sigma_{1}^{2}\left(\sum_{j} \frac{\alpha_{1 j+}}{\sigma_{2}^{2} \alpha_{1 j+}+1}\right.}{\Gamma}\left(\zeta \mathbf{6 0}==_{1}-X \quad 60={ }_{1} \beta 55^{\wedge}\right)
\end{aligned}
$$

$$
\begin{aligned}
& \left.=\frac{\sigma_{1}^{2}}{\sigma_{1}^{2}+\left(\sum_{j} \frac{\alpha_{1 j_{+}}^{2}}{\sigma_{2}^{2} \alpha_{1 j_{+}+1}}\right)}\left(\zeta 60==_{1}-X 60={ }_{1} \beta 55^{\wedge}\right\}\right) \\
& =\gamma_{11}\left(\zeta 60={ }_{1}-X 60={ }_{1} \beta 55^{\wedge}\right)
\end{aligned}
$$

where

$$
\gamma_{11}=\frac{\sigma_{1}^{2}}{\sigma_{1}^{2}+\left(\sum_{j} \frac{\alpha_{1 j+}}{\sigma_{2}^{2} \alpha_{1 j+}+1}\right)-1}
$$

is the state-level shrinkage factor in the two-level model.

Looking at a PSU effect, we have that Error!

## Error!

where

$$
\gamma_{21 j}=\frac{\sigma_{2}^{2}}{\sigma_{2}^{2}+\frac{1}{\alpha_{1 j+}}}
$$

is the PSU-level shrinkage factor for the j-th sample PSU in the first state in the 2-level model.

Similarly for the other states,

$$
\begin{gathered}
U_{i}=\gamma_{1 i}\left(\zeta 60==_{i}-X \quad 60==_{i} \beta 55^{\wedge}\right) \\
U_{i j}=\gamma_{2 i j}\left[\left(\zeta_{i j}-X_{i j} \beta 55^{\wedge}\right)-U_{i}\right],
\end{gathered}
$$

where

$$
\gamma_{1 i}=\frac{\sigma_{1}^{2}}{\sigma_{1}^{2}+\left(\sum_{j=1}^{r_{i}} \frac{\alpha_{i j+}}{\sigma_{2}^{2} \alpha_{i j+}+1}\right)-1}
$$

and

$$
\gamma_{2 i j}=\frac{\sigma_{2}^{2}}{\sigma_{2}^{2}+\frac{1}{\alpha_{i j+}}}
$$

To get a better intuitive feeling for these shrinkage factors, it is useful to introduce some additional notation. Let

$$
\mathrm{v}_{i j}=\operatorname{Var}\left[\left(\zeta_{i j}-X_{i j} \beta\right) \mid U_{i} U_{i j}\right] .
$$

This variance can be thought of as the measurement variance on the random perturbation for the j-th sample PSU in the i-th state given a particular manifestation from the superpopulation of state and PSU random effects. This variance may be derived as follows. Note that

$$
\mathrm{C}-48
$$

$$
\zeta_{i j}-X_{i j} \beta=U_{i}+U_{i j}+\sum_{k} \frac{\alpha_{i j k}}{\alpha_{i j+}} \frac{\varepsilon_{i j k}}{w_{i j k}}
$$

Now, given $U_{\mathrm{i}}$ and $U_{\mathrm{ij}}$, only $\varepsilon_{\mathrm{ijk}}$ is random. So

$$
\begin{aligned}
\mathrm{v}_{i j}= & \sum_{k}\left(\frac{\alpha_{i j k}}{\alpha_{i j+}}\right) 2 \frac{\operatorname{Var}\left(\varepsilon_{i j k} \mid U_{i}, U_{i j}\right)}{w_{i j k}^{2}} \\
= & \sum_{k}\left(\frac{\alpha_{i j k}}{\alpha_{i j+}}\right)^{2} \frac{1}{w_{i j k}^{2} \pi_{i j k}\left(1-\pi_{i j k}\right)} \\
& =\sum_{k} \frac{\alpha_{i j k}}{\left(\alpha_{i j+}\right)^{2}} \\
& =\frac{1}{\alpha_{i j+}} .
\end{aligned}
$$

Thus,

$$
\gamma_{2 i j}=\frac{\sigma_{2}^{2}}{\sigma_{2}^{2}+\mathrm{v}_{i j}}
$$

Recall that $\sigma_{2}^{2}$ is the variance of the PSU perturbations on the logit scale. This is what was referred to in Chapters 1 and 3 as the process variation. So $\gamma_{2 i j}$ is the proportion of the total variance on the perturbation for the $j$-th PSU in the i-th state that is due to the process rather than to measurement error. This is closely analogous to the definition of the shrinkage factors for the linear mixed model discussed in Section C.4. If the measurement error in negligible, then there will be no shrinkage and so the estimated random effect for the PSU will be close to the design-based estimate for the PSU. If, on the other hand, the measurement error is very large, then there will be considerable shrinkage, meaning that the estimate for the PSU will be based largely on the fixed model and on the state perturbation.

Turning attention to the state-level shrinkage factors, note that similar algebra as used to derive $\mathrm{v}_{\mathrm{ij}}$ can show that

$$
\operatorname{Var}\left[\left(\zeta_{i j}-X_{i j} \beta\right) \mid U_{i}\right]=\sigma_{2}^{2}+v_{i j}
$$

Forming the harmonic mean of these conditional variances across the $r_{\mathrm{i}}$ sample PSUs within the $i$-th state yields

$$
\mathrm{v}_{H i}=\left[\frac{1}{r_{i}} \sum_{j=1}^{r_{i}} \frac{1}{\sigma_{2}^{2}+\mathrm{v}_{i j}}\right]-1
$$

Dividing this average conditional variance by the number of sample PSUs in the states gives us a sort of measurement error on the random perturbation for the i-th state.

Now note that the state-level shrinkage factor can be rewritten as

$$
\gamma_{1 i}=\frac{\sigma_{1}^{2}}{\sigma_{1}^{2}+\frac{\mathrm{v}_{H i}}{r_{i}}}
$$

So it can be thought of as the proportion of the total variance on the random perturbation for the i-th state that is due to the process rather than to measurement error. Again, this is clearly analogous to the shrinkage factors for the linear mixed model. If measurement error is negligible (due to a large sample size), then there will be no shrinkage and so the estimated random effect for the state will be close to that estimated based on the design. If, on the other hand, measurement error is large (due to a small sample size), then there will be considerable shrinkage, even to the point of saying that projections for the state should be based almost entirely on the fixed model.

Appendix D: Block Group and Tract Level Variables Considered in Small Area Estimation Models

Table D. 1 Block Group and Tract Level Variables Considered in Small Area Estimation Models

| Variable | Label | Variable | Label |
| :---: | :---: | :---: | :---: |
| DUMMY | O: Intercept Term |  |  |
|  |  | IBLK10 | Black Interaction Of PDENLEV1 |
| UCLASS9 | T: Underclass Indicator | IBLK11 | Black Interaction Of PDENLEV2 <br> Black Interaction Of PDENLEV3 |
| IFEM1 | Female Interaction Of UCLASS9 | IBLK13 | Black Interaction Of PDENLEV4 |
| IBLK1 | Black Interaction Of UCLASS9 | IHISP10 | Hispanic Interaction Of PDENLEV1 |
|  |  | IHISP11 | Hispanic Interaction Of PDENLEV2 |
| IHISP1 | Hispanic Interaction Of UCLASS9 | IHISP12 | Hispanic Interaction Of PDENLEV3 |
|  |  | IHISP13 | Hispanic Interaction Of PDENLEV4 |
| IOTH1 | Other Interaction Of UCLASS9 |  |  |
| PURBH | T: Percent Housing Units In Urban Areas | IOTH10 IOTH11 | Other Interaction Of PDENLEV1 Other Interaction Of PDENLEV2 |
|  |  | IOTH12 | Other Interaction Of PDENLEV3 |
| IFEM2 | Female Interaction Of PURBH | IOTH13 | Other Interaction Of PDENLEV4 |
| IBLK2 | Black Interaction Of PURBH | PHH1PLN | T: Linear: Percent One Person Households |
|  |  | PHH1PQU | T: Quadratic: Percent One Person Households |
| IHISP2 | Hispanic Interaction Of PURBH | PHH1PCU | T: Cubic: Percent One Person Households |
|  |  | PHH1PQR | T: Quartic: Percent One Person Households |
| IOTH2 | Other Interaction Of PURBH |  |  |
| FEMALE | O: Female Indicator | IFEM15 | Female Interaction Of PHH1PLN Female Interaction Of PHH1PQU |
|  |  | IFEM17 | Female Interaction Of PHH1PCU |
| FEMBLCK | O: Black Interaction Of FEMALE | IFEM18 | Female Interaction Of PHH1PQR |
| FEMHISP | O : Hispanic Interaction Of FEMALE | IBLK15 | Black Interaction Of PHH1PLN |
|  |  | IBLK16 | Black Interaction Of PHH1PQU |
| FEMOTHR | O: Other Interaction Of FEMALE | IBLK17 | Black Interaction Of PHH1PCU |
|  |  | IBLK18 | Black Interaction Of PHH1PQR |
| RACEBLCK | O: Race/Black Indicator |  |  |
| RACEHISP | O: Race/Hispanic Indicator | IHISP15 | Hispanic Interaction Of PHH1PLN |
| RACEOTHR | O : Race/Other Indicator | IHISP16 | Hispanic Interaction Of PHH1PQU |
|  |  | IHISP17 | Hispanic Interaction Of PHH1PCU |
| REGNOREA | O: Northeast Region Indicator | IHISP18 | Hispanic Interaction Of PHH1PQR |
| REGSOUTH | O: South Region Indicator |  |  |
| REGWEST | O: West Region Indicator | IOTH15 | Other Interaction Of PHH1PLN |
|  |  | IOTH16 | Other Interaction Of PHH1PQU |
| IFEM7 | Female Interaction Of REGNOREA | IOTH17 | Other Interaction Of PHH1PCU |
| IFEM8 | Female Interaction Of REGSOUTH | IOTH18 | Other Interaction Of PHH1PQR |
| IFEM9 | Female Interaction Of REGWEST |  |  |
|  |  | POPRMLN | T: Linear: Average Persons Per Room |
| IBLK7 | Black Interaction Of REGNOREA | POPRMQU | T: Quadratic: Average Persons Per Room |
| IBLK8 | Black Interaction Of REGSOUTH | POPRMCU | T: Cubic: Average Persons Per Room |
| IBLK9 | Black Interaction Of REGWEST | POPRMQR | T: Quartic: Average Persons Per Room |
| IHISP7 | Hispanic Interaction Of REGNOREA | IFEM20 | Female Interaction Of POPRMLN |
| IHISP8 | Hispanic Interaction Of REGSOUTH | IFEM21 | Female Interaction Of POPRMQU |
| IHISP9 | Hispanic Interaction Of REGWEST | IFEM22 | Female Interaction Of POPRMCU |
|  |  | IFEM23 | Female Interaction Of POPRMQR |
| IOTH7 | Other Interaction Of REGNOREA |  |  |
| IOTH8 | Other Interaction Of REGSOUTH | IBLK20 | Black Interaction Of POPRMLN |
| IOTH9 | Other Interaction Of REGWEST | IBLK21 | Black Interaction Of POPRMQU |
|  |  | IBLK22 | Black Interaction Of POPRMCU |
| PDENLEV1 | O: Large MSA | IBLK23 | Black Interaction Of POPRMQR |
| PDENLEV2 | O: Medium MSA |  |  |
| PDENLEV3 | O: Small MSA | IHISP20 | Hispanic Interaction Of POPRMLN |
| PDENLEV4 | O: NonMSA, Urban | IHISP21 | Hispanic Interaction Of POPRMQU |
|  |  | IHISP22 | Hispanic Interaction Of POPRMCU |
| IFEM10 | Female Interaction Of PDENLEV1 | IHISP23 | Hispanic Interaction Of POPRMQR |
| IFEM11 | Female Interaction Of PDENLEV2 |  |  |
| IFEM12 | Female Interaction Of PDENLEV3 | IOTH20 | Other Interaction Of POPRMLN |
| IFEM13 | Female Interaction Of PDENLEV4 |  |  |
| IOTH21 | Other Interaction Of POPRMQU | IOTH23 | Other Interaction Of POPRMQR |
| IOTH22 | Other Interaction Of POPRMCU |  |  |

NOTE: T: Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other

# Table D. 1 Block Group and Tract Level Variables Considered in Small Area Estimation Models 

| Variable |  |
| :--- | :--- |
|  | Label |
| PAGE18LN | T: Linear: Percent Persons 0-18 Years |
| PAGE18QU | T: Quadratic: Percent Persons 0-18 Years |
| PAGE18CU | T: Cubic: Percent Persons 0-18 Years |
| PAGE18QR | T: Quartic: Percent Persons 0-18 Years |
| IFEM25 | Female Interaction Of PAGE18LN |
| IFEM26 | Female Interaction Of PAGE18QU |
| IFEM27 | Female Interaction Of PAGE18CU |
| IFEM28 | Female Interaction Of PAGE18QR |
| IBLK25 | Black Interaction Of PAGE18LN |
| IILK26 | Black Interaction Of PAGE18QU |
| IBLK27 | Black Interaction Of PAGE18CU |
| IBLK28 | Black Interaction Of PAGE18QR |
|  |  |
| IHISP25 | Hispanic Interaction Of PAGE18LN |
| IHISP26 | Hispanic Interaction Of PAGE18QU |
| IHISP27 | Hispanic Interaction Of PAGE18CU |
| IHISP28 | Hispanic Interaction Of PAGE18QR |
| IOTH25 | Other Interaction Of PAGE18LN |
| IOTH26 | Other Interaction Of PAGE18QU |
| IOTH27 | Other Interaction Of PAGE18CU |
| IOTH28 | Other Interaction Of PAGE18QR |
| PAGE24LN | T: Linear: Percent Persons 19-24 Years |
| PAGE24QU | T: Quadratic: Percent Persons 19-24 Years |
| PAGE24CU | T: Cubic: Percent Persons 19-24 Years |
| PAGE24QR | T: Quartic: Percent Persons 19-24 Years |
| IFEM30 | Female Interaction Of PAGE24LN |
| IFEM31 | Female Interaction Of PAGE24QU |
| IFEM32 | Female Interaction Of PAGE24CU |
| IFEM33 | Female Interaction Of PAGE24QR |
|  |  |
| IBLK30 | Black Interaction Of PAGE24LN |
| IILK31 | Black Itteraction Of PAGE24QU |
| IBLK32 | Black Interaction Of PAGE24CU |
| IBLK33 | Black Interaction Of PAGE24QR |
| IHISP30 | Hispanic Interaction Of PAGE24LN |
| IHISP31 | Hispanic Interaction Of PAGE24QU |
| IHISP32 | Hispanic Interaction Of PAGE24CU |
| IHISP33 | Hispanic Interaction Of PAGE24QR |
| IOTH30 | Other Interaction Of PAGE24LN |
| IOTH45 | Other Interaction Of PAGE24QU |
| IOTH47 | Other In31 |


| Variable | Label |
| :---: | :---: |
| IBLK35 | Black Interaction Of PAGE34LN |
| IBLK36 | Black Interaction Of PAGE34QU |
| IBLK37 | Black Interaction Of PAGE34CU |
| IBLK38 | Black Interaction Of PAGE34QR |
| IHISP35 | Hispanic Interaction Of PAGE34LN |
| IHISP36 | Hispanic Interaction Of PAGE34QU |
| IHISP37 | Hispanic Interaction Of PAGE34CU |
| IHISP38 | Hispanic Interaction Of PAGE34QR |
| IOTH35 | Other Interaction Of PAGE34LN |
| IOTH36 | Other Interaction Of PAGE34QU |
| IOTH37 | Other Interaction Of PAGE34CU |
| IOTH38 | Other Interaction Of PAGE34QR |
| PAGE44LN | T: Linear: Percent Persons 35-44 Years |
| PAGE44QU | T: Quadratic: Percent Persons 35-44 Years |
| PAGE44CU | T: Cubic: Percent Persons 35-44 Years |
| PAGE44QR | T: Quartic: Percent Persons 35-44 Years |
| IFEM40 | Female Interaction Of PAGE44LN |
| IFEM41 | Female Interaction Of PAGE44QU |
| IFEM42 | Female Interaction Of PAGE44CU |
| IFEM43 | Female Interaction Of PAGE44QR |
| IBLK40 | Black Interaction Of PAGE44LN |
| IBLK41 | Black Interaction Of PAGE44QU |
| IBLK42 | Black Interaction Of PAGE44CU |
| IBLK43 | Black Interaction Of PAGE44QR |
| IHISP40 | Hispanic Interaction Of PAGE44LN |
| IHISP41 | Hispanic Interaction Of PAGE44QU |
| IHISP42 | Hispanic Interaction Of PAGE44CU |
| IHISP43 | Hispanic Interaction Of PAGE44QR |
| IOTH40 | Other Interaction Of PAGE44LN |
| IOTH41 | Other Interaction Of PAGE44QU |
| IOTH42 | Other Interaction Of PAGE44CU |
| IOTH43 | Other Interaction Of PAGE44QR |
| PAGE54LN | T: Linear: Percent Persons 45-54 Years |
| PAGE54QU | T: Quadratic: Percent Persons 45-54 Years |
| PAGE54CU | T: Cubic: Percent Persons 45-54 Years |
| PAGE54QR | T: Quartic: Percent Persons 45-54 Years |
| IFEM45 | Female Interaction Of PAGE54LN |
| IFEM46 | Female Interaction Of PAGE54QU |
| IFEM47 | Female Interaction Of PAGE54CU |
| IFEM48 | Female Interaction Of PAGE54QR |
| IBLK45 | Black Interaction Of PAGE54LN |
| IBLK46 | Black Interaction Of PAGE54QU |
| IBLK47 | Black Interaction Of PAGE54CU |
| IBLK48 | Black Interaction Of PAGE54QR |
| IHISP45 | Hispanic Interaction Of PAGE54LN |
| IHISP46 | Hispanic Interaction Of PAGE54QU |
| IHISP47 | Hispanic Interaction Of PAGE54CU |
| IOTH48 | Other Interaction Of PAGE54QR |
| PAGE64LN | T: Linear: Percent Persons 55-64 Years |
| PAGE64QU | T: Quadratic: Percent Persons 55-64 Years |
| PAGE64CU | T: Cubic: Percent Persons 55-64 Years |

NOTE: T: Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other

# Table D. 1 Block Group and Tract Level Variables Considered in Small Area Estimation Models 

(continued)

## Variable Label

| PAGE64QR | T: Quartic: Percent Persons 55-64 Years |
| :---: | :---: |
| IFEM50 | Female Interaction Of PAGE64LN |
| IFEM51 | Female Interaction Of PAGE64QU |
| IFEM52 | Female Interaction Of PAGE64CU |
| IFEM53 | Female Interaction Of PAGE64QR |
| IBLK50 | Black Interaction Of PAGE64LN |
| IBLK51 | Black Interaction Of PAGE64QU |
| IBLK52 | Black Interaction Of PAGE64CU |
| IBLK53 | Black Interaction Of PAGE64QR |
| IHISP50 | Hispanic Interaction Of PAGE64LN |
| IHISP51 | Hispanic Interaction Of PAGE64QU |
| IHISP52 | Hispanic Interaction Of PAGE64CU |
| IHISP53 | Hispanic Interaction Of PAGE64QR |
| IOTH50 | Other Interaction Of PAGE64LN |
| IOTH51 | Other Interaction Of PAGE64QU |
| IOTH52 | Other Interaction Of PAGE64CU |
| IOTH53 | Other Interaction Of PAGE64QR |
| PSCH8LN | T: Linear: Percent 0-8 Years Of School |
| PSCH8QU | T: Quadratic: Percent 0-8 Years Of School |
| PSCH8CU | T: Cubic: Percent 0-8 Years Of School |
| PSCH8QR | T: Quartic: Percent 0-8 Years Of School |
| IFEM55 | Female Interaction Of PSCH8LN |
| IFEM56 | Female Interaction Of PSCH8QU |
| IFEM57 | Female Interaction Of PSCH8CU |
| IFEM58 | Female Interaction Of PSCH8QR |
| IBLK55 | Black Interaction Of PSCH8LN |
| IBLK56 | Black Interaction Of PSCH8QU |
| IBLK57 | Black Interaction Of PSCH8CU |
| IBLK58 | Black Interaction Of PSCH8QR |
| IHISP55 | Hispanic Interaction Of PSCH8LN |
| IHISP56 | Hispanic Interaction Of PSCH8QU |
| IHISP57 | Hispanic Interaction Of PSCH8CU |
| IHISP58 | Hispanic Interaction Of PSCH8QR |
| IOTH55 | Other Interaction Of PSCH8LN |
| IOTH56 | Other Interaction Of PSCH8QU |
| IOTH57 | Other Interaction Of PSCH8CU |
| IOTH58 | Other Interaction Of PSCH8QR |
| PSCH12LN | T: Linear: Percent 9-12 Years \& No HS Diploma |
| PSCH12QU | T: Quadratic: Percent 9-12 Years \& No HS Diploma |
| PSCH12CU | T: Cubic: Percent 9-12 Years \& No HS Diploma |
| PSCH12QR | T: Quartic: Percent 9-12 Years \& No HS Diploma |
| IFEM60 | Female Interaction Of PSCH12LN |
| IFEM61 | Female Interaction Of PSCH12QU |
| IFEM62 | Female Interaction Of PSCH12CU |
| IBLK78 | Black Interaction Of PSCHCOQR |
| IHISP75 | Hispanic Interaction Of PSCHCOLN |
| IHISP76 | Hispanic Interaction Of PSCHCOQU |
| IHISP77 | Hispanic Interaction Of PSCHCOCU |
| IHISP78 | Hispanic Interaction Of PSCHCOQR |
| IOTH75 | Other Interaction Of PSCHCOLN |


| Variable | Label |
| :---: | :---: |
| IFEM63 | Female Interaction Of PSCH12QR |
| IBLK60 | Black Interaction Of PSCH12LN |
| IBLK61 | Black Interaction Of PSCH12QU |
| IBLK62 | Black Interaction Of PSCH12CU |
| IBLK63 | Black Interaction Of PSCH12QR |
| IHISP60 | Hispanic Interaction Of PSCH12LN |
| IHISP61 | Hispanic Interaction Of PSCH12QU |
| IHISP62 | Hispanic Interaction Of PSCH12CU |
| IHISP63 | Hispanic Interaction Of PSCH12QR |
| IOTH60 | Other Interaction Of PSCH12LN |
| IOTH61 | Other Interaction Of PSCH12QU |
| IOTH62 | Other Interaction Of PSCH12CU |
| IOTH63 | Other Interaction Of PSCH12QR |
| PSCHASLN | T: Linear: Percent Associates Degree |
| PSCHASQU | T: Quadratic: Percent Associates Degree |
| PSCHASCU | T: Cubic: Percent Associates Degree |
| PSCHASQR | T: Quartic: Percent Associates Degree |
| IFEM65 | Female Interaction Of PSCHASLN |
| IFEM66 | Female Interaction Of PSCHASQU |
| IFEM67 | Female Interaction Of PSCHASCU |
| IFEM68 | Female Interaction Of PSCHASQR |
| IBLK65 | Black Interaction Of PSCHASLN |
| IBLK66 | Black Interaction Of PSCHASQU |
| IBLK67 | Black Interaction Of PSCHASCU |
| IBLK68 | Black Interaction Of PSCHASQR |
| IHISP65 | Hispanic Interaction Of PSCHASLN |
| IHISP66 | Hispanic Interaction Of PSCHASQU |
| IHISP67 | Hispanic Interaction Of PSCHASCU |
| IHISP68 | Hispanic Interaction Of PSCHASQR |
| IOTH65 | Other Interaction Of PSCHASLN |
| IOTH66 | Other Interaction Of PSCHASQU |
| IOTH67 | Other Interaction Of PSCHASCU |
| IOTH68 | Other Interaction Of PSCHASQR |
| PSCHCOLN | T: Linear: Bachelors, Graduate, Or Professional Degree |
| PSCHCOQU | T: Quadratic: Bachelors, Graduate, Or Professional |
| Degree |  |
| PSCHCOCU | T: Cubic: Bachelors, Graduate, Or Professional Degree |
| PSCHCOQR | T: Quartic: Bachelors, Graduate, Or Professional Degree |
| IFEM75 | Female Interaction Of PSCHCOLN |
| IFEM76 | Female Interaction Of PSCHCOQU |
| IFEM77 | Female Interaction Of PSCHCOCU |
| IFEM78 | Female Interaction Of PSCHCOQR |
| IBLK75 | Black Interaction Of PSCHCOLN |
| IBLK76 | Black Interaction Of PSCHCOQU |
| IBLK77 | Black Interaction Of PSCHCOCU |
| IOTH76 | Other Interaction Of PSCHCOQU |
| IOTH77 | Other Interaction Of PSCHCOCU |
| IOTH78 | Other Interaction Of PSCHCOQR |
| PSCHSCLN | T: Linear: Percent Some College And No Degree |
| PSCHSCQU | T: Quadratic: Percent Some College And No Degree |
| PSCHSCCU | T: Cubic: Percent Some College And No Degree |
| PSCHSCQR | T: Quartic: Percent Some College And No Degree |

NOTE: T: Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other

# Table D. 1 Block Group and Tract Level Variables Considered in Small Area Estimation Models 

(continued)

| Variab | Label | Variable | Label |
| :---: | :---: | :---: | :---: |
|  |  | IFEM93 | Female Interaction Of PPUBASQR |
| IFEM80 | Female Interaction Of PSCHSCLN |  |  |
| IFEM81 | Female Interaction Of PSCHSCQU | IBLK90 | Black Interaction Of PPUBASLN |
| IFEM82 | Female Interaction Of PSCHSCCU | IBLK91 | Black Interaction Of PPUBASQU |
| IFEM83 | Female Interaction Of PSCHSCQR | IBLK92 | Black Interaction Of PPUBASCU |
|  |  | IBLK93 | Black Interaction Of PPUBASQR |
| IBLK80 | Black Interaction Of PSCHSCLN |  |  |
| IBLK81 | Black Interaction Of PSCHSCQU | IHISP90 | Hispanic Interaction Of PPUBASLN |
| IBLK82 | Black Interaction Of PSCHSCCU | IHISP91 | Hispanic Interaction Of PPUBASQU |
| IBLK83 | Black Interaction Of PSCHSCQR | IHISP92 | Hispanic Interaction Of PPUBASCU |
|  |  | IHISP93 | Hispanic Interaction Of PPUBASQR |
| IHISP80 | Hispanic Interaction Of PSCHSCLN |  |  |
| IHISP81 | Hispanic Interaction Of PSCHSCQU | IOTH90 | Other Interaction Of PPUBASLN |
| IHISP82 | Hispanic Interaction Of PSCHSCCU | IOTH91 | Other Interaction Of PPUBASQU |
| IHISP83 | Hispanic Interaction Of PSCHSCQR | IOTH92 | Other Interaction Of PPUBASCU |
|  |  | IOTH93 | Other Interaction Of PPUBASQR |
| IOTH80 | Other Interaction Of PSCHSCLN |  |  |
| IOTH81 | Other Interaction Of PSCHSCQU | P64DISLN | T: Linear: Percent 16-64 With A Work Disability |
| IOTH82 | Other Interaction Of PSCHSCCU | P64DISQU | T: Quadratic: Percent 16-64 With A Work Disability |
| IOTH83 | Other Interaction Of PSCHSCQR | P64DISCU | T: Cubic: Percent 16-64 With A Work Disability |
|  |  | P64DISQR | T: Quartic: Percent 16-64 With A Work Disability |
| PPOVERLN | T: Linear: Percent Families Below Poverty Level |  |  |
| PPOVERQU | T: Quadratic: Percent Families Below Poverty Level | IFEM95 | Female Interaction Of P64DISLN |
| PPOVERCU | T: Cubic: Percent Families Below Poverty Level | IFEM96 | Female Interaction Of P64DISQU |
| PPOVERQR | T: Quartic: Percent Families Below Poverty Level | IFEM97 | Female Interaction Of P64DISCU |
|  |  | IFEM98 | Female Interaction Of P64DISQR |
| IFEM85 | Female Interaction Of PPOVERLN |  |  |
| IFEM86 | Female Interaction Of PPOVERQU | IBLK95 | Black Interaction Of P64DISLN |
| IFEM87 | Female Interaction Of PPOVERCU | IBLK96 | Black Interaction Of P64DISQU |
| IFEM88 | Female Interaction Of PPOVERQR | IBLK97 | Black Interaction Of P64DISCU |
|  |  | IBLK98 | Black Interaction Of P64DISQR |
| IBLK85 | Black Interaction Of PPOVERLN |  |  |
| IBLK86 | Black Interaction Of PPOVERQU | IHISP95 | Hispanic Interaction Of P64DISLN |
| IBLK87 | Black Interaction Of PPOVERCU | IHISP96 | Hispanic Interaction Of P64DISQU |
| IBLK88 | Black Interaction Of PPOVERQR | IHISP97 | Hispanic Interaction Of P64DISCU |
|  |  | IHISP98 | Hispanic Interaction Of P64DISQR |
| IHISP85 | Hispanic Interaction Of PPOVERLN |  |  |
| IHISP86 | Hispanic Interaction Of PPOVERQU | IOTH95 | Other Interaction Of P64DISLN |
| IHISP87 | Hispanic Interaction Of PPOVERCU | IOTH96 | Other Interaction Of P64DISQU |
| IHISP88 | Hispanic Interaction Of PPOVERQR | IOTH97 | Other Interaction Of P64DISCU |
|  |  | IOTH98 | Other Interaction Of P64DISQR |
| IOTH85 | Other Interaction Of PPOVERLN |  |  |
| IOTH86 | Other Interaction Of PPOVERQU | PBLACKLN | T: Linear: Percent Black Nonhispanic |
| IOTH87 | Other Interaction Of PPOVERCU | PBLACKQU | T: Quadratic: Percent Black Nonhispanic |
| IOTH88 | Other Interaction Of PPOVERQR | PBLACKCU | T: Cubic: Percent Black Nonhispanic |
| PPUBASLN | T: Linear: \% HHS With Public Assist Income | PBLACKQR | T: Quartic: Percent Black Nonhispanic |
| PPUBASQU | T: Quadratic: \% HHS With Public Assist Income |  |  |
| PPUBASCU | T: Cubic: \% HHS With Public Assist Income | IFEM100 | Female Interaction Of PBLACKLN |
| PPUBASQR | T: Quartic: \% HHS With Public Assist Income | IFEM101 | Female Interaction Of PBLACKQU |
|  |  | IFEM102 | Female Interaction Of PBLACKCU |
| IFEM90 | Female Interaction Of PPUBASLN | IFEM103 | Female Interaction Of PBLACKQR |
| IFEM91 | Female Interaction Of PPUBASQU |  |  |
| IFEM92 | Female Interaction Of PPUBASCU | IBLK100 | Black Interaction Of PBLACKLN |
| IBLK101 | Black Interaction Of PBLACKQU | IOTH102 | Other Interaction Of PBLACKCU |
| IBLK102 | Black Interaction Of PBLACKCU | IOTH103 | Other Interaction Of PBLACKQR |
| IBLK103 | Black Interaction Of PBLACKQR |  |  |
|  |  | PHISPLN | T: Linear: Percent Hispanic |
| IHISP100 | Hispanic Interaction Of PBLACKLN | PHISPQU | T: Quadratic: Percent Hispanic |
| IHISP101 | Hispanic Interaction Of PBLACKQU | PHISPCU | T: Cubic: Percent Hispanic |
| IHISP102 | Hispanic Interaction Of PBLACKCU | PHISPQR | T: Quartic: Percent Hispanic |
| IHISP103 | Hispanic Interaction Of PBLACKQR |  |  |
|  |  | IFEM105 | Female Interaction Of PHISPLN |
| IOTH100 | Other Interaction Of PBLACKLN | IFEM106 | Female Interaction Of PHISPQU |
| IOTH101 | Other Interaction Of PBLACKQU | IFEM107 | Female Interaction Of PHISPCU |

NOTE: T: Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other

# Table D. 1 Block Group and Tract Level Variables Considered in Small Area Estimation Models 

(continued)

| Varia | Label | Variable | Label |
| :---: | :---: | :---: | :---: |
| IFEM108 | Female Interaction Of PHISPQR | IFEM122 | Female Interaction Of PHHF18CU |
|  |  | IFEM123 | Female Interaction Of PHHF18QR |
| IBLK105 | Black Interaction Of PHISPLN |  |  |
| IBLK106 | Black Interaction Of PHISPQU | IBLK120 | Black Interaction Of PHHF 18LN |
| IBLK107 | Black Interaction Of PHISPCU | IBLK121 | Black Interaction Of PHHF18QU |
| IBLK108 | Black Interaction Of PHISPQR | IBLK122 | Black Interaction Of PHHF18CU |
|  |  | IBLK123 | Black Interaction Of PHHF18QR |
| IHISP105 | Hispanic Interaction Of PHISPLN |  |  |
| IHISP106 | Hispanic Interaction Of PHISPQU | IHISP120 | Hispanic Interaction Of PHHF18LN |
| IHISP107 | Hispanic Interaction Of PHISPCU | IHISP121 | Hispanic Interaction Of PHHF18QU |
| IHISP108 | Hispanic Interaction Of PHISPQR | IHISP122 | Hispanic Interaction Of PHHF18CU |
|  |  | IHISP123 | Hispanic Interaction Of PHHF18QR |
| IOTH105 | Other Interaction Of PHISPLN |  |  |
| IOTH106 | Other Interaction Of PHISPQU | IOTH120 | Other Interaction Of PHHF18LN |
| IOTH107 | Other Interaction Of PHISPCU | IOTH121 | Other Interaction Of PHHF18QU |
| IOTH108 | Other Interaction Of PHISPQR | IOTH122 | Other Interaction Of PHHF18CU |
|  |  | IOTH123 | Other Interaction Of PHHF18QR |
| POTHLN | T: Linear: Percent Other Race/Hispanicity |  |  |
| POTHQU | T: Quadratic: Percent Other Race/Hispanicity | PFLABLN | T: Linear: \% Females 16+ Years Old In Labor Force |
| POTHCU | T: Cubic: Percent Other Race/Hispanicity | PFLABQU | T: Quadratic: \% Females 16+ Years Old In Labor Force |
| POTHQR | T: Quartic: Percent Other Race/Hispanicity | PFLABCU | T: Cubic: \% Females 16+ Years Old In Labor Force |
|  |  | PFLABQR | T: Quartic: \% Females 16+ Years Old In Labor Force |
| IFEM110 | Female Interaction Of POTHLN |  |  |
| IFEM111 | Female Interaction Of POTHQU | IFEM125 | Female Interaction Of PFLABLN |
| IFEM112 | Female Interaction Of POTHCU | IFEM126 | Female Interaction Of PFLABQU |
| IFEM113 | Female Interaction Of POTHQR | IFEM127 | Female Interaction Of PFLABCU |
|  |  | IFEM128 | Female Interaction Of PFLABQR |
| IBLK110 | Black Interaction Of POTHLN |  |  |
| IBLK111 | Black Interaction Of POTHQU | IBLK125 | Black Interaction Of PFLABLN |
| IBLK112 | Black Interaction Of POTHCU | IBLK126 | Black Interaction Of PFLABQU |
| IBLK113 | Black Interaction Of POTHQR | IBLK127 | Black Interaction Of PFLABCU |
|  |  | IBLK128 | Black Interaction Of PFLABQR |
| IHISP110 | Hispanic Interaction Of POTHLN |  |  |
| IHISP111 | Hispanic Interaction Of POTHQU | IHISP125 | Hispanic Interaction Of PFLABLN |
| IHISP112 | Hispanic Interaction Of POTHCU | IHISP126 | Hispanic Interaction Of PFLABQU |
| IHISP113 | Hispanic Interaction Of POTHQR | IHISP127 | Hispanic Interaction Of PFLABCU |
|  |  | IHISP128 | Hispanic Interaction Of PFLABQR |
| IOTH110 | Other Interaction Of POTHLN |  |  |
| IOTH111 | Other Interaction Of POTHQU | IOTH125 | Other Interaction Of PFLABLN |
| IOTH1 12 | Other Interaction Of POTHCU | IOTH126 | Other Interaction Of PFLABQU |
| IOTH113 | Other Interaction Of POTHQR | IOTH127 | Other Interaction Of PFLABCU |
|  |  | IOTH128 | Other Interaction Of PFLABQR |
| PHHF18LN | T: Linear: \% F-Headed HH W/No Spouse \& Chld <18 | PFNEVLN | T: Linear: Percent Females Never Married |
| PHHF18QU | T: Quad.: \% F-Headed HH W/No Spouse \& Chld <18 | PFNEVQU | T: Quadratic: Percent Females Never Married |
| PHHF18CU | T: Cubic: \% F-Headed HH W/No Spouse \& Chld <18 | PFNEVCU | T: Cubic: Percent Females Never Married |
| PHHF18QR | T: Quartic: \% F-Headed HH W/No Spouse \& Chld <18 | PFNEVQR | T: Quartic: Percent Females Never Married |
| IFEM120 | Female Interaction Of PHHF18LN | IFEM130 | Female Interaction Of PFNEVLN |
| IFEM121 | Female Interaction Of PHHF18QU | IFEM131 | Female Interaction Of PFNEVQU |
| IFEM132 | Female Interaction Of PFNEVCU | IOTH131 | Other Interaction Of PFNEVQU |
| IFEM133 | Female Interaction Of PFNEVQR | IOTH132 | Other Interaction Of PFNEVCU |
|  |  | IOTH133 | Other Interaction Of PFNEVQR |
| IBLK130 | Black Interaction Of PFNEVLN |  |  |
| IBLK131 | Black Interaction Of PFNEVQU | PFNOTLN | T: Linear: \% Females Separated, Divorced Or Widowed |
| IBLK132 | Black Interaction Of PFNEVCU | PFNOTQU | T: Quadratic: \% Fem Separated, Divorced Or Widowed |
| IBLK133 | Black Interaction Of PFNEVQR | PFNOTCU | T: Cubic: \% Fem Separated, Divorced Or Widowed |
|  |  | PFNOTQR | T: Quartic: \% Fem Separated, Divorced Or Widowed |
| IHISP130 | Hispanic Interaction Of PFNEVLN |  |  |
| IHISP131 | Hispanic Interaction Of PFNEVQU | IFEM135 | Female Interaction Of PFNOTLN |
| IHISP132 | Hispanic Interaction Of PFNEVCU | IFEM136 | Female Interaction Of PFNOTQU |
| IHISP133 | Hispanic Interaction Of PFNEVQR | IFEM137 | Female Interaction Of PFNOTCU |
|  |  | IFEM138 | Female Interaction Of PFNOTQR |
| IOTH130 | Other Interaction Of PFNEVLN |  |  |

NOTE: T: Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other

# Table D. 1 Block Group and Tract Level Variables Considered in Small Area Estimation Models 



| Variable | Label |
| :---: | :---: |
| IFEM146 | Female Interaction Of PMLABQU |
| IFEM147 | Female Interaction Of PMLABCU |
| IFEM148 | Female Interaction Of PMLABQR |
| IBLK145 | Black Interaction Of PMLABLN |
| IBLK146 | Black Interaction Of PMLABQU |
| IBLK147 | Black Interaction Of PMLABCU |
| IBLK148 | Black Interaction Of PMLABQR |
| IHISP145 | Hispanic Interaction Of PMLABLN |
| IHISP146 | Hispanic Interaction Of PMLABQU |
| IHISP147 | Hispanic Interaction Of PMLABCU |
| IHISP148 | Hispanic Interaction Of PMLABQR |
| IOTH145 | Other Interaction Of PMLABLN |
| IOTH146 | Other Interaction Of PMLABQU |
| IOTH147 | Other Interaction Of PMLABCU |
| IOTH148 | Other Interaction Of PMLABQR |
| PMNOTLN | T: Linear: \% M Separated, Divorced Or Widowed |
| PMNOTQU | T: Quadratic: \% M Separated, Divorced Or Widowed |
| PMNOTCU | T: Cubic: \% M Separated, Divorced Or Widowed |
| PMNOTQR | T: Quartic: \% M Separated, Divorced Or Widowed |
| IFEM150 | Female Interaction Of PMNOTLN |
| IFEM151 | Female Interaction Of PMNOTQU |
| IFEM152 | Female Interaction Of PMNOTCU |
| IFEM153 | Female Interaction Of PMNOTQR |
| IBLK150 | Black Interaction Of PMNOTLN |
| IBLK151 | Black Interaction Of PMNOTQU |
| IBLK152 | Black Interaction Of PMNOTCU |
| IBLK153 | Black Interaction Of PMNOTQR |
| IHISP150 | Hispanic Interaction Of PMNOTLN |
| IHISP151 | Hispanic Interaction Of PMNOTQU |
| IHISP152 | Hispanic Interaction Of PMNOTCU |
| IHISP153 | Hispanic Interaction Of PMNOTQR |
| IOTH150 | Other Interaction Of PMNOTLN |
| IOTH151 | Other Interaction Of PMNOTQU |
| IOTH152 | Other Interaction Of PMNOTCU |
| IOTH153 | Other Interaction Of PMNOTQR |
| POLDHULN | T: Linear: \% Housing Units Built 1939 Or Earlier |
| POLDHUQU | T: Quadratic: \% Housing Units Built 1939 Or Earlier |
| POLDHUCU | T: Cubic: \% Housing Units Built 1939 Or Earlier |
| IOTH155 | Other Interaction Of POLDHULN |
| IOTH156 | Other Interaction Of POLDHUQU |
| IOTH157 | Other Interaction Of POLDHUCU |
| IOTH158 | Other Interaction Of POLDHUQR |
| P40HULN | T: Linear: Percent Housing Units Built 1940-1949 |
| P40HUQU | T: Quadratic: Percent Housing Units Built 1940-1949 |
| P40HUCU | T: Cubic: Percent Housing Units Built 1940-1949 |
| P40HUQR | T: Quartic: Percent Housing Units Built 1940-1949 |
| IFEM160 | Female Interaction Of P40HULN |
| IFEM161 | Female Interaction Of P40HUQU |
| IFEM162 | Female Interaction Of P40HUCU |
| IFEM163 | Female Interaction Of P40HUQR |
| IBLK160 | Black Interaction Of P40HULN |
| IBLK161 | Black Interaction Of P40HUQU |

NOTE: T: Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other

# Table D. 1 Block Group and Tract Level Variables Considered in Small Area Estimation Models 

(continued)

| Variab | Label | Variable | Label |
| :---: | :---: | :---: | :---: |
| IBLK162 | Black Interaction Of P40HUCU | IFEM171 | Female Interaction Of PURBPQU |
| IBLK163 | Black Interaction Of P40HUQR | IFEM172 | Female Interaction Of PURBPCU |
|  |  | IFEM173 | Female Interaction Of PURBPQR |
| IHISP160 | Hispanic Interaction Of P40HULN |  |  |
| IHISP161 | Hispanic Interaction Of P40HUQU | IBLK170 | Black Interaction Of PURBPLN |
| IHISP162 | Hispanic Interaction Of P40HUCU | IBLK171 | Black Interaction Of PURBPQU |
| IHISP163 | Hispanic Interaction Of P40HUQR | IBLK172 | Black Interaction Of PURBPCU |
|  |  | IBLK173 | Black Interaction Of PURBPQR |
| IOTH160 | Other Interaction Of P40HULN |  |  |
| IOTH161 | Other Interaction Of P40HUQU | IHISP170 | Hispanic Interaction Of PURBPLN |
| IOTH162 | Other Interaction Of P40HUCU | IHISP171 | Hispanic Interaction Of PURBPQU |
| IOTH163 | Other Interaction Of P40HUQR | IHISP172 | Hispanic Interaction Of PURBPCU |
|  |  | IHISP173 | Hispanic Interaction Of PURBPQR |
| PRENTLN | T: Linear: Percent Housing Rented |  |  |
| PRENTQU | T: Quadratic: Percent Housing Rented | IOTH170 | Other Interaction Of PURBPLN |
| PRENTCU | T: Cubic: Percent Housing Rented | IOTH171 | Other Interaction Of PURBPQU |
| PRENTQR | T: Quartic: Percent Housing Rented | IOTH172 | Other Interaction Of PURBPCU |
|  |  | IOTH173 | Other Interaction Of PURBPQR |
| IFEM165 | Female Interaction Of PRENTLN |  |  |
| IFEM166 | Female Interaction Of PRENTQU | ADRATELN | C: Linear: Death Rate For All Alcohol-Related Cases |
| IFEM167 | Female Interaction Of PRENTCU | ADRATEQU | C: Quadratic: Death Rate For All Alcohol-Related Cases |
| IFEM168 | Female Interaction Of PRENTQR | ADRATECU | C: Cubic: Death Rate For All Alcohol-Related Cases |
|  |  | ADRATEQR | C: Quartic: Death Rate For All Alcohol-Related Cases |
| IBLK165 | Black Interaction Of PRENTLN |  |  |
| IBLK166 | Black Interaction Of PRENTQU | IFEM175 | Female Interaction Of ADRATELN |
| IBLK167 | Black Interaction Of PRENTCU | IFEM176 | Female Interaction Of ADRATEQU |
| IBLK168 | Black Interaction Of PRENTQR | IFEM177 | Female Interaction Of ADRATECU |
| IHISP165 | Hispanic Interaction Of PRENTLN | IFEM178 | Female Interaction Of ADRATEQR |
| IHISP166 | Hispanic Interaction Of PRENTQU |  |  |
| IHISP167 | Hispanic Interaction Of PRENTCU | IBLK175 | Black Interaction Of ADRATELN |
| IHISP168 | Hispanic Interaction Of PRENTQR | IBLK176 | Black Interaction Of ADRATEQU |
|  |  | IBLK177 | Black Interaction Of ADRATECU |
| IOTH165 | Other Interaction Of PRENTLN | IBLK178 | Black Interaction Of ADRATEQR |
| IOTH166 | Other Interaction Of PRENTQU |  |  |
| IOTH167 | Other Interaction Of PRENTCU | IHISP175 | Hispanic Interaction Of ADRATELN |
| IOTH168 | Other Interaction Of PRENTQR | IHISP176 | Hispanic Interaction Of ADRATEQU |
|  |  | IHISP177 | Hispanic Interaction Of ADRATECU |
|  |  | IHISP178 | Hispanic Interaction Of ADRATEQR |
| PURBPLN | T: Linear: Percent Population In Urban Areas |  |  |
| PURBPQU | T: Quadratic: Percent Population In Urban Areas | IOTH175 | Other Interaction Of ADRATELN |
| PURBPCU | T: Cubic: Percent Population In Urban Areas | IOTH176 | Other Interaction Of ADRATEQU |
| PURBPQR | T: Quartic: Percent Population In Urban Areas | IOTH177 | Other Interaction Of ADRATECU |
|  |  | IOTH178 | Other Interaction Of ADRATEQR |
| IFEM170 | Female Interaction Of PURBPLN |  |  |
| ADRAT1LN | C: Linr: Death Rate With Explicit Mention Of Alcohol | IOTH180 | Other Interaction Of ADRAT1LN |
| ADRATIQU | C: Quad: Death Rate With Explicit Mention Of Alcohol | IOTH181 | Other Interaction Of ADRATIQU |
| ADRATICU | C: Cubic: Death Rate With Explicit Mention Of Alcohol | IOTH182 | Other Interaction Of ADRATICU |
| ADRAT1QR | C: Quart: Death Rate With Explicit Mention Of Alcohol | IOTH183 | Other Interaction Of ADRAT1QR |
| IFEM180 | Female Interaction Of ADRAT1LN | V18FLN | C: Linear: Marijuana Posession Arrest Rate |
| IFEM181 | Female Interaction Of ADRATIQU | V18FQU | C: Quadratic: Marijuana Posession Arrest Rate |
| IFEM182 | Female Interaction Of ADRAT1CU | V18FCU | C: Cubic: Marijuana Posession Arrest Rate |
| IFEM183 | Female Interaction Of ADRATIQR | V18FQR | C: Quartic: Marijuana Posession Arrest Rate |
| IBLK180 | Black Interaction Of ADRAT1LN | IFEM185 | Female Interaction Of V18FLN |
| IBLK181 | Black Interaction Of ADRAT1QU | IFEM186 | Female Interaction Of V18FQU |
| IBLK182 | Black Interaction Of ADRATICU | IFEM187 | Female Interaction Of V18FCU |
| IBLK183 | Black Interaction Of ADRAT1QR | IFEM188 | Female Interaction Of V18FQR |
| IHISP180 | Hispanic Interaction Of ADRAT1LN | IBLK185 | Black Interaction Of V18FLN |
| IHISP181 | Hispanic Interaction Of ADRATIQU | IBLK186 | Black Interaction Of V18FQU |
| IHISP182 | Hispanic Interaction Of ADRATICU | IBLK187 | Black Interaction Of V18FCU |
| IHISP183 | Hispanic Interaction Of ADRAT1QR | IBLK188 | Black Interaction Of V18FQR |

NOTE: T: Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other

# Table D. 1 Block Group and Tract Level Variables Considered in Small Area Estimation Models 

(continued)

|  | Label | Variable | Label |
| :---: | :---: | :---: | :---: |
| IHISP185 | Hispanic Interaction Of V18FLN |  |  |
| IHISP186 | Hispanic Interaction Of V18FQU | IFEM200 | Female Interaction Of V18ALN |
| IHISP187 | Hispanic Interaction Of V18FCU | IFEM201 | Female Interaction Of V18AQU |
| IHISP188 | Hispanic Interaction Of V18FQR | IFEM202 | Female Interaction Of V18ACU |
|  |  | IFEM203 | Female Interaction Of V18AQR |
| IOTH185 | Other Interaction Of V18FLN |  |  |
| IOTH186 | Other Interaction Of V18FQU | IBLK200 | Black Interaction Of V18ALN |
| IOTH187 | Other Interaction Of V18FCU | IBLK201 | Black Interaction Of V18AQU |
| IOTH188 | Other Interaction Of V18FQR | IBLK202 | Black Interaction Of V18ACU |
|  |  | IBLK203 | Black Interaction Of V18AQR |
| V18BLN | C: Linear: Marijuana Sale/Manufacture Arrest Rate |  |  |
| V18BQU | C: Quadratic: Marijuana Sale/Manufacture Arrest Rate | IHISP200 | Hispanic Interaction Of V18ALN |
| V18BCU | C: Cubic: Marijuana Sale/Manufacture Arrest Rate | IHISP201 | Hispanic Interaction Of V18AQU |
| V18BQR | C: Quartic: Marijuana Sale/Manufacture Arrest Rate | IHISP202 | Hispanic Interaction Of V18ACU |
|  |  | IHISP203 | Hispanic Interaction Of V18AQR |
| IFEM190 | Female Interaction Of V18BLN |  |  |
| IFEM191 | Female Interaction Of V18BQU | IOTH200 | Other Interaction Of V18ALN |
| IFEM192 | Female Interaction Of V18BCU | IOTH201 | Other Interaction Of V18AQU |
| IFEM193 | Female Interaction Of V18BQR | IOTH202 | Other Interaction Of V18ACU |
|  |  | IOTH203 | Other Interaction Of V18AQR |
| IBLK190 | Black Interaction Of V18BLN |  |  |
| IBLK191 | Black Interaction Of V18BQU | V18HLN | C: Linear: Other (Non-Narcotics) Posession Arrest Rate |
| IBLK192 | Black Interaction Of V18BCU | V18HQU | C: Quad: Other (Non-Narcotics) Posession Arst Rate |
| IBLK193 | Black Interaction Of V18BQR | V18HCU | C: Cubic: Other (Non-Narcotics) Posession Arrest Rate |
|  | Hispanic Interaction Of V18BLN | V18HQR | C: Quartic: Other (Non-Narcotics) Posession Arrest Rate |
| IHISP191 | Hispanic Interaction Of V18BQU | IFEM205 | Female Interaction Of V18HLN |
| IHISP192 | Hispanic Interaction Of V18BCU | IFEM206 | Female Interaction Of V18HQU |
| IHISP193 | Hispanic Interaction Of V18BQR | IFEM207 | Female Interaction Of V18HCU |
|  |  | IFEM208 | Female Interaction Of V18HQR |
| IOTH190 | Other Interaction Of V18BLN |  |  |
| IOTH191 | Other Interaction Of V18BQU | IBLK205 | Black Interaction Of V18HLN |
| IOTH192 | Other Interaction Of V18BCU | IBLK206 | Black Interaction Of V18HQU |
| IOTH193 | Other Interaction Of V18BQR | IBLK207 | Black Interaction Of V18HCU |
|  |  | IBLK208 | Black Interaction Of V18HQR |
|  |  | IHISP205 | Hispanic Interaction Of V18HLN |
| V18ALN | C: Linr: Opium/Cocaine \& Deriv Sale/Manuf Arst Rate | IHISP206 | Hispanic Interaction Of V18HQU |
| V18AQU | C: Quad: Opium/Cocaine \& Deriv Sale/Manuf Arst Rate | IHISP207 | Hispanic Interaction Of V18HCU |
| V18ACU | C: Cub: Opium/Cocaine \& Deriv Sale/Manuf Arst Rate | IHISP208 | Hispanic Interaction Of V18HQR |
| V18AQR | C: Qurt: Opium/Cocaine \& Deriv Sale/Manuf Arst Rate |  |  |
| IOTH205 | Other Interaction Of V18HLN | IHISP213 | Hispanic Interaction Of V18DQR |
| IOTH206 | Other Interaction Of V18HQU |  |  |
| IOTH207 | Other Interaction Of V18HCU | IOTH210 | Other Interaction Of V18DLN |
| IOTH208 | Other Interaction Of V18HQR | IOTH211 | Other Interaction Of V18DQU |
|  |  | IOTH212 | Other Interaction Of V18DCU |
| V18DLN | C: Linear: Other (Non-Narcotics) Sale/Manuf Arst Rate | IOTH213 | Other Interaction Of V18DQR |
| V18DQU | C: Quad: Other (Non-Narcotics) Sale/Manuf Arst Rate |  |  |
| V18DCU | C: Cubic: Other (Non-Narcotics) Sale/Manuf Arst Rate | V18GLN | C: Linear: Synthetic Narcotics Posession Arrest Rate |
| V18DQR | C: Quartic: Other (Non-Narcotics) Sale/Manuf Arst Rate | V18GQU | C: Quadratic: Synthetic Narcotics Posession Arrest Rate |
|  |  | V18GCU | C: Cubic: Synthetic Narcotics Posession Arrest Rate |
| IFEM210 | Female Interaction Of V18DLN | V18GQR | C: Quartic: Synthetic Narcotics Posession Arrest Rate |
| IFEM211 | Female Interaction Of V18DQU |  |  |
| IFEM212 | Female Interaction Of V18DCU | IFEM215 | Female Interaction Of V18GLN |
| IFEM213 | Female Interaction Of V18DQR | IFEM216 | Female Interaction Of V18GQU |
|  |  | IFEM217 | Female Interaction Of V18GCU |
| IBLK210 | Black Interaction Of V18DLN | IFEM218 | Female Interaction Of V18GQR |
| IBLK211 | Black Interaction Of V18DQU |  |  |
| IBLK212 | Black Interaction Of V18DCU | IBLK215 | Black Interaction Of V18GLN |
| IBLK213 | Black Interaction Of V18DQR | IBLK216 | Black Interaction Of V18GQU |
|  |  | IBLK217 | Black Interaction Of V18GCU |
| IHISP210 | Hispanic Interaction Of V18DLN | IBLK218 | Black Interaction Of V18GQR |
| IHISP211 | Hispanic Interaction Of V18DQU |  |  |
| IHISP212 | Hispanic Interaction Of V18DCU | IHISP215 | Hispanic Interaction Of V18GLN |

NOTE: T: Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other

# Table D. 1 Block Group and Tract Level Variables Considered in Small Area Estimation Models 

(continued)

| Varia | Label | Variable | Label |
| :---: | :---: | :---: | :---: |
| IHISP216 | Hispanic Interaction Of V18GQU |  |  |
| IHISP217 | Hispanic Interaction Of V18GCU | IFEM225 | Female Interaction Of V18LN |
| IHISP218 | Hispanic Interaction Of V18GQR | IFEM226 | Female Interaction Of V18QU |
|  |  | IFEM227 | Female Interaction Of V18CU |
| IOTH215 | Other Interaction Of V18GLN | IFEM228 | Female Interaction Of V18QR |
| IOTH216 | Other Interaction Of V18GQU |  |  |
| IOTH217 | Other Interaction Of V18GCU | IBLK225 | Black Interaction Of V18LN |
| IOTH218 | Other Interaction Of V18GQR | IBLK226 | Black Interaction Of V18QU |
|  |  | IBLK227 | Black Interaction Of V18CU |
| V18CLN | C: Linear: Synthetic Narcotics Sale/Manuf Arrest Rate | IBLK228 | Black Interaction Of V18QR |
| V18CQU | C: Quadratic: Synthetic Narcotics Sale/Manuf Arrest Rate |  |  |
| V18CCU | C: Cubic: Synthetic Narcotics Sale/Manuf Arrest Rate | IHISP225 | Hispanic Interaction Of V18LN |
| V18CQR | C: Quartic: Synthetic Narcotics Sale/Manuf Arrest Rate | IHISP226 | Hispanic Interaction Of V18QU |
|  |  | IHISP227 | Hispanic Interaction Of V18CU |
| IFEM220 | Female Interaction Of V18CLN | IHISP228 | Hispanic Interaction Of V18QR |
| IFEM221 | Female Interaction Of V18CQU |  |  |
| IFEM222 | Female Interaction Of V18CCU | IOTH225 | Other Interaction Of V18LN |
| IFEM223 | Female Interaction Of V18CQR | IOTH226 | Other Interaction Of V18QU |
|  |  | IOTH227 | Other Interaction Of V18CU |
| IBLK220 | Black Interaction Of V18CLN | IOTH228 | Other Interaction Of V18QR |
| IBLK221 | Black Interaction Of V18CQU |  |  |
| IBLK222 | Black Interaction Of V18CCU | VIOLLN | C: Linear: Total Violent Offenses Arrest Rate |
| IBLK223 | Black Interaction Of V18CQR | VIOLQU | C: Quadratic: Total Violent Offenses Arrest Rate |
|  |  | VIOLCU | C: Cubic: Total Violent Offenses Arrest Rate |
| IHISP220 | Hispanic Interaction Of V18CLN | VIOLQR | C: Quartic: Total Violent Offenses Arrest Rate |
| IHISP221 | Hispanic Interaction Of V18CQU |  |  |
| IHISP222 | Hispanic Interaction Of V18CCU | IFEM230 | Female Interaction Of VIOLLN |
| IHISP223 | Hispanic Interaction Of V18CQR | IFEM231 | Female Interaction Of VIOLQU |
|  |  | IFEM232 | Female Interaction Of VIOLCU |
| IOTH220 | Other Interaction Of V18CLN | IFEM233 | Female Interaction Of VIOLQR |
| IOTH221 | Other Interaction Of V18CQU |  |  |
| IOTH222 | Other Interaction Of V18CCU | IBLK230 | Black Interaction Of VIOLLN |
| IOTH223 | Other Interaction Of V18CQR | IBLK231 | Black Interaction Of VIOLQU |
|  |  | IBLK232 | Black Interaction Of VIOLCU |
| V18LN | C: Linear: Total Drug Abuse Violations Arrest Rate | IBLK233 | Black Interaction Of VIOLQR |
| V18QU | C: Quadratic: Total Drug Abuse Violations Arrest Rate |  |  |
| V18CU | C: Cubic: Total Drug Abuse Violations Arrest Rate | IHISP230 | Hispanic Interaction Of VIOLLN |
| V18QR | C: Quartic: Total Drug Abuse Violations Arrest Rate |  |  |
| IHISP231 | Hispanic Interaction Of VIOLQU | IHISP237 | Hispanic Interaction Of DRATECU |
| IHISP232 | Hispanic Interaction Of VIOLCU | IHISP238 | Hispanic Interaction Of DRATEQR |
| IHISP233 | Hispanic Interaction Of VIOLQR |  |  |
|  |  | IOTH235 | Other Interaction Of DRATELN |
| IOTH230 | Other Interaction Of VIOLLN | IOTH236 | Other Interaction Of DRATEQU |
| IOTH231 | Other Interaction Of VIOLQU | IOTH237 | Other Interaction Of DRATECU |
| IOTH232 | Other Interaction Of VIOLCU | IOTH238 | Other Interaction Of DRATEQR |
| IOTH233 | Other Interaction Of VIOLQR |  |  |
|  |  | RH43ALN | T: Linear: Recoded Median Rents For Rental Units |
| DRATELN | C: Linear: Mean Drug Client Treatment Rate 1991 \& 92 | RH43AQU | T: Quadratic: Recoded Median Rents For Rental Units |
| DRATEQU | C: Quad: Mean Drug Client Treatment Rate 1991 \& 92 | RH43ACU | T: Cubic: Recoded Median Rents For Rental Units |
| DRATECU | C: Cubic: Mean Drug Client Treatment Rate 1991 \& 92 | RH43AQR | T: Quartic: Recoded Median Rents For Rental Units |
| DRATEQR | C: Quart: Mean Drug Client Treatment Rate 1991 \& 92 |  |  |
|  |  | IFEM240 | Female Interaction Of RH43ALN |
| IFEM235 | Female Interaction Of DRATELN | IFEM241 | Female Interaction Of RH43AQU |
| IFEM236 | Female Interaction Of DRATEQU | IFEM242 | Female Interaction Of RH43ACU |
| IFEM237 | Female Interaction Of DRATECU | IFEM243 | Female Interaction Of RH43AQR |
| IFEM238 | Female Interaction Of DRATEQR |  |  |
|  |  | IBLK240 | Black Interaction Of RH43ALN |
| IBLK235 | Black Interaction Of DRATELN | IBLK241 | Black Interaction Of RH43AQU |
| IBLK236 | Black Interaction Of DRATEQU | IBLK242 | Black Interaction Of RH43ACU |
| IBLK237 | Black Interaction Of DRATECU | IBLK243 | Black Interaction Of RH43AQR |
| IBLK238 | Black Interaction Of DRATEQR |  |  |
|  |  | IHISP240 | Hispanic Interaction Of RH43ALN |
| IHISP235 | Hispanic Interaction Of DRATELN | IHISP241 | Hispanic Interaction Of RH43AQU |
| IHISP236 | Hispanic Interaction Of DRATEQU | IHISP242 | Hispanic Interaction Of RH43ACU |

NOTE: T: Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other

# Table D. 1 Block Group and Tract Level Variables Considered in Small Area Estimation Models 

(continued)

## Variable Label

| IHISP243 | Hispanic Interaction Of RH43AQR | RP80AQR | T: Quartic: Recoded Median Household Income |
| :--- | :--- | :--- | :--- |
| IOTH240 | Other Interaction Of RH43ALN |  |  |
| IOTH241 | Other Interaction Of RH43AQU | IFEM250 | Female Interaction Of RP80ALN |
| IOTH242 | Other Interaction Of RH43ACU | IFEM251 | Female Interaction Of RP80AQU |
| IOTH243 | Other Interaction Of RH43AQR | IFEM252 | Female Interaction Of RP80ACU |
|  |  |  | Female Interaction Of RP80AQR |
| RH61ALN | T: Linear: Recod Median Value Of Owner Occup HUs | IBLK250 | Black Interaction Of RP80ALN |
| RH61AQU | T: Quad: Recod Median Value Of Owner Occup HUs | IBLK251 | Black Interaction Of RP80AQU |
| RH61ACU | T: Cubic: Recod Median Value Of Owner Occup HUs | IBLK252 | Black Interaction Of RP80ACU |
| RH61AQR | T: Quartic: Recod Median Value Of Owner Occup HUs | IBLK253 | Black Interaction Of RP80AQR |
|  |  |  |  |
| IFEM245 | Female Interaction Of RH61ALN | IHISP250 | Hispanic Interaction Of RP80ALN |
| IFEM246 | Female Interaction Of RH61AQU | IHISP251 | Hispanic Interaction Of RP80AQU |
| IFEM247 | Female Interaction Of RH61ACU | IHISP252 | Hispanic Interaction Of RP80ACU |
| IFEM248 | Female Interaction Of RH61AQR | IHISP253 | Hispanic Interaction Of RP80AQR |
|  |  |  | IOTH250 |

NOTE: T: Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other

# Table D. 1 Block Group and Tract Level Variables Considered in Small Area Estimation Models 

(continued)

| Varia | Label | Variable | Label |
| :---: | :---: | :---: | :---: |
| IOTH266 | Other Interaction Of BAGE34QU |  |  |
| IOTH267 | Other Interaction Of BAGE34CU | IFEM275 | Female Interaction Of BAGE54LN |
| IOTH268 | Other Interaction Of BAGE34QR | IFEM276 | Female Interaction Of BAGE54QU |
| BAGE44LN | B: Linear: Percent Persons 35-44 Years | IFEM277 | Female Interaction Of BAGE54CU |
| BAGE44QU | B: Quadratic: Percent Persons 35-44 Years | IFEM278 | Female Interaction Of BAGE54QR |
| BAGE44CU | B: Cubic: Percent Persons 35-44 Years |  |  |
| BAGE44QR | B: Quartic: Percent Persons 35-44 Years | IBLK275 | Black Interaction Of BAGE54LN |
|  |  | IBLK276 | Black Interaction Of BAGE54QU |
| IFEM270 | Female Interaction Of BAGE44LN | IBLK277 | Black Interaction Of BAGE54CU |
| IFEM271 | Female Interaction Of BAGE44QU | IBLK278 | Black Interaction Of BAGE54QR |
| IFEM272 | Female Interaction Of BAGE44CU |  |  |
| IFEM273 | Female Interaction Of BAGE44QR | IHISP275 | Hispanic Interaction Of BAGE54LN |
|  |  | IHISP276 | Hispanic Interaction Of BAGE54QU |
| IBLK270 | Black Interaction Of BAGE44LN | IHISP277 | Hispanic Interaction Of BAGE54CU |
| IBLK271 | Black Interaction Of BAGE44QU | IHISP278 | Hispanic Interaction Of BAGE54QR |
| IBLK272 | Black Interaction Of BAGE44CU |  |  |
| IBLK273 | Black Interaction Of BAGE44QR | IOTH275 | Other Interaction Of BAGE54LN |
|  |  | IOTH276 | Other Interaction Of BAGE54QU |
| IHISP270 | Hispanic Interaction Of BAGE44LN | IOTH277 | Other Interaction Of BAGE54CU |
| IHISP271 | Hispanic Interaction Of BAGE44QU | IOTH278 | Other Interaction Of BAGE54QR |
| IHISP272 | Hispanic Interaction Of BAGE44CU |  |  |
| IHISP273 | Hispanic Interaction Of BAGE44QR | BAGE64LN | B: Linear: Percent Persons 55-64 Years |
|  |  | BAGE64QU | B: Quadratic: Percent Persons 55-64 Years |
| IOTH270 | Other Interaction Of BAGE44LN | BAGE64CU | B: Cubic: Percent Persons 55-64 Years |
| IOTH271 | Other Interaction Of BAGE44QU | BAGE64QR | B: Quartic: Percent Persons 55-64 Years |
| IOTH272 | Other Interaction Of BAGE44CU |  |  |
| IOTH273 | Other Interaction Of BAGE44QR | IFEM280 | Female Interaction Of BAGE64LN |
|  |  | IFEM281 | Female Interaction Of BAGE64QU |
| BAGE54LN | B: Linear: Percent Persons 45-54 Years | IFEM282 | Female Interaction Of BAGE64CU |
| BAGE54QU | B: Quadratic: Percent Persons 45-54 Years | IFEM283 | Female Interaction Of BAGE64QR |
| BAGE54CU | B: Cubic: Percent Persons 45-54 Years |  |  |
| BAGE54QR | B: Quartic: Percent Persons 45-54 Years | IBLK280 | Black Interaction Of BAGE64LN |
| IBLK281 | Black Interaction Of BAGE64QU | IHISP288 | Hispanic Interaction Of BASIANQR |
| IBLK282 | Black Interaction Of BAGE64CU |  |  |
| IBLK283 | Black Interaction Of BAGE64QR | IOTH285 | Other Interaction Of BASIANLN |
|  |  | IOTH286 | Other Interaction Of BASIANQU |
| IHISP280 | Hispanic Interaction Of BAGE64LN | IOTH287 | Other Interaction Of BASIANCU |
| IHISP281 | Hispanic Interaction Of BAGE64QU | IOTH288 | Other Interaction Of BASIANQR |
| IHISP282 | Hispanic Interaction Of BAGE64CU |  |  |
| IHISP283 | Hispanic Interaction Of BAGE64QR | BCUBANLN | B: Linear: Percent Hispanics: Cuban |
|  |  | BCUBANQU | B: Quadratic: Percent Hispanics: Cuban |
| IOTH280 | Other Interaction Of BAGE64LN | BCUBANCU | B: Cubic: Percent Hispanics: Cuban |
| IOTH281 | Other Interaction Of BAGE64QU | BCUBANQR | B: Quartic: Percent Hispanics: Cuban |
| IOTH282 | Other Interaction Of BAGE64CU |  |  |
| IOTH283 | Other Interaction Of BAGE64QR | IFEM290 | Female Interaction Of BCUBANLN |
|  |  | IFEM291 | Female Interaction Of BCUBANQU |
| BASIANLN | B: Linear: Percent Population: Asian, Pacific Islander | IFEM292 | Female Interaction Of BCUBANCU |
| BASIANQU | B: Quadratic: Percent Population: Asian, Pacific Islander | IFEM293 | Female Interaction Of BCUBANQR |
| BASIANCU | B: Cubic: Percent Population: Asian, Pacific Islander |  |  |
| BASIANQR | B: Quartic: Percent Population: Asian, Pacific Islander | IBLK290 | Black Interaction Of BCUBANLN |
|  |  | IBLK291 | Black Interaction Of BCUBANQU |
| IFEM285 | Female Interaction Of BASIANLN | IBLK292 | Black Interaction Of BCUBANCU |
| IFEM286 | Female Interaction Of BASIANQU | IBLK293 | Black Interaction Of BCUBANQR |
| IFEM287 | Female Interaction Of BASIANCU |  |  |
| IFEM288 | Female Interaction Of BASIANQR | IHISP290 | Hispanic Interaction Of BCUBANLN |
|  |  | IHISP291 | Hispanic Interaction Of BCUBANQU |
| IBLK285 | Black Interaction Of BASIANLN | IHISP292 | Hispanic Interaction Of BCUBANCU |
| IBLK286 | Black Interaction Of BASIANQU | IHISP293 | Hispanic Interaction Of BCUBANQR |
| IBLK287 | Black Interaction Of BASIANCU |  |  |
| IBLK288 | Black Interaction Of BASIANQR | IOTH290 | Other Interaction Of BCUBANLN |
|  |  | IOTH291 | Other Interaction Of BCUBANQU |
| IHISP285 | Hispanic Interaction Of BASIANLN | IOTH292 | Other Interaction Of BCUBANCU |
| IHISP286 | Hispanic Interaction Of BASIANQU | IOTH293 | Other Interaction Of BCUBANQR |
| IHISP287 | Hispanic Interaction Of BASIANCU |  |  |

NOTE: T: Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other

# Table D. 1 Block Group and Tract Level Variables Considered in Small Area Estimation Models 

(continued)

## Variable Label

| BFNOTLN | B: Linear: \% Fem Separated, Divorced or Widowed |  |
| :--- | :--- | :--- |
| BFNOTQU | B: Quadratic: \% Fem Separated, Divorced or Widowed | IFEM300 |
| BFNOTCU | B: Cubic: \% Fem Separated, Divorced or Widowed | IFEM301 |
| BFNOTQR | B: Quartic: \% Fem Separated, Divorced or Widowed | IFEM302 |
|  |  |  |
| IFEM295 | Female Interaction Of BFNOTLN | Female Interaction Of BINDIALN |
| IFEM296 | Female Interaction Of BFNOTQU | Female Interaction Of BINDIAQU BINDIACU |
| IFEM297 | Female Interaction Of BFNOTCU | IBLK300 |
| IFEM298 | Female Interaction Of BFNOTQR | IBLK301 |

NOTE: T: Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other

# Table D. 1 Block Group and Tract Level Variables Considered in Small Area Estimation Models 

(continued)

| Varia | Label | Variable | Label |
| :---: | :---: | :---: | :---: |
|  |  | IFEM325 | Female Interaction Of PASIANLN |
| IFEM320 | Female Interaction Of BSCHASLN | IFEM326 | Female Interaction Of PASIANQU |
| IFEM321 | Female Interaction Of BSCHASQU | IFEM327 | Female Interaction Of PASIANCU |
| IFEM322 | Female Interaction Of BSCHASCU | IFEM328 | Female Interaction Of PASIANQR |
| IFEM323 | Female Interaction Of BSCHASQR |  |  |
|  |  | IBLK325 | Black Interaction Of PASIANLN |
| IBLK320 | Black Interaction Of BSCHASLN | IBLK326 | Black Interaction Of PASIANQU |
| IBLK321 | Black Interaction Of BSCHASQU | IBLK327 | Black Interaction Of PASIANCU |
| IBLK322 | Black Interaction Of BSCHASCU | IBLK328 | Black Interaction Of PASIANQR |
| IBLK323 | Black Interaction Of BSCHASQR |  |  |
|  |  | IHISP325 | Hispanic Interaction Of PASIANLN |
| IHISP320 | Hispanic Interaction Of BSCHASLN | IHISP326 | Hispanic Interaction Of PASIANQU |
| IHISP321 | Hispanic Interaction Of BSCHASQU | IHISP327 | Hispanic Interaction Of PASIANCU |
| IHISP322 | Hispanic Interaction Of BSCHASCU | IHISP328 | Hispanic Interaction Of PASIANQR |
| IHISP323 | Hispanic Interaction Of BSCHASQR |  |  |
|  |  | IOTH325 | Other Interaction Of PASIANLN |
| IOTH320 | Other Interaction Of BSCHASLN | IOTH326 | Other Interaction Of PASIANQU |
| IOTH321 | Other Interaction Of BSCHASQU | IOTH327 | Other Interaction Of PASIANCU |
| IOTH322 | Other Interaction Of BSCHASCU | IOTH328 | Other Interaction Of PASIANQR |
| IOTH323 | Other Interaction Of BSCHASQR |  |  |
|  |  | PCUBANLN | T: Linear: Percent Hispanics: Cuban |
| PASIANLN | T: Linear: Percent Population: Asian, Pacific Islander | PCUBANQU | T: Quadratic: Percent Hispanics: Cuban |
| PASIANQU | T: Quadratic: Percent Population: Asian, Pacific Islander | PCUBANCU | T: Cubic: Percent Hispanics: Cuban |
| PASIANCU | T: Cubic: Percent Population: Asian, Pacific Islander | PCUBANQR | T: Quartic: Percent Hispanics: Cuban |
| PASIANQR | T: Quartic: Percent Population: Asian, Pacific Islander |  |  |
|  |  | IFEM330 | Female Interaction Of PCUBANLN |
| IFEM331 | Female Interaction Of PCUBANQU |  |  |
| IFEM332 | Female Interaction Of PCUBANCU | IOTH335 | Other Interaction Of PINDIALN |
| IFEM333 | Female Interaction Of PCUBANQR | IOTH336 | Other Interaction Of PINDIAQU |
|  |  | IOTH337 | Other Interaction Of PINDIACU |
| IBLK330 | Black Interaction Of PCUBANLN | IOTH338 | Other Interaction Of PINDIAQR |
| IBLK331 | Black Interaction Of PCUBANQU |  |  |
| IBLK332 | Black Interaction Of PCUBANCU | HSDROPLN | T: Linear: Underclass Indicator: High School Dropouts |
| IBLK333 | Black Interaction Of PCUBANQR | HSDROPQU | T: Quadratic: Underclass Indicator: HS Dropouts |
|  |  | HSDROPCU | T: Cubic: Underclass Indicator: HS Dropouts |
| IHISP330 | Hispanic Interaction Of PCUBANLN | HSDROPQR | T: Quartic: Underclass Indicator: HS Dropouts |
| IHISP331 | Hispanic Interaction Of PCUBANQU |  |  |
| IHISP332 | Hispanic Interaction Of PCUBANCU | IFEM340 | Female Interaction Of HSDROPLN |
| IHISP333 | Hispanic Interaction Of PCUBANQR | IFEM341 | Female Interaction Of HSDROPQU |
|  |  | IFEM342 | Female Interaction Of HSDROPCU |
| IOTH330 | Other Interaction Of PCUBANLN | IFEM343 | Female Interaction Of HSDROPQR |
| IOTH331 | Other Interaction Of PCUBANQU |  |  |
| IOTH332 | Other Interaction Of PCUBANCU |  |  |
| IOTH333 | Other Interaction Of PCUBANQR | IBLK340 | Black Interaction Of HSDROPLN |
|  |  | IBLK341 | Black Interaction Of HSDROPQU |
| PINDIALN | T: Linear: \% Pop: American Indian, Eskimo, Aleut | IBLK342 | Black Interaction Of HSDROPCU |
| PINDIAQU | T: Quadratic: \% Pop: American Indian, Eskimo, Aleut | IBLK343 | Black Interaction Of HSDROPQR |
| PINDIACU | T: Cubic: \% Pop: American Indian, Eskimo, Aleut |  |  |
| PINDIAQR | T: Quartic: \% Pop: American Indian, Eskimo, Aleut | IHISP340 | Hispanic Interaction Of HSDROPLN |
|  |  | IHISP341 | Hispanic Interaction Of HSDROPQU |
| IFEM335 | Female Interaction Of PINDIALN | IHISP342 | Hispanic Interaction Of HSDROPCU |
| IFEM336 | Female Interaction Of PINDIAQU | IHISP343 | Hispanic Interaction Of HSDROPQR |
| IFEM337 | Female Interaction Of PINDIACU |  |  |
| IFEM338 | Female Interaction Of PINDIAQR | IOTH340 | Other Interaction Of HSDROPLN |
|  |  | IOTH341 | Other Interaction Of HSDROPQU |
| IBLK335 | Black Interaction Of PINDIALN | IOTH342 | Other Interaction Of HSDROPCU |
| IBLK336 | Black Interaction Of PINDIAQU | IOTH343 | Other Interaction Of HSDROPQR |
| IBLK337 | Black Interaction Of PINDIACU |  |  |
| IBLK338 | Black Interaction Of PINDIAQR | HSDROP9 | T: Underclass Indicator: High School Dropouts |
| IHISP335 | Hispanic Interaction Of PINDIALN | IFEM339 | Female Interaction Of HSDROP9 |
| IHISP336 | Hispanic Interaction Of PINDIAQU |  |  |
| IHISP337 | Hispanic Interaction Of PINDIACU | IBLK339 | Black Interaction Of HSDROP9 |
| IHISP338 | Hispanic Interaction Of PINDIAQR |  |  |

NOTE: T: Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other

# Table D. 1 Block Group and Tract Level Variables Considered in Small Area Estimation Models 

 (continued)Variable Label
IHISP339 Hispanic Interaction Of HSDROP9
IOTH339 Other Interaction Of HSDROP9

Variable Label

NOTE: T: Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other
D-16

NOTE: T: Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other
D-17

## Appendix E: Fixed Effect Coefficients for Logistic Models

E1. Coefficients of Model Parameters for Past Month Alcohol Use

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | $35+$ |
| DUMMY | O: Intercept Term | -1.371 | 0.862 | 1.003 | 0.392 | -1.258 | 0.970 | 0.991 | 0.913 |
| FEMALE | O : Female Indicator | -0.070 | -0.277 | -0.448 | -0.570 | -0.203 | -0.481 | -0.704 | -0.797 |
| FEMBLCK | O: Black Interaction Of FEMALE | -0.172 | -0.105 | -0.442 | -0.340 | -0.156 | -0.138 | 0.220 | -0.200 |
| FEMHISP | O: Hispanic Interaction Of FEMALE | -0.309 | -0.564 | -0.823 | -0.622 | -0.005 | -0.585 | -0.511 | -0.461 |
| FEMOTHR | O: Other Interaction Of FEMALE | -0.167 | -0.080 | -0.883 | -0.609 | 0.742 | 0.010 | 0.128 | 0.576 |
| RACEBLCK RACEHISP | O: Race/Black Indicator | -0.731 0.005 -0.031 | -0.589 <br> -0.208 | -0.455 -0.013 | -0.064 <br> -0.005 | -0.303 -0.000 -0.000 | -0.407 -0.407 -0.105 | -0.471 -0.077 -0.87 | -0.343 0.343 0.143 |
| RACEOTHR | O: Race/Other Indicator | -0.631 | -1.065 | -0.912 | -0.939 | -0.967 | -2.323 | -0.896 | -3.210 |
| REGNOREA REGSOUTH | O: Northeast Region Indicator |  |  |  |  |  | 0.143 -0.262 |  | -0.173 <br> -0.451 |
| REGWEST | O: West Region Indicator |  |  |  |  |  | 0.097 |  | -0.138 |
| IOTH7 IOTH8 | Other Interaction Of REGNOREA Other Interaction Of REGSOUTH |  |  |  |  |  | 1.864 1.558 |  | 2.478 3.241 |
| IOTH9 | Other Interaction Of REGWEST |  |  |  |  |  | 1.154 |  | 1.051 |
| UCLASS9 | T: Underclass Indicator |  |  |  |  |  |  |  | 0.864 |
| PAGE18LN | T: Linear: Percent Persons 0-18 Y ears |  |  |  | -0.074 |  |  |  | -0.014 |
| PAGE18QU | T: Quadratic: Percent Persons 0-18 Years |  |  |  |  |  |  |  | -0.038 |
| $\begin{aligned} & \text { IOTH25 } \\ & \text { IOTH26 } \end{aligned}$ | Other Interaction Of PAGE18LN Other Interaction Of PAGE18QU |  |  |  |  |  |  |  | 0.375 -0.503 |
| $\begin{aligned} & \text { PAGE24LN } \\ & \text { PAGE24QU } \end{aligned}$ | T: Linear: Percent Persons 19-24 Years <br> T: Quadratic: Percent Persons 19-24 Years |  |  |  |  |  | -0.037 -0.087 |  |  |
| IFEM30 <br> IFEM31 | Female Interaction Of PAGE24LN Female Interaction Of PAGE24QU |  |  |  |  |  | $\begin{gathered} -0.009 \\ 0.141 \end{gathered}$ |  |  |
| PAGE34LN | T: Linear: Percent Persons 25-34 Years | -0.076 |  |  |  |  |  |  |  |
| PAGE44LN | T: Linear: Percent Persons 35-44 Years |  |  |  | 0.108 |  |  |  | 0.044 |
| PAGE44QU | T: Quadratic: Percent Persons 35-44 Years |  |  |  |  |  |  |  | 0.013 |
| PAGE44CU | T: Cubic: Percent Persons 35-44 Years |  |  |  |  |  |  |  | 0.004 |
| PAGE44QR | T: Quartic: Percent Persons 35-44 Years |  |  |  |  |  |  |  | 0.023 |
| PAGE64LN | T: Linear: Percent Persons 55-64 Years | 0.043 |  |  |  |  |  |  |  |
| PSCH8LN | T: Linear: Percent 0-8 Years Of School |  | -0.097 |  |  |  |  |  |  |
| PSCHCOLN | T: Linear: Bachelors, Graduate, Or Professional Degree |  | 0.155 |  |  |  | 0.165 | 0.153 |  |
| 1BLK75 | Black Interaction Of PSCHCOLN |  |  |  |  |  | -0.226 | -0.170 |  |
| PSCHSCLN | T: Linear: Percent Some College And No Degree |  | -0.060 |  |  |  |  |  |  |
| PPOVERLN | T: Linear: Percent Families Below Poverty Level |  |  |  |  | -0.076 |  |  |  |
| PPOVERQU | T: Quadratic: Percent Families Below Poverty Level |  |  |  |  | -0.030 |  |  |  |
| PPOVERCU | T: Cubic: Percent Families Below Poverty Level |  |  |  |  | -0.116 |  |  |  |
| PPOVERQR | T: Quartic: Percent Families Below Poverty Level |  |  |  |  | -0.023 |  |  |  |
| IBLK85 | Black Interaction Ot PPOVERLN |  |  |  |  | 0.235 |  |  |  |
| 1BLK86 | Black Interaction Ot PPOVERQU |  |  |  |  | 0.048 |  |  |  |
| IBLK87 | Black Interaction Of PPOVERCU |  |  |  |  | 0.078 |  |  |  |
| 1BLK88 | Black Interaction Of PPOVERQR |  |  |  |  | 0.063 |  |  |  |
| PBLACKLN | T: Linear: Percent Black Nonhispanic |  | -0.132 |  |  |  |  |  |  |
| POTHLN | T: Linear: Percent Other Race/Hispanicity |  |  |  |  |  | 0.034 |  |  |
| POTHQU | T: Quadratic: Percent Other Race/Hispanicity |  |  |  |  |  | -0.052 |  |  |
| PFLABLN | T: Linear: Percent Females 16+ Y ears Old In Labor Force | 0.039 |  |  |  |  |  |  |  |
| PFLABQU | T: Quadratic: Percent Females 16+ Years Old In Labor Force | 0.049 |  |  |  |  |  |  |  |
| PFNEVLN | T: Linear: Percent Females Never Married |  |  |  |  |  | 0.091 |  |  |
| PFNOTLN PFNOTQU PFNOTCU PFNOTQR | T: Linear: Percent Females Separated, Divorced Or Widowed T: Quadratic: Percent Females Separated, Divorced Or Widowed T: Cubic: Percent Females Separated, Divorced Or Widowed T: Quartic: Percent Females Separated, Divorced Or Widowed |  |  |  | $\begin{array}{r} -0.037 \\ -0.002 \\ -0.060 \\ 0.028 \end{array}$ |  |  |  |  |
| PMNEVLN | T: Linear: Percent Males Never Married |  |  | 0.067 |  | 0.103 |  | 0.046 | 0.069 |
| PMNEVQU | T: Quadratic: Percent Males Never Married |  |  |  |  |  |  | -0.021 | -0.044 |
| PMNEVCU | T: Cubic: Percent Males Never Married |  |  |  |  |  |  | 0.031 | 0.003 |
| PMNEVQR | T: Quartic: Percent Males Never Married |  |  |  |  |  |  |  |  |
| IFEM140 IFEM141 | Female Interaction Of PMNEVLN Female Interaction Of PMNEVQU |  |  |  |  |  |  |  | 0.038 0.162 |
| IBLK140 | Black Interaction Of PMNEVLN |  |  |  |  | -0.262 |  |  |  |
| IHISP140 | Hispanic Interaction Of PMNEVLN |  |  | -0.152 |  |  |  |  |  |
| 10TH140 | Other Interaction Of PMNEVLN |  |  | 0.289 |  |  |  | 0.079 0.079 |  |
| 10TH142 | Other Interaction Of PMNEVQU Other Interaction Of PMNEVCU |  |  |  |  |  |  | -0.425 |  |
| P40HULN | T: Linear: Percent Housing Units Built 1940-1949 |  |  |  |  | 0.124 |  |  |  |
| IFEM160 | Female Interaction Of P40HULN |  |  |  |  | -0.161 |  |  |  |
| PRENTLN | T: Linear: Percent Housing Rented |  |  | -0.026 |  | -0.008 |  |  |  |
| IBLK165 | Black Interaction Of PRENTLN |  |  | 0.059 |  |  |  |  |  |
| ADRATELN ADRATEQU | C: Linear: Death Rate For All Alcohol-Related Cases <br> C: Quadratic: Death Rate For All Alcohol-Related Cases |  | $\begin{array}{r} 0.002 \\ -0.077 \end{array}$ |  |  |  |  |  |  |
| VI8FLN | C: Linear: Marijuana Posession Arrest Rate |  |  |  |  |  |  |  | 0.068 |

NOTE:

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| 10TH185 | Other Interaction Of V18FLN |  |  |  |  |  |  |  | -0.514 |
| V18ALN | C: Linear: Opium/Cocaine \& Deriv Sale/Manuf Arrest Rate |  | ${ }_{-0}^{-0.003}$ |  | -0.027 -0.041 -0.034 |  |  |  | -0.082 -0.026 -0.018 |
| V18ACU | C: Cubic: Opium/Cocaine \& Deriv Sale/Manuf Arrest Rate |  |  |  | -0.034 |  |  |  | ${ }^{-0.0214}$ |
| V18AQR | C: Quartic: Opium/Cocaine \& Deriv Sale/Manuf Arrest Rate |  |  |  |  |  |  |  | -0.038 |
| IHISP200 | Hispanic Interaction Of V18ALN |  | -0.164 |  |  |  |  |  |  |
| IHISP201 | Hispanic Interaction Of V18AQU |  | 0.117 |  |  |  |  |  |  |
| VI8LN | C: Linear: Total Drug Abuse Violations Arrest Rate |  |  |  |  |  |  |  | 0.174 |
| DRATELN | C: Linear: Mean Drug Client Treatment Rate 1991 \& 1992 C: Quadratic: Mean Drug Client Ireatment Rate 1991 ¢ 1992 |  |  |  |  | 0.051 -0.013 |  |  |  |
| DRATECU | C: Cubic: Mean Drug Client Treatment Rate 1991 \& 1992 |  |  |  |  | -0.024 |  |  |  |
| IOTH235 | Other Interaction Of DRATELN |  |  |  |  | -0.020 |  |  |  |
| IOTH236 IOTH237 | Other Interaction Of DRATEQU Other Interaction Of DRATECU |  |  |  |  | 0.070 -0.436 |  |  |  |
| RH61ALN | T: Linear: Recoded Median Value Of Owner Occupied HUs T: Quadratic: Recoded Median Value Of Owner Occupied HUs |  | $\begin{aligned} & -0.003 \\ & -0.0006 \end{aligned}$ |  |  |  |  |  | 0.227 |
| IHISP245 IHISP246 | Hispanic Interaction Of RH61ALN Hispanic Interaction Of RH61AQU |  | $\begin{array}{r} -0.099 \\ 0.103 \end{array}$ |  |  |  |  |  |  |
| RP80ALN RP80AQU | T: Linear: Recoded Median Household Income T: Quadratic: Recoded Median Household Income |  |  |  | $\begin{aligned} & 0.035 \\ & 0.051 \end{aligned}$ |  |  |  |  |
| ARATELN ARATEQU | C: Linear: Mean A-Only Client Treatment Rate 1991 \& 1992 <br> C: Quadratic: Mean A-Only Client Treatment Rate 1991 \& 1992 |  | 0.015 0.013 -0.013 |  |  |  |  |  |  |
| ARATECU | C: Cubic: Mean A-Only Client Treatment Rate 1991 \& 1992 |  | -0.013 |  |  |  |  |  |  |
| IFEM255 | Female Interaction Of ARATELN |  | -0.073 |  |  |  |  |  |  |
| IFEM256 | Female Interaction Of ARATEQU Female Interaction Of ARATECU |  | 0.035 -0.097 |  |  |  |  |  |  |
| B64DISLN | B: Linear: Percent Persons 16-64 With A Work Disability |  |  |  | -0.009 |  | -0.017 |  | -0.150 |
| B64DISQU B64DISCU | B: Quadratic: Percent Persons 16-64 With A Work Disability B: Cubic: Percent Persons 16-64 With A Work Disability |  |  |  | 0.040 |  | -0.007 0.054 |  |  |
| B64DISCU | B: Cubic: Percent Persons 16-64 With A Work Disability |  |  |  |  |  |  |  |  |
| IHISP260 | Hispanic Interaction Of B64DISLN |  |  |  |  |  | -0.046 |  | 0.202 |
| IHISP261 IHISP262 | Hispanic Interaction Of B64DISQU Hispanic Interaction Of B64DISCU |  |  |  |  |  | 0.116 -0.160 |  |  |
| BAGE34LN | B: Linear: Percent Persons 25-34 Years |  |  |  |  |  |  | 0.027 |  |
| IOTH265 | Other Interaction Of BAGE34LN |  |  |  |  |  |  | -0.437 |  |
| BAGE44LN BAGE44QU | B: Linear: Percent Persons 35-44 Years B: Quadratic: Percent Persons $35-44$ Years |  |  |  |  |  |  |  | $\begin{aligned} & -0.022 \\ & -0.005 \\ & \hline 0 \end{aligned}$ |
| IHISP270 | Hispanic Interaction Of BAGGE44LN |  |  |  |  |  |  |  | 0.130 |
| 1HISP271 | Hispanic Interaction Of BAGE44QU |  |  |  |  |  |  |  | 0.182 |
| BAGE54LN | B: Linear: Percent Persons 45-54 Years |  |  |  | 0.057 |  |  |  | 0.038 |
| IBLK275 | Black Interaction Of BAGE54LN |  |  |  |  |  |  |  | -0.164 |
| BASIANLN | ${ }^{\text {B: }}$ Linear: Percent Population: Asian, Pacitic Islander |  |  |  |  |  |  | 0.002 | -0.040 |
| BASIANQU | B: Quadratic: Percent Population: Asian, Pacific Islander |  |  |  |  |  |  | -0.007 | $-0.004$ |
| BASIANCU | B: Cubic: Percent Population: Asian, Pacific Islander |  |  |  |  |  |  | $-0.055$ | 0.005 |
| BASIANQR | B: Quartic: Percent Population: Asian, Pacific Islander |  |  |  |  |  |  | -0.003 |  |
| IOTH285 | Other Interaction Of BASIANLN |  |  |  |  |  |  | -0.221 |  |
| IOTH286 | Other Interaction Of BASIANQU |  |  |  |  |  |  | 0.002 | -0.761 |
| IUTH287 | Other Interaction Of BASIANCU |  |  |  |  |  |  | 0.242 | 0.757 |
| 101H288 | Other Interaction Of BASIANQR |  |  |  |  |  |  |  |  |
| BCUBANLN | B: Linear: Percent Hispanics: Cuban |  | -0.032 |  |  | 0.091 |  |  |  |
| BCUBANQU | B: Quadratic: Percent Hispanics: Cuban |  |  |  |  | 0.042 |  |  |  |
| bCUBANCU | B: Cubic: Percent Hispanics: Cuban |  |  |  |  | 0.057 |  |  |  |
| IHISP290 | Hispanic Interaction Of BCUBANLN |  | 0.185 |  |  |  |  |  |  |
| IOTH290 | Other Interaction Of BCUBANLN |  |  |  |  |  |  |  |  |
| IOTH291 | Other Interaction Of BCUBANQU |  |  |  |  | 0.055 |  |  |  |
| IOTH292 | Other Interaction Of BCUBANCU |  |  |  |  | -1.073 |  |  |  |
| BFNOTLN | B: Linear: Percent Females Separated, Divorced or Widowed |  | 0.034 |  |  |  | -0.030 |  |  |
| BFNOTQU | B: Quadratic: Percent Females Separated, Divorced or Widowed |  | 0.001 0.024 |  |  |  | -0.034 |  |  |
| BFNOTCU BFNOTQR | B: Cubic: Percent Females Separated, Divorced or Widowed B: Quartic: Percent Females Separated, Divorced or Widowed |  | 0.024 -0.010 |  |  |  |  |  |  |
| IOTH295 | Other Interaction Of BFNOTLN |  | 0.103 |  |  |  | 0.093 |  |  |
| IUTH296 | Other Interaction Of BFNOTRU |  | ${ }^{-0.001}$ |  |  |  | 0.263 |  |  |
| IOTH297 | Other Interaction Of BFNOTCU |  | $-0.145$ |  |  |  |  |  |  |
| IOTH298 | Other Interaction Of BFNOTQR |  | 0.062 |  |  |  |  |  |  |
| BINDIALN | B: Linear: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  | -0.109 | -0.030 |  |  |
| BINDIAQU BINDIACU | B: Quadratic: Percent Pop: American Indian, Eskimo, Aleut <br> B: Cubic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  | -0.017 0.171 |  |  |
| IFEM300 | Female Interaction Of BINDIALN |  |  |  |  | 0.225 |  |  |  |
| IFEM301 | Female Interaction Of BINDIAQU |  |  |  |  |  | -0.008 |  |  |
| IFEM302 | Female Interaction Of BINDIACU |  |  |  |  |  | -0.185 |  |  |
| IBLK300 | Black Interaction Of BINDIALN |  |  |  |  | 0.291 |  |  |  |
| BMNOTLN | B: Linear: Percent Males Separated, Divorced or Widowed | 0.045 |  |  |  |  |  |  |  |
| BMNOTQU | B: Quadratic: Percent Males Separated, Divorced or Widowed |  |  |  |  |  |  |  | 0.002 |
| BMNOTCU | B: Cubic: Percent Males Separated, Divorced or Widowed |  |  |  |  |  |  |  | -0.042 |
| IHISP305 | Hispanic Interaction OfBMNOTLN | -0.127 |  |  |  |  |  |  | 0.086 |
| IHISP306 | Hispanic Interaction Of BMNOTQU |  |  |  |  |  |  |  | ${ }_{0}^{0.012}$ |
| IHISP307 | Hispanic Interaction Of BMNOTCU |  |  |  |  |  |  |  |  |
| BPOVERLN | B: Linear: Percent Families Below Poverty Level |  |  | -0.084 |  |  |  |  |  |
| BPRICALN | B: Linear: Percent Hispanics: Puerto Rican | -0.052 |  |  |  | -0.016 | -0.027 |  |  |
| BPRICAQU BPRICACU | B: Quadratic: Percent Hispanics: Puerto Rican B: Cubic: Percent Hispanics: Puerto Rican | 0.010 0.075 |  |  |  | 0.000 -0.031 | -0.083 0.017 |  |  |

NOTE:

|  | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Variable |  | 12-17 | 18-25 | 26-34 | $35+$ | 12-17 | 18-25 | 26-34 | $35+$ |
| BPKILAUK | B: Quartic: Percent Hispanics: Puerto Kıcan |  |  |  |  |  | 0.012 |  |  |
| IBLK315 | Black Interaction Of BPRICALN |  |  |  |  |  | $-0.124$ |  |  |
| 1BLK316 | Black Interaction Of BPRICAQU |  |  |  |  |  |  |  |  |
| BSCHASLN | B: Linear: Percent Associates Degree |  |  |  | 0.053 |  |  |  | 0.059 |
| BSCHASQU | B: Quadratic: Percent Associates Degree |  |  |  | -0.026 |  |  |  |  |
| BSCHASCU | B: Cubic: Percent Associates Degree |  |  |  | 0.013 |  |  |  |  |
| IBLK320 | Black Interaction Of BSCHASLN |  |  |  | -0.072 |  |  |  |  |
| 1BLK321 | Black Interaction Of BSCHASQU |  |  |  | 0.083 |  |  |  |  |
| 1BLK322 | Black Interaction Of BSCHASCU |  |  |  |  |  |  |  |  |
| PASIANLN | T: Linear: Percent Population: Asian, Pacific Islander |  |  | 0.035 |  |  |  |  |  |
| PASIANQU | T: Quadratic: Percent Population: Asian, Pacitic Islander |  |  | -0.062 |  |  |  |  |  |
| IBLK325 |  |  |  | 0.055 |  |  |  |  |  |
| IBLK326 | Black Interaction Of PASIANQU |  |  | 0.090 |  |  |  |  |  |
| PCUBANLN | T: Linear: Percent Hispanics: Cuban |  |  |  | -0.025 |  |  |  |  |
| PCUBANQU | T: Quadratic: Percent Hispanics: Cuban |  |  |  | -0.007 |  |  |  |  |
| PCUBANCU | T: Cubic: Percent Hispanics: Cuban |  |  |  | -0.109 |  |  |  |  |
| IFEM330 | Female Interaction Of PCUBANLN |  |  |  | 0.013 |  |  |  |  |
| IFEM331 | Female Interaction Of PCUBANQU |  |  |  | 0.019 |  |  |  |  |
| IFEM332 | Female Interaction Of PCUBANCU |  |  |  | 0.129 |  |  |  |  |
| PINDIALN | T: Linear: Percent Pop: American Indian, Eskimo, Aleut |  |  | -0.040 |  |  |  |  | -0.005 |
| PINDIAQU | T: Quadratic: Percent Pop: American Indian, Eskimo, Aleut |  |  | 0.028 |  |  |  |  | -0.086 |
| PINDIACU | T: Cubic: Percent Pop: American Indian, Eskimo, Aleut |  |  | -0.011 |  |  |  |  | $0.051$ |
| PINDIAQR | T: Quartic: Percent Pop: American Indian, Eskimo, Aleut |  |  | 0.015 |  |  |  |  | -0.039 |
| IFEM335 | Female Interaction Of PINDIALN |  |  |  |  |  |  |  | -0.026 |
| IFEM336 | Female Interaction Of PINDIAQU |  |  |  |  |  |  |  | 0.035 |
| IFEM337 | Female Interaction Of PINDIACU |  |  |  |  |  |  |  | -0.099 |
| IFEM338 | Female Interaction Of PINDIAQR |  |  |  |  |  |  |  | 0.059 |

## E2. Coefficients of Model Parameters for Past Month Any Illicit Drug Use

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | $35+$ | 12-17 | 18-25 | 26-34 | 35+ |
| DUMMY | O : Intercept Term | -2.903 | -1.573 | $-1.738$ | -3.271 | -2.807 | -1.406 | -2.537 | -3.825 |
| Female | O: Female Indicator | 0.049 | -0.420 | -0.769 | -0.581 | 0.088 | -0.718 | -0.353 | -0.424 |
| FEMBLCK | O: Black Interaction Of FEMALE | -0.534 | -0.327 | 0.257 | 0.062 | -0.050 | 0.203 | -0.148 | -0.277 |
| FEMHISP | 0 : Hispanic Interaction Of FEMALE | -0.274 | -0.085 | 0.330 | -0.180 |  | 0.282 | -0.258 | 0.116 |
| FEMOTHR | O: Other Interaction Of FEMALE | 0.459 | -0.055 | -0.549 |  |  | -0.165 | 1.096 | 0.600 |
| RACEBLCK RACEHISP | O: Race/Black Indicator | 0.49 0.074 0.255 | $\begin{aligned} & -0.103 \\ & -0.518 \end{aligned}$ | $\begin{aligned} & -0.354 \\ & -0.878 \end{aligned}$ | 0.192 <br> 0.101 <br> 1.05 | -0.357 0.144 | -1.613 -0.581 | 0.016 0.614 | 0.437 -0.511 |
| RACEHIS | O: Race//IIspanic Indicator | -1.180 | $\begin{aligned} & -0.518 \\ & -1.001 \end{aligned}$ | $\begin{array}{r} -0.878 \\ -1.000 \end{array}$ | -1.055 |  | ${ }_{-0.541}$ | -0.951 | ${ }_{-1.295}$ |
| Regnorea | O: Northeast Region Indicator |  |  |  |  |  | 0.336 | 0.411 |  |
| Regisouth | O: South Region Indicator O: West Region Indicator |  |  |  |  |  | 0.217 0.662 | 0.173 0.813 |  |
| PDENLEV1 | O: Large MSA |  |  |  |  | 0.073 | -0.476 | -0.077 |  |
| PUENLEV2 | O: Medium MSA |  |  |  |  | 0.201 | -0.321 | $-0.004$ |  |
| PDENLEV3 PDENLEV4 | O: Small MSA O: NonMSA, Urban |  |  |  |  | 0.297 0.121 | -0.428 -0.347 | 0.024 -0.054 |  |
| 1BLK10 | Black Interaction Of PDENLEV1 |  |  |  |  |  | 1.150 |  |  |
| 1BLK11 | Black Interaction Of PDENLEV2 |  |  |  |  |  | 0.770 |  |  |
| 1BLK12 | Black Interaction Of PDENLEV3 |  |  |  |  |  | 1.469 |  |  |
| 1BLK13 | Black Interaction Of PDENLEV4 |  |  |  |  |  | 1.484 |  |  |
| IHISP 10 | Hispanic Interaction Of PDENLEV1 |  |  |  |  |  |  | -1.284 |  |
| 1HISP11 |  |  |  |  |  |  |  | -1.705 |  |
| IHISP12 IHISP13 | Hispanic Interaction Of PDENLEV3 Hispanic Interaction Of PDENLEV4 |  |  |  |  |  |  | -1.047 -0.962 |  |
| 1HISP13 |  |  |  |  |  |  |  |  |  |
| UCLASS9 | T: Underclass Indicator |  |  |  |  |  | 0.774 |  |  |
| PHHIPLN PHHIPQU | 1: Linear: Percent One Person Households <br> T: Quadratic: Percent One Person Households |  |  |  |  |  | $\begin{aligned} & 0.062 \\ & 0.061 \end{aligned}$ |  |  |
| POPRMLN POPRMQU | I: Linear: Average Persons Per Room <br> I: Quadratic: Average Persons Per Room |  |  | -0.012 |  |  |  | $\begin{aligned} & -0.196 \\ & -0.138 \end{aligned}$ |  |
| $\begin{aligned} & \text { IFEM20 } \\ & \text { IFEM21 } \end{aligned}$ | Female Interaction Of POPRMLN Female Interaction Of POPRMQU |  |  |  |  |  |  | $\begin{aligned} & 0.157 \\ & 0.137 \end{aligned}$ |  |
| PAGEISLN PAGE180U | T: Linear: Percent Persons 0-18 Years |  |  |  |  |  | 0.077 0.020 |  |  |
| ${ }^{\text {PAGEIGEI }}$ PCU | T: Cubic: Percent Persons 0-18 Years |  |  |  |  |  | ${ }_{0}^{0.108}$ |  |  |
| IFEM25 IFEM26 | Female Interaction Of PAGE18LN Female Interaction Of PAGGE18QU |  |  |  |  |  | $\begin{aligned} & -0.147 \\ & -0.001 \end{aligned}$ |  |  |
| IFEM27 | Female Interaction Of PAGE18CU |  |  |  |  |  | $\begin{array}{r} -0.001 \\ -0.146 \end{array}$ |  |  |
| PAGE24LN | T: Linear: Percent Persons 19-24 Years |  |  |  |  |  |  | 0.136 |  |
| PAGE24QU | T: Quadratic: Percent Persons 19-24 Y ears |  |  |  |  |  |  | -0.032 |  |
| PAGE24CU PAGE24QR | T: Cubic: Percent Persons 19-24 Years |  |  |  |  |  |  | -0.0.089 0 0.005 |  |
| IHISP30 | Hispanic Interaction Of PAGE24LN |  |  |  |  |  |  | 0.047 |  |
| 1HISP31 | Hispanic Interaction Of PAGE24QU |  |  |  |  |  |  | 0.039 |  |
| ${ }^{\text {IHISP32 }}$ | Hispanic Interaction Of PAGE24CU |  |  |  |  |  |  | 0.023 0.020 |  |
| IHISP33 | Hispanic Interaction Of PAGE24QR |  |  |  |  |  |  |  |  |
| PAGE34LN <br> PAGE34QU | I: Linear: Percent Persons 25-34 Years <br> T: Quadratic: Percent Persons 25-34 Years |  |  |  |  | $\begin{aligned} & -0.002 \\ & -0.119 \end{aligned}$ | $\begin{aligned} & -0.022 \\ & -0.038 \end{aligned}$ |  |  |
| $\begin{aligned} & \text { IHISP35 } \\ & \text { IHISP36 } \end{aligned}$ | Hispanic Interaction Of PAGE34LN Hispanic Interaction Of PAGE34QU |  |  |  |  |  | $\begin{gathered} -0.076 \\ 0.186 \end{gathered}$ |  |  |
| PAGE44LN | T: Linear: Percent Persons 35-44 Years |  |  |  |  |  |  | 0.060 |  |
| PAGEE54LN PAGE540U | T: Linear: Percent Persons 45-54 Years T: Quadratic: Percent Persons $45-54$ Years |  |  |  | 0.068 0.012 |  | -0.136 -0.032 |  | -0.066 -0.057 |
| PAGE54CU | T: Cubic: Percent Persons 45-54 Years |  |  |  |  |  | -0.057 |  |  |
| IHISP45 | Hispanic Interaction Of PAGE54LN |  |  |  |  |  | 0.267 |  |  |
| PSCH8LN PSCH8QU | T: Linear: Percent 0-8 Years Of School <br> T: Quadratic: Percent 0-8 Years Of School |  |  |  |  |  |  | -0.081 0.026 |  |
| ${ }_{\text {1BLK }}^{\text {1BLK5 }}$ | Black Interaction Of PSCH8LN |  |  |  |  |  |  | $\begin{gathered} 0.296 \\ -0.228 \end{gathered}$ |  |
| PSCHI2LN | T: Linear: Percent 9-12 Years \& No High School Diploma | -0.002 |  |  | -0.182 | 0.113 |  |  | 0.043 |
| PSCH12QU | 1: Quadratic: Percent 9-12 Years \& No High School Diploma | 0.067 |  |  |  | 0.133 |  |  | 0.137 |
| PSCH12CU | T: Cubic: Percent 9-12 Y Yers \& No High School Diploma | 0.036 |  |  |  |  |  |  |  |
| PSCHI2QR | T: Quartic: Percent 9-12 Years \& No High School Diploma | 0.028 |  |  |  |  |  |  |  |
| IFEM60 IFEM61 | Female Interaction Of PSCHI2LN Female Interaction Of PSCHI2QU |  |  |  |  | $\begin{aligned} & -0.115 \\ & -0.181 \end{aligned}$ |  |  |  |
| PSCHASLN PSCHASQU | T: Linear: Percent Associates Degree T: Quadratic: Percent Associates Degree |  |  |  |  |  |  | 0.023 -0.088 |  |
| IBLK65 IBLK66 | Black Interaction Of PSCHASLN Black Interaction Of PSCHASQU |  |  |  |  |  |  | $\begin{aligned} & 0.100 \\ & 0.158 \end{aligned}$ |  |
| PSCHCOLN PSCHCOQU PSCHCOCU | I: Linear: Bachelors, Graduate, Or Professional Degree <br> I: Quadratic: Bachelors, Graduate, Or Professional Degree <br> I: Cubic: Bachelors, Graduate, Or Protessional Degree |  |  |  |  | $\begin{array}{r} 0.134 \\ -0.007 \\ 0.082 \end{array}$ |  |  | -0.003 -0.042 |
| IFEM75 <br> IFEM76 | Female Interaction Of PSCHCOLN Female Interaction Of PSCHCOQU |  |  |  |  | $\begin{aligned} & 0.024 \\ & 0.024 \end{aligned}$ |  |  |  |
| PPPOVERLN | T: Linear: Percent Families Below Poverty Level | $\begin{gathered} -0.134 \\ 0.009 \end{gathered}$ |  |  |  | $\begin{aligned} & -0.122 \\ & -0.006 \end{aligned}$ | -0.174 | $\begin{aligned} & 0.126 \\ & 0.021 \end{aligned}$ |  |

NOTE:
T: Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other


NOTE:
T : Indicates a tract-level variable, C : Indicates a county-level variable, B : Indicates a block-level variable, O : Other


| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | $35+$ | 12-17 | 18-25 | 26-34 | 35+ |
| IBLK300 | Black Interaction Of BINDIALN |  |  |  |  | 0.563 | 0.099 |  |  |
| IHISP300 | Hispanic Interaction Of BINDIALN |  |  |  |  |  |  |  | 0.351 |
| IHISP301 | Hispanic Interaction Of BINDIAQU |  |  |  |  |  |  |  |  |
| BMNOTLN | B: Linear: Percent Males Separated, Divorced or Widowed |  |  |  | 0.259 | 0.064 | 0.019 | -0.008 |  |
| BMNOTQU | B: Quadratic: Percent Males Separated, Divorced or Widowed |  |  |  | -0.007 | 0.019 | 0.015 | -0.007 |  |
| BMNOTCU | B: Cubic: Percent Males Separated, Divorced or Widowed |  |  |  | 0.082 |  |  | 0.049 |  |
| IFEM305 | Female Interaction Of BMNOTLN |  |  |  | -0.276 |  |  | -0.081 |  |
| IFEM306 | Female Interaction Of BMNOTQU |  |  |  | 0.000 |  |  | -0.007 |  |
| IFEM307 | Female Interaction Of BMNOTCU |  |  |  | -0.038 |  |  | -0.108 |  |
| IHISP305 | Hispanic Interaction Of BMNOTLN |  |  |  |  |  | -0.049 |  |  |
| IHISP306 | Hispanic Interaction Of BMNOTQU |  |  |  |  |  | -0.112 |  |  |
| BPOVERLN | B: Linear: Percent Families Below Poverty Level |  | 0.059 |  |  |  | -0.030 |  | -0.271 |
| BPOVERQU | B: Quadratic: Percent Families Below Poverty Level |  | 0.007 |  |  |  |  |  | -0.035 |
| BPOVERCU | B: Cubic: Percent Families Below Poverty Level |  | -0.012 |  |  |  |  |  | 0.043 |
| BPOVERQR | B: Quartic: Percent Families Below Poverty Level |  | -0.010 |  |  |  |  |  | -0.101 |
| IFEM310 | Female Interaction Of BPOVERLN |  |  |  |  |  | 0.151 |  | 0.063 |
| IFEM311 | Female Interaction Of BPOVERQU |  |  |  |  |  |  |  | -0.029 |
| IFEM312 | Female Interaction Of BPOVERCU |  |  |  |  |  |  |  | -0.135 |
| IFEM313 | Female Interaction Of BPOVERQR |  |  |  |  |  |  |  | 0.138 |
| BPRICALN | B: Linear: Percent Hispanics: Puerto Rican | -0.071 | -0.098 |  |  | -0.168 | 0.010 | 0.046 |  |
| BPRICAQU | B: Quadratic: Percent Hispanics: Puerto Rican |  | -0.094 |  |  | -0.159 | -0.004 | -0.051 |  |
| BPRICACU | B: Cubic: Percent Hispanics: Puerto Rican |  |  |  |  | -0.016 | -0.078 | 0.022 |  |
| BPRICAQR | B: Quartic: Percent Hispanics: Puerto Rican |  |  |  |  | 0.010 |  |  |  |
| IFEM315 | Female Interaction Of BPRICALN |  |  |  |  | 0.064 |  |  |  |
| IFEM316 | Female Interaction Of BPRICAQU |  |  |  |  | 0.150 |  |  |  |
| IFEM317 | Female Interaction Of BPRICACU |  |  |  |  | -0.064 |  |  |  |
| IFEM318 | Female Interaction Of BPRICAQR |  |  |  |  | -0.102 |  |  |  |
| IBLK315 | Black Interaction Of BPRICALN |  | -0.035 |  |  |  | -0.114 | -0.168 |  |
| 1BLK316 | Black Interaction Of BPRICAQU |  | 0.200 |  |  |  | 0.210 | 0.080 |  |
| 1BLK317 | Black Interaction Of BPRICACU |  |  |  |  |  |  | 0.204 |  |
| IHISP315 | Hispanic Interaction Of BPRICALN |  |  |  |  |  | -0.147 |  |  |
| IHISP316 | Hispanic Interaction Of BPRICAQU |  |  |  |  |  | -0.019 |  |  |
| IHISP317 | Hispanic Interaction Of BPRICACU |  |  |  |  |  | 0.303 |  |  |
| BSCHASLN | B: Linear: Percent Associates Degree |  | -0.037 |  |  | 0.057 | -0.016 | 0.031 |  |
| BSCHASQU | B: Quadratic: Percent Associates Degree |  | 0.013 |  |  | -0.029 | 0.035 | 0.031 | 0.026 |
| BSCHASCU | B: Cubic: Percent Associates Degree |  |  |  |  | -0.013 | -0.028 | 0.066 | -0.012 |
| BSCHASQR | B: Quartic: Percent Associates Degree |  |  |  |  | -0.026 |  |  |  |
| IFEM320 | Female Interaction Of BSCHASLN |  |  |  |  | -0.071 |  |  |  |
| IFEM321 | Female Interaction Of BSCHASQU |  |  |  |  | 0.080 |  |  |  |
| IFEM322 | Female Interaction Of BSCHASCU |  |  |  |  | 0.053 |  |  |  |
| IFEM323 | Female Interaction Of BSCHASQR |  |  |  |  | 0.064 |  |  |  |
| IBLK320 | Black Interaction Of BSCHASLN |  |  |  |  | 0.038 |  | 0.041 |  |
| IBLK321 | Black Interaction Of BSCHASQU |  |  |  |  | 0.126 |  | 0.063 |  |
| 1BLK322 | Black Interaction Of BSCHASCU |  |  |  |  | 0.281 |  | -0.087 |  |
| PASIANLN | T: Linear: Percent Population: Asian, Pacitic Islander |  |  |  | -0.143 |  | -0.073 | 0.002 |  |
| PASIANQU | T: Quadratic: Percent Population: Asian, Pacitic Islander |  |  |  |  |  | -0.000 | -0.051 |  |
| PASIANCU | T: Cubic: Percent Population: Asian, Pacific Islander |  |  |  |  |  | -0.067 | -0.111 |  |
| PASIANQR | T: Quartic: Percent Population: Asian, Pacific Islander |  |  |  |  |  | 0.023 |  |  |
| IFEM325 | Female Interaction Ot PASIANLN |  |  |  |  |  | -0.035 |  |  |
| IFEM326 | Female Interaction Of PASIANQU |  |  |  |  |  | -0.053 |  |  |
| IFEM327 | Female Interaction Of PASIANCU |  |  |  |  |  | 0.015 |  |  |
| IFEM328 | Female Interaction Of PASIANQR |  |  |  |  |  | -0.045 |  |  |
| IHISP325 | Hispanic Interaction Of PASIANLN |  |  |  |  |  |  |  |  |
| IHISP326 | Hispanic Interaction Of PASIANQU |  |  |  |  |  | 0.099 |  |  |
| IHISP327 | Hispanic Interaction Of PASIANCU |  |  |  |  |  | 0.169 |  |  |
| PCUBANLN | T: Linear: Percent Hispanics: Cuban | -0.060 |  | -0.055 |  | -0.141 |  | -0.019 |  |
| PCUBANQU | T: Quadratic: Percent Hispanics: Cuban | -0.114 |  | 0.015 |  | -0.167 |  | 0.052 |  |
| PCUBANCU | T: Cubic: Percent Hispanics: Cuban | -0.080 |  |  |  | -0.123 |  | 0.012 |  |
| PCUBANQR | T: Quartic: Percent Hispanics: Cuban |  |  |  |  |  |  | 0.007 |  |
| IFEM330 | Female Interaction Of PCUBANLN |  |  |  |  | 0.137 |  |  |  |
| IFEM331 | Female Interaction Of PCUBANQU |  |  |  |  | 0.155 |  |  |  |
| IFEM332 | Female Interaction Of PCUBANCU |  |  |  |  | 0.356 |  |  |  |
| IBLK330 | Black Interaction Of PCUBANLN | 0.016 |  |  |  |  |  |  |  |
| 1BLK331 | Black Interaction Of PCUBANQU | 0.060 |  |  |  |  |  |  |  |
| 1BLK332 | Black Interaction Of PCUBANCU | 0.044 |  |  |  |  |  |  |  |
|  | T: Linear: Percent Pop: American Indian, Eskimo, Aleut |  |  | 0.008 |  |  | -0.019 |  |  |
| PINDIAQU | T: Quadratic: Percent Pop: American Indian, Eskimo, Aleut | 0.069 |  | -0.035 |  |  |  |  | 0.004 |
| PINDIACU | T: Cubic: Percent Pop: American Indian, Eskimo, Aleut | -0.108 |  |  |  |  |  |  | -0.017 |
| PINDIAQR | T: Quartic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  |  |  | 0.025 |
| IFEM335 | Female Interaction Of PINDIALN |  |  |  |  |  |  |  | 0.055 |
| IFEM336 | Female Interaction Of PINDIAQU |  |  |  |  |  |  |  | 0.055 |
| IFEM337 | Female Interaction Of PINDIACU |  |  |  |  |  |  |  | 0.054 |
| IFEM338 | Female Interaction Of PINDIAQR |  |  |  |  |  |  |  | -0.096 |
| IHISP335 | Hispanic Interaction Of PINDIALN |  |  | -0.083 |  |  |  |  |  |
| 1HISP336 | Hispanic Interaction Of PINDIAQU |  |  | 0.152 |  |  |  |  |  |

E3. Coefficients of Model Parameters for Past Month Cigarette Use

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| DUMMY | O: Intercept Term | -2.096 | -0.561 | -0.606 | -1.067 | -2.495 | -0.560 | -0.930 | -0.919 |
| FEMALE | O : Female Indicator | 0.115 | -0.224 | -0.098 | -0.133 | 0.040 | 0.083 | 0.155 | -0.328 |
| FEMBLCK | O: Black Interaction Of FEMALE | -0.681 | 0.081 | -0.271 | -0.385 | -0.022 | -0.273 | -0.376 | -0.080 |
| FEMHISP | O: Hispanic Interaction Of FEMALE | -0.186 | -0.555 | -0.640 | -0.511 |  |  | -0.947 | -0.240 |
| FEMOTHR | O: Other Interaction Of FEMALE | -0.212 | -0.942 | -1.580 | -1.273 | 0.319 | -1.145 | -0.980 | -0.064 |
| RACEBLCK RACEHISP | O: Race/Black Indicator O: Race/Hispanic Indicator | -1.242 -0.441 -1.922 | -1.112 -0.251 -0.251 | 0.049 -0.194 | 0.355 0.282 | -1.334 | -0.903 | 0.075 0.124 | 0.145 -0.094 |
| RACEOTHR | O: Race/Other Indicator |  |  | 0.047 | -0.217 | -2.685 | -0.008 | 0.200 | 0.350 |
| REGNOREA REGSOUTH | O: Northeast Region Indicator |  |  |  |  |  | 0.332 0.073 |  |  |
| REGWEST | O: West Region Indicator |  |  |  |  |  | -0.060 |  |  |
| PDENLEV1 | O: Large MSA |  |  |  |  | 0.191 | -0.121 | 0.105 |  |
| PDENLEV2 | O: Medium MSA |  |  |  |  | 0.476 | -0.085 | 0.122 |  |
| PDENLEV3 | O: Small MSA O: NonMSA, Urban |  |  |  |  | 0.353 0.436 | -0.108 0.004 | 0.010 0.014 |  |
| IHISP10 IHISP11 | Hispanic Interaction Of PDENLEVI Hispanic Interaction Of PDENLEV2 |  |  |  |  |  |  | $\begin{aligned} & -0.255 \\ & -0.193 \end{aligned}$ |  |
| POPRMLN | T: Linear: Average Persons Per Room | 0.081 |  |  |  | -0.023 |  | -0.014 |  |
| POPRMQU | T: Quadratic: Average Persons Per Room |  |  |  |  | -0.059 |  |  |  |
| POPRMCU | T: Cubic: Average Persons Per Room |  |  |  |  | -0.083 |  |  |  |
| IFEM20 | Female Interaction Of POPRMLN |  |  |  |  |  |  | 0.095 |  |
| 1BLK20 | Black Interaction Of POPRMLN |  |  |  |  | 0.126 |  |  |  |
| 1BLK21 1BLK22 | Black Interaction Of POPRMQU Black Interaction Of POPRMCU |  |  |  |  | 0.070 0.351 |  |  |  |
| IOTH20 | Other Interaction Of POPRMLN |  |  |  |  | -0.949 |  |  |  |
| IOTH21 | Other Interaction Of POPRMQU |  |  |  |  | -0.118 |  |  |  |
| 10TH22 | Other Interaction Of POPRMCU |  |  |  |  | 0.894 |  |  |  |
| PAGE18LN | T: Linear: Percent Persons 0-18 Years | 0.123 |  |  |  |  |  |  |  |
| PAGE18QU PAGE18CU | T: Quadratic: Percent Persons 0-18 Years T: Cubic: Percent Persons 0-18 Years |  |  |  |  |  | $\begin{array}{r} -0.020 \\ 0.094 \end{array}$ |  |  |
| IFEM25 | Female Interaction Of PAGE18LN | -0.150 |  |  |  |  |  |  |  |
| IFEM26 | Female Interaction Of PAGEE18QU |  |  |  |  |  | $0.056$ |  |  |
| IFEM27 | Female Interaction Of PAGE18CU |  |  |  |  |  |  |  |  |
| PAGE24LN | T: Linear: Percent Persons 19-24 Years |  |  |  |  | 0.069 |  | -0.019 | 0.006 |
| PAGE24QU | T: Quadratic: Percent Persons 19-24 Years |  |  |  |  | -0.074 |  | -0.030 | -0.032 |
| PAGE24CU | T: Cubic: Percent Persons 19-24 Years |  |  |  |  |  |  | $-0.027$ | $-0.011$ |
| PAGE24QR | T: Quartic: Percent Persons 19-24 Years |  |  |  |  |  |  | -0.007 |  |
| IHISP30 | Hispanic Interaction Of PAGE24LN |  |  |  |  |  |  | 0.157 |  |
| 1HISP31 | Hispanic Interaction Of PAGE24QU |  |  |  |  |  |  | 0.085 |  |
| IHISP32 IHISP33 | Hispanic Interaction Of PAGE24CU Hispanic Interaction Of PAGE24QR |  |  |  |  |  |  | -0.010 0.021 |  |
| IOTH30 | Other Interaction Of PAGE24LN |  |  |  |  |  |  |  | 0.153 |
| IOTH31 | Other Interaction Of PAGE24QU |  |  |  |  |  |  |  | 0.067 |
| IOTH32 | Other Interaction Of PAGE24CU |  |  |  |  |  |  |  | 0.062 |
| IOTH33 | Other Interaction Of PAGE24QR |  |  |  |  |  |  |  | 0.261 |
| PAGE44LN | T: Linear: Percent Persons 35-44 Years |  |  |  |  |  |  | $-0.023$ |  |
| PAGE54LN | T: Linear: Percent Persons 45-54 Years |  |  |  | 0.029 | 0.028 |  |  | 0.056 |
| PAGE54QU | T: Quadratic: Percent Persons 45-54 Years |  |  |  | 0.001 | 0.064 |  |  | -0.034 |
| $\begin{aligned} & \text { IBLK45 } \\ & \text { IBLK46 } \end{aligned}$ | Black Interaction Of PAGGE54LN Black Interaction Of PAGE54QU |  |  |  | $\begin{array}{r} -0.057 \\ 0.078 \end{array}$ | $\begin{array}{r} 0.018 \\ -0.238 \end{array}$ |  |  |  |
| PAGE64LN | T: Linear: Percent Persons 55-64 Years |  |  |  |  | 0.069 |  |  |  |
| PAGE64QU | T: Quadratic: Percent Persons 55-64 Years |  |  |  |  | 0.022 |  |  |  |
| PAGE64CU | T: Cubic: Percent Persons 55-64 Years |  |  |  |  | 0.010 |  |  |  |
| PAGE64QR | T: Quartic: Percent Persons 55-64 Years |  |  |  |  | 0.031 |  |  |  |
| PSCH8LN | T: Linear: Percent 0-8 Years Of School |  |  |  |  | -0.043 |  |  |  |
| IOTH55 | Other Interaction Of PSCH8LN |  |  |  |  | 1.716 |  |  |  |
| PSCHI2LN | T: Linear: Percent 9-12 Years \& No High School Diploma |  |  |  |  |  |  |  |  |
| PSCH12QU <br> PSCH12CU | T: Quadratic: Percent 9-12 Years \& No High School Diploma T: Cubic: Percent 9-12 Years \& No High School Diploma |  |  |  |  | $\begin{array}{r} 0.033 \\ -0.045 \end{array}$ |  |  |  |
| PSCHASLN | T: Linear: Percent Associates Degree |  |  |  |  | 0.034 |  | 0.010 |  |
| PSCHASQU | T: Quadratic: Percent Associates Degree |  |  |  |  | 0.043 |  | 0.003 |  |
| PSCHASCU | T: Cubic: Percent Associates Degree |  |  |  |  | -0.029 |  |  |  |
| PSCHASQR | T: Quartic: Percent Associates Degree |  |  |  |  | -0.063 |  |  |  |
| IFEM65 | Female Interaction Of PSCHASLN |  |  |  |  | 0.075 |  |  |  |
| IFEM66 | Female Interaction Of PSCHASQU |  |  |  |  | -0.087 |  |  |  |
| IFEM67 | Female Interaction Of PSCHASCU |  |  |  |  | 0.005 0.075 |  |  |  |
| IFEM68 | Female Interaction Of PSCHASQR |  |  |  |  | 0.075 |  |  |  |
| PSCHCOLN <br> PSCHCOQU | I: Linear: Bachelors, Graduate, Or Professional Degree <br> T: Quadratic: Bachelors, Graduate, Or Professional Degree |  |  |  |  | -0.103 -0.051 |  |  | -0.111 -0.048 |
| IFEM75 | Female Interaction Of PSCHCOLN |  |  |  |  | 0.148 |  |  |  |
| IFEM76 | Female Interaction Of PSCHCOQU |  |  |  |  | 0.130 |  |  |  |
| PPOVERLN | T: Linear: Percent Families Below Poverty Level |  |  |  |  | 0.031 |  |  | 0.084 |
| PPOVERQU | T: Quadratic: Percent Families Below Poverty Level |  |  |  |  | 0.047 |  |  | 0.092 |
| PPOVERCU | T: Cubic: Percent Families Below Poverty Level |  |  |  |  | -0.072 |  |  |  |
| PPOVERQR | T: Quartic: Percent Families Below Poverty Level |  |  |  |  | 0.002 |  |  |  |
| IFEM85 | Female Interaction OfPPOVERLN |  |  |  |  | -0.170 |  |  | -0.203 |
| IFEM86 IFEM87 | Female Interaction Of PPOVERQU Female Interaction Of PPOVERCU |  |  |  |  | $\begin{array}{r} -0.170 \\ -0.075 \\ 0.014 \end{array}$ |  |  | -0.103 |

NOTE: $\quad \mathrm{T}:$ Indicates a tract-level variable, $\mathrm{C}:$ Indicates a county-level variable, $\mathrm{B}:$ Indicates a block-level variable, $\mathrm{O}:$ Other


NOTE:


NOTE: $\quad \mathrm{T}:$ Indicates a tract-level variable, $\mathrm{C}:$ Indicates a county-level variable, $\mathrm{B}:$ Indicates a block-level variable, O : Other

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | $35+$ | 12-17 | 18-25 | 26-34 | 35+ |
| IFEM275 | Female Interaction Of BAGE54LN |  |  |  |  |  | 0.024 |  | -0.001 |
| IFEM276 | Female Interaction Of BAGE54QU |  |  |  |  |  | 0.051 |  | 0.021 |
| IFEM277 | Female Interaction Of BAGE54CU |  |  |  |  |  | 0.135 |  | 0.008 |
| IBLK275 | Black Interaction Of BAGE54LN |  |  |  |  |  | -0.005 |  |  |
| IBLK276 | Black Interaction Of BAGE54QU |  |  |  |  |  | 0.013 |  |  |
| IOTH275 | Other Interaction Of BAGE54LN |  |  |  |  | 0.404 |  | 0.057 |  |
| IOTH276 | Other Interaction Of BAGE54QU |  |  |  |  | $-0.054$ |  | -0.049 |  |
| IUTH277 | Other Interaction Of BAGE54CU |  |  |  |  | -0.754 |  | 0.187 |  |
| $10 T H 278$ | Other Interaction Of BAGE54QR |  |  |  |  |  |  | 0.144 |  |
| BAGE64LN | B: Linear: Percent Persons 55-64 Years |  | -0.010 | 0.004 | -0.084 | -0.097 | 0.018 |  | -0.036 |
| BAGE64QU | B: Quadratic: Percent Persons 55-64 Years |  | $-0.043$ | ${ }^{0.008}$ | 0.014 |  | 0.006 |  | 0.001 |
| BAGE64CU | B: Cubic: Percent Persons 55-64 Years |  | 0.007 | -0.004 |  |  | 0.025 |  | -0.021 |
| BAGE64QR | B: Quartic: Percent Persons 55-64 Years |  |  |  |  |  | -0.008 |  |  |
| IFEM280 | Female Interaction Of BAGE64LN |  |  |  | 0.028 |  |  |  | 0.056 |
| IFEM281 IFEM282 | Female Interaction Of BAGE64QU Female Interaction Of BAGE64CU |  |  |  | -0.004 |  |  |  | -0.026 -0.001 |
| IBLK280 | Black Interaction Of BAGE64LN |  |  |  |  |  |  |  | -0.040 |
| 1BLK281 | Black Interaction Of BAGE64QU |  |  |  |  |  |  |  | 0.033 |
| IHISP280 | Hispanic Interaction Of BAGE64LN |  | 0.003 | -0.063 |  |  |  |  |  |
| IHISP281 | Hispanic Interaction Of BAGE64QU |  | 0.007 | $-0.030$ |  |  |  |  |  |
| IHISP282 | Hispanic Interaction Of BAGE64CU |  | -0.042 | 0.008 |  |  |  |  |  |
| BASIANLN | B: Linear: Percent Population: Asian, Pacitic Islander |  | -0.040 | -0.005 |  |  | -0.002 | -0.079 | -0.078 |
| BASIANQU | B: Quadratic: Percent Population: Asian, Pacitic Islander |  | -0.014 | 0.008 |  |  | 0.052 | 0.001 | 0.010 |
| BASIANCU | B: Cubic: Percent Population: Asian, Pacitic Islander |  |  | -0.008 |  |  | 0.085 | 0.035 | -0.140 |
| BASIANQR | B: Quartic: Percent Population: Asian, Pacitic Islander |  |  | 0.003 |  |  | 0.012 | 0.030 |  |
| IFEM285 | Female Interaction Of BASIANLN |  |  |  |  |  | -0.033 |  | 0.031 |
| IFEM286 | Female Interaction Of BASIANQU |  |  |  |  |  | -0.028 |  | 0.006 |
| IFEM287 | Female Interaction Of BASIANCU |  |  |  |  |  | -0.055 |  | 0.183 |
| IFEM288 | Female Interaction Of BASIANQR |  |  |  |  |  | -0.047 |  |  |
| IHISP285 | Hispanic Interaction Of BASIANLN |  |  | -0.003 |  |  |  | 0.197 |  |
| 1HISP286 | Hispanic Interaction Of BASIANQU |  |  | 0.058 |  |  |  |  |  |
| IHISP287 | Hispanic Interaction Of BASIANCU |  |  | 0.003 |  |  |  |  |  |
| IHISP288 | Hispanic Interaction Of BASIANQR |  |  | -0.041 |  |  |  |  |  |
| BCUBANLN | B: Linear: Percent Hispanics: Cuban |  |  |  |  |  | -0.079 | 0.052 |  |
| BCUBANQU | B: Quadratic: Percent Hispanics: Cuban |  |  |  |  |  | ${ }_{0}^{0.029}$ |  |  |
| BCUBANCU | B: Cubic: Percent Hispanics: Cuban |  |  |  |  |  | 0.064 |  |  |
| IFEM290 | Female Interaction Of BCUBANLN |  |  |  |  |  |  | -0.114 |  |
| BFNOTLN | B: Linear: Percent Females Separated, Divorced or Widowed |  |  |  |  | 0.025 |  | 0.004 |  |
| BFNOTQU | B: Quadratic: Percent Females Separated, Divorced or Widowed |  |  |  |  | 0.008 |  | -0.095 |  |
| BFNOTCU | B: Cubic: Percent Females Separated, Divorced or Widowed |  |  |  |  | 0.061 |  |  |  |
| IFEM295 | Female Interaction Of BFNOTLN |  |  |  |  | 0.008 |  | 0.026 |  |
| IFEM296 | Female Interaction Of BFNOTQU |  |  |  |  | -0.045 |  | 0.085 |  |
| IFEM297 | Female Interaction Of BFNOTCU |  |  |  |  | -0.176 |  |  |  |
| BINDIALN | B: Linear: Percent Pop: American Indian, Eskimo, Aleut |  | 0.061 | -0.003 |  |  | 0.057 |  |  |
| BINDIAQU | B: Quadratic: Percent Pop: American Indian, Eskimo, Aleut |  |  | 0.024 |  |  | -0.014 |  |  |
| BINDIACU | B: Cubic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  | 0.004 |  |  |
| BINDIAQR | B: Quartic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  | 0.006 |  |  |
| IBLK300 | Black Interaction Of BINDIALN |  |  |  |  |  | 0.222 |  |  |
| IHISP300 | Hispanic Interaction Of BINDIALN |  |  | -0.120 |  |  |  |  |  |
| 1 IHISP301 | Hispanic Interaction Of BINDIAQU |  |  | 0.168 |  |  |  |  |  |
| IOTH300 | Other Interaction Of BINDIALN |  |  |  |  |  | 0.440 |  |  |
| IOTH301 | Other Interaction Of BINDIAQU |  |  |  |  |  | -0.426 |  |  |
| BMNOTLN | B: Linear: Percent Males Separated, Divorced or Widowed |  |  | 0.041 | 0.132 | 0.024 | 0.058 |  | 0.067 |
| BMNOTQU | B: Quadratic: Percent Males Separated, Divorced or Widowed |  |  | 0.016 | 0.030 | -0.111 | 0.000 |  | -0.025 |
| BMNOTCU | B: Cubic: Percent Males Separated, Divorced or Widowed |  |  | -0.014 | 0.070 |  | 0.023 |  |  |
| BMNOTQR | B: Quartic: Percent Males Separated, Divorced or Widowed |  |  | -0.011 |  |  |  |  |  |
| IFEM305 | Female Interaction Of BMNOTLN |  |  |  | -0.146 | -0.030 |  |  |  |
| IFEM306 | Female Interaction Of BMNOTQU |  |  |  | $-0.060$ | 0.157 |  |  |  |
| IFEM307 | Female Interaction Of BMNOTCU |  |  |  | -0.011 |  |  |  |  |
| IHISP305 | Hispanic Interaction Of BMNOTLN |  |  | -0.011 |  |  |  |  |  |
| IHISP306 | Hispanic Interaction Of BMNOTQU |  |  | -0.011 |  |  |  |  | 0.171 |
| $1 \mathrm{HISP307}$ | Hispanic Interaction Of BMNOTCU |  |  | 0.028 |  |  |  |  |  |
| $1 \mathrm{HISP308}$ | Hispanic Interaction Of BMNOTQR |  |  | 0.041 |  |  |  |  |  |
| BPOVERLN | B: Linear: Percent Families Below Poverty Level |  | 0.105 |  |  | 0.006 | -0.035 |  | 0.089 |
| BPOVERQU | B: Quadratic: Percent Families Below Poverty Level |  | 0.025 |  |  | 0.015 | -0.017 |  | -0.030 |
| BPOVERCU | B: Cubic: Percent Families Below Poverty Level |  | 0.040 |  |  | -0.039 | -0.045 |  | 0.054 |
| BPOVERQR | B: Quartic: Percent Families Below Poverty Level |  | 0.008 |  |  |  | 0.004 |  |  |
| IFEM310 | Female Interaction Of BPOVERLN |  |  |  |  |  |  |  | 0.057 |
| IFEM311 | Female Interaction Of BPOVERQU |  |  |  |  |  |  |  | -0.012 -0.126 |
| IFEM312 | Female Interaction Of BPOVERCU |  |  |  |  |  |  |  |  |
| BPRICALN | B: Linear: Percent Hispanics: Puerto Rican | 0.040 |  |  |  | -0.082 |  | 0.097 |  |
| BPRICAQU | B: Quadratic: Percent Hispanics: Puerto Rican |  |  |  |  | 0.046 |  | -0.009 |  |
| BPRICACU | B: Cubic: Percent Hispanics: Puerto Rican |  |  |  |  | -0.189 |  | $-0.050$ |  |
| BPRICAQR | B: Quartic: Percent Hispanics: Puerto Rican |  |  |  |  |  |  | $-0.039$ |  |
| IFEM315 | Female Interaction Of BPRICALN |  |  |  |  | 0.128 |  |  |  |
| IBLK315 | Black Interaction Of BPRICALN |  |  |  |  |  |  | -0.177 |  |
| IBLK316 | Black Interaction Of BPRICAQU |  |  |  |  |  |  | 0.094 |  |
| IBLK317 | Black Interaction Of BPRICACU |  |  |  |  |  |  | 0.026 |  |
| 1BLK318 | Black Interaction Of BPRICAQR |  |  |  |  |  |  | 0.080 |  |
| BSCHASLN | B: Linear: Percent Associates Degree |  | 0.031 |  |  | 0.019 | 0.048 | -0.003 | 0.011 |
| BSCHASQU | B: Quadratic: Percent Associates Degree |  | 0.047 |  |  | -0.051 | 0.004 | $-0.023$ | 0.042 |
| BSCHASCU | B: Cubic: Percent Associates Degree |  |  |  |  |  | ${ }^{0.016}$ | 0.007 | 0.023 |
| BSCHASQR | B: Quartic: Percent Associates Degree |  |  |  |  |  | -0.014 |  |  |
| IFEM320 <br> IFEM321 | Female Interaction Of BSCHASLN Female Interaction Of BSCHASQU |  |  |  |  | $\begin{array}{r} -0.157 \\ 0.094 \end{array}$ | -0.072 |  |  |

NOTE: $\quad \mathrm{T}:$ Indicates a tract-level variable, $\mathrm{C}:$ Indicates a county-level variable, $\mathrm{B}:$ Indicates a block-level variable, $\mathrm{O}:$ Other


## E4. Coefficients of Model Parameters for Past Month Cocaine Use

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | $35+$ |
| DUMMY | O: Intercept Term | -6.184 | -3.510 | -3.721 | -5.496 | -6.529 | -4.421 | -5.037 | -7.819 |
| FEMALE | O: Female Indicator | 0.941 | -0.810 | -0.624 | -1.825 | -0.262 | -0.811 | -0.335 | -0.100 |
| FEMBLCK | O: Black Interaction Of FEMALE | -1.977 | 0.086 | 0.319 | 0.875 | 0.246 | -0.386 | -0.538 | -2.219 |
| FEMHISP | O: Hispanic Interaction Of FEMALE | -0.554 | 0.197 | -0.208 | 0.432 | 0.330 | -0.419 | -0.621 | -1.322 |
| RACEBLCK RACEHISP | O: Race/Black Indicator O: Race/Hispanic Indicator | 0.539 0.992 | -0.182 -0.703 -2.301 | -0.175 -0.488 | 1.287 0.850 | $\begin{array}{r}-0.530 \\ \hline 1.358\end{array}$ | -0.286 0.247 0.0 | $\begin{array}{r}-0.215 \\ -0.797 \\ \hline 0.051\end{array}$ | 2.995 1.442 |
| RACEOTHR | O: Race/Other Indicator | -0.937 | $-2.396$ |  |  |  | -0.246 | -0.051 |  |
| PDENLEV1 PDENLEV2 | O: Large MSA O: Medium MSA |  |  |  |  |  | 0.186 0.285 | 0.133 0.277 |  |
| PDENLEV3 | O: Small MSA |  |  |  |  |  | 0.285 0.538 | 0.277 -0.319 |  |
| PDENLEV4 | O: NonMSA, Urban |  |  |  |  |  | 0.856 | -0.344 |  |
| POPRMLN | T: Linear: Average Persons Per Room |  |  | -0.141 |  |  |  | -0.439 |  |
| IFEM20 | Female Interaction Of POPRMLN |  |  |  |  |  |  | 0.529 |  |
| PAGE24LN | T: Linear: Percent Persons 19-24 Years |  |  |  |  |  |  | 0.091 |  |
| PAGE24QU | T: Quadratic: Percent Persons 19-24 Years |  |  |  |  |  |  | -0.002 |  |
| PAGE24CU | T: Cubic: Percent Persons 19-24 Years |  |  |  |  |  |  | $-0.223$ |  |
| PAGE24QR | T: Quartic: Percent Persons 19-24 Years |  |  |  |  |  |  | 0.077 |  |
| IHISP30 IHSP31 | Hispanic Interaction Of PAGE24LN Hispanic Interaction Of PAGE24OU |  |  |  |  |  |  | 0.114 -0.010 |  |
| IHISP31 IHISP32 | Hispanic Interaction Of PAGE24QU Hispanic Interaction Of PAGE24CU |  |  |  |  |  |  | -0.1010 0.344 |  |
| 1HISP33 | Hispanic Interaction Of PAGE24QK |  |  |  |  |  |  | -0.154 |  |
| PAGE44LN | T: Linear: Percent Persons 35-44 Years |  |  |  |  |  |  | 0.250 |  |
| $\begin{aligned} & \text { PAGE54LN } \\ & \text { PAGE54QU } \end{aligned}$ | T: Linear: Percent Persons 45-54 Years <br> T: Quadratic: Percent Persons 45-54 Years |  |  |  | $\begin{aligned} & -0.128 \\ & -0.160 \end{aligned}$ |  |  |  | $\begin{aligned} & -0.065 \\ & -0.315 \end{aligned}$ |
| IBLK45 <br> IBLK46 | Black Interaction Of PAGE54LN <br> Black Interaction Of PAGE54QU |  |  |  | $\begin{aligned} & 0.103 \\ & 0.325 \end{aligned}$ |  |  |  |  |
| PSCHASLN PSCHASQU | I: Linear: Percent Associates Degree <br> T: Quadratic: Percent Associates Degree |  |  |  |  |  |  | $\begin{aligned} & -0.042 \\ & -0.185 \end{aligned}$ |  |
| PSCHCOLN <br> PSCHCOOU | I: Linear: Bachelors, Graduate, Or Professional Degree <br> T: Quadratic: Bachelors, Graduate, Or Professional Degree |  |  |  |  | -0.169 0.356 |  |  | -0.117 -0.290 |
| IFEM75 IFEM76 | Female Interaction Of PSCHCOLN Female Interaction Of PSCHCOQU |  |  |  |  | $\begin{array}{r} 0.606 \\ -0.710 \end{array}$ |  |  |  |
| PBLACKLN | T: Linear: Percent Black Nonhispanic |  |  | 0.155 |  |  |  |  |  |
| PBLACKQU PBLACKCU | T: Quadratic: Percent Black Nonhispanic <br> T: Cubic: Percent Black Nonhispanic |  |  | 0.035 0.107 |  |  |  | $\begin{aligned} & 0.052 \\ & 0.189 \end{aligned}$ |  |
| PHISPLN PHISPQU PHISPCU PHISPQR | T: Linear: Percent Hispanic <br> T: Quadratic: Percent Hispanic <br> T: Cubic: Percent Hispanic <br> T: Quartic: Percent Hispanic |  |  |  |  |  |  |  | 0.128 -0.112 0.063 0.140 |
| POTHLN | T: Linear: Percent Other Race/Hispanicity |  |  |  |  | -0.046 |  |  |  |
| POTHQU | T: Quadratic: Percent Other Race/Hispanicity |  |  |  |  | $-0.165$ |  |  |  |
| POTHCU | T: Cubic: Percent Other Race/Hispanicity |  |  |  |  | 0.239 |  |  |  |
| $\begin{aligned} & \text { PHHF18LN } \\ & \text { PHHF18QU } \end{aligned}$ | T: Linear: \% Female-Headed HH W/No Spouse \& Chld Under 18 T: Quadratic: \% Female-Headed HH W/No Spouse \& Chld Under 18 |  |  |  |  | 0.252 -0.070 |  |  | -0.498 |
| PHHF18CU | T: Cubic: \% Female-Headed HH W/No Spouse \& Chld Under 18 |  |  |  |  | 0.140 |  |  |  |
| PHHF18QR | T: Quartic: \% Female-Headed HH W/No Spouse \& Chld Under 18 |  |  |  |  | 0.129 |  |  |  |
| IFEM120 | Female Interaction Of PHHF18LN |  |  |  |  |  |  |  | 0.979 |
| PFNOTLN <br> PFNOTQU | T: Linear: Percent Females Separated, Divorced Or Widowed <br> T: Quadratic: Percent Females Separated, Divorced Or Widowed |  |  | 0.172 |  |  |  | $\begin{aligned} & 0.176 \\ & 0.191 \end{aligned}$ |  |
| IHISP135 <br> IHISP136 | Hispanic Interaction Of PFNOTLN Hispanic Interaction Of PFNOTQU |  |  |  |  |  |  | $\begin{aligned} & -0.322 \\ & -0.381 \end{aligned}$ |  |
| PMNOTLN <br> PMNOTQU | T: Linear: Percent Males Separated, Divorced Or Widowed T: Quadratic: Percent Males Separated, Divorced Or Widowed |  |  |  |  |  | $\begin{array}{r} -0.178 \\ 0.171 \end{array}$ | $\begin{aligned} & -0.066 \\ & -0.121 \end{aligned}$ |  |
| IFEM150 <br> IFEM151 | Female Interaction Of PMNOTLN Female Interaction Of PMNOTQU |  |  |  |  |  | $\begin{array}{r} 0.550 \\ -0.299 \end{array}$ |  |  |
| $\begin{aligned} & \text { IHISP150 } \\ & \text { IHISP151 } \end{aligned}$ | Hispanic Interaction Of PMNOTLN Hispanic Interaction Of PMNOTQU |  |  |  |  |  |  | $\begin{array}{r} -0.053 \\ 0.285 \end{array}$ |  |
| PRENTLN PRENTQU PRENTCU PRENTQR | T: Linear: Percent Housing Rented <br> T: Quadratic: Percent Housing Rented <br> T: Cubic: Percent Housing Rented <br> T: Quartic: Percent Housing Rented |  |  |  |  |  |  |  | 0.586 0.155 0.74 -0.136 |
| V18BLN <br> V18BQU <br> V18BCU | C: Linear: Marijuana Sale/Manufacture Arrest Rate <br> C: Quadratic: Marijuana Sale/Manufacture Arrest Rate <br> C: Cubic: Marijuana Sale/Manufacture Arrest Rate |  |  |  |  |  |  | $\begin{aligned} & 0.192 \\ & 0.028 \\ & 0.288 \end{aligned}$ |  |
| VI8ELN <br> V18EQU <br> V18ECU <br> V18EQR | C: Linear: Opium/Cocaine \& Deriv Posession Arrest Rate <br> C: Quadratic: Opium/Cocaine \& Deriv Posession Arrest Rate <br> C: Cubic: Opium/Cocaine \& Deriv Posession Arrest Rate <br> C: Quartic: Opium/Cocaine \& Deriv Posession Arrest Rate |  |  |  |  |  |  |  | $\begin{aligned} & 0.250 \\ & 0.446 \\ & 0.088 \\ & 0.165 \end{aligned}$ |
| V18ALN | C: Linear: Opium/Cocaine \& Deriv Sale/Manuf Arrest Rate |  | 0.240 |  |  |  |  | 0.272 |  |
| IHISP200 | Hispanic Interaction Of VI8ALN |  | -0.361 |  |  |  |  |  |  |
| $\begin{aligned} & \text { VI8LN } \\ & \text { V18QU } \\ & \text { V18CU } \\ & \text { V18QR } \end{aligned}$ | C: Linear: Total Drug Abuse Violations Arrest Rate C: Quadratic: Total Drug Abuse Violations Arrest Rate C: Cubic: Total Drug Abuse Violations Arrest Rate C: Quartic: Total Drug Abuse Violations Arrest Rate |  | $-0.279$ | $\begin{array}{r} 0.072 \\ -0.004 \\ -0.106 \\ 0.012 \end{array}$ |  |  | $\begin{array}{r} 0.028 \\ -0.072 \end{array}$ | $\begin{array}{r} -0.691 \\ 0.018 \\ -0.069 \\ 0.140 \end{array}$ |  |


| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| IFEM225 | Female Interaction Of V18LN |  |  |  |  |  |  | 0.161 |  |
| IFEM226 | Female Interaction Of V18QU |  |  |  |  |  |  | -0.039 |  |
| IFEM227 | Female Interaction Of V18CU Female Interaction Of V18QR |  |  |  |  |  |  | 0.174 -0.132 |  |
| IHISP225 | Hispanic Interaction Of V18LN |  | 0.432 |  |  |  |  |  |  |
| VIOLL | C: Linear: Total Violent Offenses Arrest Rate |  |  |  | 0.164 |  |  |  | -0.310 |
| VIOLQU | C: Quadratic: Total Violent Offenses Arrest Rate |  |  |  | -0.116 |  |  |  | -0.551 |
| IBLK230 IBLK231 | Black Interaction Of VIOLLN Black Interaction Of VIOLQU |  |  |  | -0.331 0.208 0.0 |  |  |  |  |
| DRATEL |  |  |  |  |  |  | 0.046 |  |  |
| DRATEQU | C: Quadratic: Mean Drug Client Treatment Rate 1991 \& 1992 |  |  |  |  |  | -0.171 |  |  |
| - IFEM235 | Female Interaction Of DRATELN |  |  |  |  |  | $\begin{array}{r} -0.048 \\ 0.334 \end{array}$ |  |  |
| RH43ALN | T: Linear: Recoded Median Rents For Rental Units | -0.068 |  |  |  |  |  | 0.489 |  |
| RH43AQU | T: Quadratic: Recoded Median Rents For Rental Units | 0.052 |  |  |  |  |  |  |  |
| RH43ACU | T: Cubic: Recoded Median Rents For Rental Units | -0.178 |  |  |  |  |  |  |  |
| RH43AQR | T: Quartic: Recoded Median Rents For Rental Units | -0.083 |  |  |  |  |  |  |  |
| RProaln | T: Linear: Recoded Median Household Income |  |  |  |  | -0.026 | -0.027 | -0.686 |  |
| RP80AQU | T: Quadratic: Recoded Median Household Income |  |  |  |  | 0.190 | $-0.071$ |  |  |
| RP80ACU | T: Cubic: Recoded Median Household Income |  |  |  |  | 0.014 | -0.183 |  |  |
| RP80AQR | T: Quartic: Recoded Median Household Income |  |  |  |  | -0.054 |  |  |  |
| IBLK250 | Black Interaction Of RP80ALN |  |  |  |  |  | -0.280 |  |  |
| IBLK251 IBLK252 | Black Interaction Of RP80AQU |  |  |  |  |  | 0.2175 0.438 |  |  |
| arateln | C: Linear: Mean A-Only Client Treatment Rate 1991 \& 1992 | 0.339 |  |  |  |  |  |  |  |
| BAGE54LN | B: Linear: Percent Persons $45-54$ Years |  |  |  |  |  | -0.016 |  | -0.270 |
| BAGE54QU | B: Quadratic: Percent Persons 45-54 Years |  |  |  |  |  | -0.194 |  | -0.154 |
| BAGE54CU | B: Cubic: Percent Persons 45-54 Years |  |  |  |  |  |  |  | 0.163 |
| IFEM275 | Female Interaction Of BAGE54LN |  |  |  |  |  |  |  | 0.578 |
| IFEM276 | Female Interaction Of BAGE54QU |  |  |  |  |  |  |  | 0.417 |
| 1FEM277 | Female Interaction Of BAGE54CU |  |  |  |  |  |  |  | -0.840 |
| IBLK275 | Black Interaction Of BAGE54LN |  |  |  |  |  | 0.013 |  |  |
| IBLK276 | Black Interaction Of BAGE54QU |  |  |  |  |  | 0.438 |  |  |
| BAGE64LN | B: Linear: Percent Persons 55-64 Years |  | -0.089 | -0.020 | -0.156 |  | 0.176 |  | -0.004 |
| BAGE64QU | B: Quadratic: Percent Persons 55-64 Years |  | $-0.100$ | 0.005 | 0.195 |  | -0.032 |  | $-0.579$ |
| BAGE64CU | B: Cubic: Percent Persons 55-64 Years |  | 0.039 | 0.058 |  |  | 0.110 -0.003 |  | 0.204 |
| BAGE64QR | B: Quartic: Percent Persons 55-64 Years |  |  |  |  |  |  |  |  |
| IFEM280 | Female Interaction Of BAGE64LN |  |  |  | 0.027 -0.272 |  |  |  |  |
| IFEM281 IFEM282 | Female Interaction Of BAGE64QU Female Interaction Of BAGE64CU |  |  |  | -0.272 |  |  |  | 0.491 -0.629 |
| IBLK280 | Black Interaction Of BAGE64LN |  |  |  |  |  |  |  | 0.208 |
| IBLK281 | Black Interaction Of BAGE64QU |  |  |  |  |  |  |  | 0.628 |
| IHISP280 | Hispanic Interaction Of BAGE64LN |  | -0.002 | -0.110 |  |  |  |  |  |
| IHISP281 | Hispanic Interaction Of BAGE64QU |  | 0.057 | 0.047 |  |  |  |  |  |
| 1HISP282 | Hispanic Interaction Of BAGE64CU |  | -0.352 | -0.415 |  |  |  |  |  |
| BASIANLN | B: Linear: Percent Population: Asian, Pacitic Islander |  | -0.037 |  |  |  | 0.074 |  |  |
| BASIANQU | B: Quadratic: Percent Population: Asian, Pacitic Islander |  | -0.115 |  |  |  | 0.088 |  |  |
| BASIANCU | B: Cubic: Percent Population: Asian, Pacific Islander |  |  |  |  |  | ${ }^{-0.022}$ |  |  |
| BASIANQR | B: Quartic: Percent Population: Asian, Pacific Islander |  |  |  |  |  | -0.083 |  |  |
| bcubanln | B: Linear: Percent Hispanics: Cuban |  |  |  |  |  | 0.028 | -0.605 |  |
| BCUBANQU | B: Quadratic: Percent Hispanics: Cuban |  |  |  |  |  | 0.071 |  |  |
| BCUBANCU | B: Cubic: Percent Hispanics: Cuban |  |  |  |  |  | -0.348 |  |  |
| IFEM290 | Female Interaction Of BCUBANLN |  |  |  |  |  |  | 0.686 |  |
| BMNOTLN | B: Linear: Percent Males Separated, Divorced or Widowed |  |  |  | 0.373 | 0.250 | 0.124 |  |  |
| BMNOTQU | B: Quadratic: Percent Males Separated, Divorced or Widowed |  |  |  | -0.187 | 0.269 | -0.062 |  |  |
| BMNOTCU | B: Cubic: Percent Males Separated, Divorced or Widowed |  |  |  | 0.303 |  | 0.120 |  |  |
| IFEM305 | Female Interaction Of BMNOTLN |  |  |  | -0.394 |  |  |  |  |
| IFEM306 | Female Interaction Of BMNOTQU |  |  |  | 0.159 |  |  |  |  |
| 1FEM307 | Female Interaction Of BMNOTCU |  |  |  | -0.380 |  |  |  |  |
| BPOVERLN | B: Linear: Percent families Below Poverty Level |  | 0.172 |  |  |  | 0.077 |  |  |
| BPOVERQU | B: Quadratic: Percent Families Below Poverty Level |  | -0.050 |  |  |  | ${ }^{0.022}$ |  |  |
| BPOVERCU BPOVERQR | B: Cubic: Percent Families Below Poverty Level B: Quartic: Percent Families Below Poverty Level |  | -0.050 -0.049 |  |  |  | -0.070 -0.055 |  |  |
| bpricaln | B: Linear: Percent Hispanics: Puerto Rican | 0.165 |  |  |  | 0.072 |  |  |  |
| BPRICAQU | B: Quadratic: Percent Hispanics: Puerto Rican |  |  |  |  |  |  | 0.174 |  |
| BPRICACU | B: Cubic: Percent Hispanics: Puerto Rican |  |  |  |  |  |  | -0.296 |  |
| IFEM315 | Female Interaction Of BPRICALN |  |  |  |  | $-0.388$ |  |  |  |
| IBLK315 | Black Interaction Of BPRICALN |  |  |  |  |  |  | 0.028 |  |
| 1BLK316 | Black Interaction Of BPRICAQU |  |  |  |  |  |  | -0.352 |  |
| 1BLK317 | Black Interaction Of BPRICACU |  |  |  |  |  |  | 1.067 |  |
| BSCHASLN | B: Linear: Percent Associates Degree |  | -0.083 |  |  | 0.181 | 0.120 |  |  |
| BSCHASQU | B: Quadratic: Percent Associates Degree |  | 0.106 |  |  | -0.336 | 0.029 | -0.038 | 0.033 |
| BSCHASCU | B: Cubic: Percent Associates Degree |  |  |  |  |  |  | 0.155 | -0.370 |
| IFEM320 | Female Interaction OfBSCHASLN Female Interaction Of BSCHASQU |  |  |  |  | $\begin{gathered} -0.243 \\ 0.552 \\ 0.24 \end{gathered}$ | -0.369 |  |  |
| IBLK320 | Black Interaction Of BSCHASLN |  |  |  |  |  |  | -0.174 |  |
| 1BLK321 | Black Interaction Of BSCHASQU |  |  |  |  |  |  | 0.164 |  |
| IBLK322 | Black Interaction Of BSCHASCU |  |  |  |  |  |  | -0.379 |  |
| PCUBANLN | T: Linear: Percent Hispanics: Cuban | 0.284 |  | -0.147 |  |  |  | 0.143 |  |
| PCUBANQU | T: Quadratic: Percent Hispanics: Cuban | $-0.227$ |  | 0.102 |  |  |  | -0.083 |  |
| PCUBANCU | T: Cubic: Percent Hispanics: Cuban | -0.144 |  |  |  |  |  | 0.172 |  |
| PCUBANQK | T: Quartic: Percent Hispanics: Cuban |  |  |  |  |  |  | 0.126 |  |
| IBLK330 | Black Interaction Of PCUBANLN | 0.256 |  |  |  |  |  |  |  |

NOTE:
T : Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other

|  | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Variable |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| IBLK331 lbLK332 | Black interaction Ut PCUBANQU Black Interaction Ut PCUBANCU | -0.301 0.598 |  |  |  |  |  |  |  |

E5. Coefficients of Model Parameters for Past Month Any Illicit Drug But Marijuana

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | $35+$ |
| DUMMY | O : Intercept Term | -3.502 | -2.451 | $-2.988$ | -4.111 | -3.613 | -2.902 | -3.810 | -5.295 |
| female | O: Female Indicator | 0.173 | -0.545 | -0.343 | -0.442 | -0.199 | -0.457 | -0.271 | 0.051 |
| FEMBLCK | O: Black Interaction Of FEMALE | -0.547 | -0.150 | 0.136 | 0.267 | 0.696 | 0.263 | -0.345 | -0.580 |
| Fembisp | 0 : Hispanic Interaction Of FEMALE | 0.093 | 0.358 | 0.370 | -0.239 |  | -0.001 | -0.035 | 0.087 |
| FEMOTHR | O: Other Interaction Of FEMALE | 0.380 | 1.261 | -0.015 |  | -0.670 | -0.526 |  | 1.072 |
| RACEBLCK RACEHISP | O: Race/Black Indicator O: $\mathrm{Race/Hispanic}$ Indicator | -0.409 -0.022 | -0.732 -0.717 | -0.371 -0.549 | $\begin{aligned} & 0.225 \\ & 0.615 \end{aligned}$ | -0.914 | $\begin{array}{r} -0.497 \\ -0.320 \end{array}$ | -0.313 -0.227 | $\begin{array}{r}1.159 \\ -0.305 \\ \hline\end{array}$ |
| RACEOTHR | O: Race/Other Indicator | -1.119 | -2.089 | -1.395 |  | -0.929 | -3.417 | -1.208 | -0.812 |
| REGNOREA REGSOUTH | O: Northeast Region Indicator |  |  |  |  |  |  | 0.540 0.380 1.50 |  |
| REGWEST | O: West Region Indicator |  |  |  |  |  | 0.606 | 1.056 |  |
| PDENLEV1 | O: Large MSA |  |  |  |  |  |  |  | 0.371 |
| PDENLEV2 | O: Medium MSA |  |  |  |  |  |  |  | -0.035 -1.149 |
| PDENLEV3 PDENLEV4 | O: Small MSA |  |  |  |  |  |  |  | 1.149 0.023 |
| PHHIPLN | T: Linear: Percent One Person Households |  |  |  |  | 0.222 |  |  |  |
| PAGE24LN <br> PAGE24QU | T: Linear: Percent Persons 19-24 Years |  |  |  |  |  |  | 0.087 -0.021 | -0.124 0.127 |
| PAGE24CU | T: Cubic: Percent Persons 19-24 Years |  |  |  |  |  |  | -0.121 |  |
| PAGE24QR | T: Quartic: Percent Persons 19-24 Years |  |  |  |  |  |  | 0.045 |  |
| PAGE34LN | T: Linear: Percent Persons 25-34 Years |  |  |  |  | -0.080 -0.168 |  |  |  |
| PAGE34QU | T: Quadratic: Percent Persons 25-34 Years |  |  |  |  | -0.168 |  |  |  |
| PAGE44LN <br> PAGE44QU | I: Linear: Percent Persons 35-44 Years <br> T: Quadratic: Percent Persons 35-44 Years |  |  |  |  | $\begin{array}{r} 0.037 \\ -0.002 \end{array}$ |  |  |  |
| PAGE54LN <br> PAGE54QU | T: Linear: Percent Persons 45-54 Years <br> T: Quadratic: Percent Persons 45-54 Years |  |  |  |  |  |  |  | $\begin{aligned} & -0.115 \\ & -0.347 \end{aligned}$ |
| $\begin{aligned} & \text { IFEM45 } \\ & \text { IFEM46 } \end{aligned}$ | Female Interaction Of PAGE54LN Female Interaction Of PAGE54QU |  |  |  |  |  |  |  | $\begin{aligned} & 0.010 \\ & 0.328 \end{aligned}$ |
| PSCH8LN | T: Linear: Percent 0-8 Years Of School |  |  |  |  |  |  | -0.171 |  |
| PSCHI2LN | T: Linear: Percent 9-12 Years \& No High School Diploma | 0.042 |  |  |  | 0.103 |  |  |  |
| PSCH2LU | T: Quadratic: Percent 9-12 Years \& No High School Diploma | 0.104 |  |  |  | ${ }^{0} .101$ |  |  |  |
| PSCH12CU PSCH12QR | T: Cubic: Percent $9-12$ Years \& No High School Diploma T: Quartic: Percent 9-12 Years \& No High School Diploma | 0.005 0.052 |  |  |  | 0.010 0.040 |  |  |  |
| IFEM60 IFEM61 | Female Interaction Of PSCH12LN Female Interaction Of PSCH12QU | $\begin{aligned} & -0.122 \\ & -0.183 \end{aligned}$ |  |  |  | $\begin{aligned} & -0.166 \\ & -0.187 \end{aligned}$ |  |  |  |
| PSCHASLN PSCHASQU | T: Linear: Percent Associates Degree <br> T: Quadratic: Percent Associates Degree |  |  |  |  | $\begin{gathered} 0.065 \\ -0.081 \end{gathered}$ |  |  |  |
| IBLK65 | Black Interaction Of PSCHASLN |  |  |  |  | 0.228 |  |  |  |
| IBLK66 | Black Interaction Of PSCHASQU |  |  |  |  | 0.370 |  |  |  |
| PSCHSCLN | T: Linear: Percent Some College And No Degree |  |  |  |  | 0.012 |  |  |  |
| PSCHSCQU | T: Quadratic: Percent Some College And No Degree |  |  |  |  | 0.106 |  |  |  |
| PPOVERLN | T: Linear: Percent Families Below Poverty Level |  |  |  |  |  |  | 0.074 |  |
| PPOVERQU | T: Quadratic: Percent Families Below Poverty Level |  |  |  |  |  |  | -0.037 |  |
| PPOVERCU | T: Cubic: Percent Families Below Poverty Level |  |  |  |  |  |  | -0.003 |  |
| PPOVERQR | T: Quartic: Percent Families Below Poverty Level |  |  |  |  |  |  | -0.051 |  |
| P64DISLN | T: Linear: Percent 16-64 With A Work Disability | 0.073 |  |  |  | 0.126 |  |  |  |
| P64DIISQU P64DISCU | T: Quadratic: Percent 16-64 With A Work Disability T: Cubic: Percent 16-64 With A Work Disability | 0.057 0.084 |  |  |  | 0.085 0.075 |  |  |  |
| IBLK95 | Black Interaction Of P64DISLN | -0.215 |  |  |  | 0.094 |  |  |  |
| 1BLK96 | Black Interaction Of P64DISQU | 0.007 -0.296 |  |  |  | 0.252 -0.579 |  |  |  |
| 1BLK97 | Black Interaction Of P64DISCU | -0.296 |  |  |  | -0.579 |  |  |  |
| PBLACKLN | T: Linear: Percent Black Nonhispanic |  |  | 0.064 |  |  |  | 0.129 |  |
| PBLACKQU | T: Quadratic: Percent Black Nonhispanic |  |  | 0.004 |  |  |  | -0.015 |  |
| PBLACKCU | T: Cubic: Percent Black Nonhispanic |  |  | 0.078 |  |  |  | 0.125 |  |
| PFNOTLN | T: Linear: Percent Females Separated, Divorced Or Widowed |  |  | 0.168 |  |  |  | 0.228 |  |
| PMNEVLN | T: Linear: Percent Males Never Married |  |  |  |  | -0.177 |  |  |  |
| PMNOTLN PMNOTQU PMNOTCU PMNOTQR | T: Linear: Percent Males Separated, Divorced Or Widowed <br> T: Quadratic: Percent Males Separated, Divorced Or Widowed <br> T: Cubic: Percent Males Separated, Divorced Or Widowed <br> T: Quartic: Percent Males Separated, Divorced Or Widowed |  |  |  |  | $\begin{array}{r} 0.015 \\ 0.004 \\ 0.035 \\ -0.036 \end{array}$ |  |  |  |
| P40HULN | T: Linear: Percent Housing Units Built 1940-1949 |  |  |  |  | -0.145 |  | 0.123 |  |
| P40HUQU | T: Quadratic: Percent Housing Units Built 1940-1949 |  |  |  |  |  |  | -0.039 |  |
| P40HUCU | T: Cubic: Percent Housing Units Built 1940-1949 |  |  |  |  |  |  | -0.077 |  |
| P40HUQR | T: Quartic: Percent Housing Units Built 1940-1949 |  |  |  |  |  |  | -0.044 |  |
| PRENTLN PRENTQU | T: Linear: Percent Housing Rented <br> T: Quadratic: Percent Housing Rented |  |  |  |  |  |  | $\begin{gathered} -0.084 \\ 0.111 \end{gathered}$ | 0.354 |
| ADRATEQR | C: Quartic: Death Rate For All Alcohol-Related Cases |  |  |  |  |  | 0.048 |  |  |
| ADRATILN | C: Linear: Death Rate With Explicit Mention Of Alcohol |  |  |  |  |  | -0.176 |  |  |
| V18FLN | C: Linear: Mariiuana Posession Arrest Rate ${ }_{\text {c }}$ (Quadratic: Marijuana Posession Arrest Rate |  |  |  |  | $\begin{gathered} 0.092 \\ -0.081 \end{gathered}$ |  | -0.119 -0.035 |  |
| V18FCU | C: Cubic: Marijuana Posession Arrest Rate |  |  |  |  |  |  | -0.083 |  |
| V18FQR | C: Quartic: Marijuana Posession Arrest Rate |  |  |  |  |  |  | -0.053 |  |
| 1HISP185 | Hispanic Interaction Of V18FLN |  |  |  |  |  |  | 0.246 |  |
| V18BLN | C: Linear: Marijuana Sale/Manufacture Arrest Rate <br> C: Quadratic: Marijuana Sale/Manufacture Arrest Rate |  |  |  |  |  |  |  | $\begin{aligned} & -0.016 \\ & -0.155 \end{aligned}$ |



| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | $35+$ |
| BSCHADCU BSCHASQR | B: Cubic: Percent Associates Degree <br> B: Quartic: Percent Associates Degree | $\begin{aligned} & 0.0 / 2 \\ & 0.041 \end{aligned}$ |  |  |  | $\begin{aligned} & -0.08 y \\ & -0.038 \end{aligned}$ |  | 0.119 |  |
| IFEM320 <br> IFEM321 <br> IFEM322 <br> IFEM323 | Female Interaction Of BSCHASLN Female Interaction Of BSCHASQU Female Interaction Of BSCHASCU Female Interaction Of BSCHASQR |  |  |  |  | $\begin{array}{r} -0.033 \\ 0.257 \\ 0.190 \\ 0.061 \end{array}$ |  |  |  |
| PASIANLN PASIANQU PASIANCU | T: Linear: Percent Population: Asian, Pacific Islander <br> T: Quadratic: Percent Population: Asian, Pacific Islander <br> T: Cubic: Percent Population: Asian, Pacitic Islander |  |  |  |  |  | $\begin{array}{r} -0.004 \\ -0.036 \\ -0.110 \end{array}$ | $\begin{array}{r} 0.039 \\ -0.046 \\ -0.124 \end{array}$ | 0.215 |
| IHISP325 IHISP326 IHISP327 | Hispanic Interaction Of PASIANLN Hispanic Interaction Of PASIANQU Hispanic Interaction Of PASIANCU |  |  |  |  |  | $\begin{array}{r} -0.161 \\ 0.093 \\ 0.209 \end{array}$ |  |  |
| IOTH325 | Other Interaction Of PASIANLN |  |  |  |  |  | -1.705 |  |  |
| PINDIALN | T: Linear: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  | -0.056 | 0.116 |  |
| IHISP335 | Hispanic Interaction Of PINDIALN |  |  |  |  |  |  | -0.325 |  |
| IOTH335 | Other Interaction Of PINDIALN |  |  |  |  |  | 1.008 |  |  |

E6. Coefficients of Model Parameters for Past Year Alcohol Treatment

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | $35+$ |
| DUMMY | O: Intercept Term | -6.554 | -5.328 | -4.383 | -5.549 | -6.694 | -6.307 | -4.376 | -7.191 |
| female | O : Female Indicator | 0.006 | -1.113 | $-0.878$ | -0.744 | -0.111 | -1.695 | -1.074 | -1.606 |
| FEMBLCK | O: Black Interaction Of FEMALE | 0.075 |  | 0.354 | -1.245 | 0.372 | 0.461 | -0.522 | -1.905 |
| FEMHISP | O: Hispanic Interaction Of FEMALE | 0.658 | -1.013 | -0.610 | -1.864 | 0.406 | -1.665 | -1.319 | -1.947 |
| RACEBLCK RACEHISP | O: Race/Black Indicator <br> O: Race/Hispanic Indicator | $\begin{aligned} & -0.946 \\ & -0.130 \end{aligned}$ | $\begin{aligned} & -1.951 \\ & -0.067 \end{aligned}$ | $\begin{aligned} & -1.432 \\ & -2.533 \end{aligned}$ | $\begin{aligned} & -1.170 \\ & -1.033 \end{aligned}$ | $\begin{aligned} & -1.783 \\ & -0.244 \end{aligned}$ | $\begin{aligned} & -1.335 \\ & -0.632 \end{aligned}$ | $\begin{aligned} & -0.602 \\ & -0.649 \end{aligned}$ | $\begin{array}{r} 0.362 \\ -3.137 \end{array}$ |
| REGNOREA REGWEST | O: Northeast Region Indicator O : West Region Indicator |  |  |  |  |  | $\begin{array}{r} -0.058 \\ 0.079 \end{array}$ |  |  |
| PAGE18LN | T: Linear: Percent Persons 0-18 Years |  | 0.513 |  |  |  | -0.254 |  |  |
| PAGE18QU | T: Quadratic: Percent Persons 0-18 Y ears |  |  |  |  |  | -0.284 |  |  |
| PAGE18CU | T: Cubic: Percent Persons 0-18 Y ears |  |  |  |  |  | 0.085 |  |  |
| PAGE18QR | T: Quartic: Percent Persons 0-18 Y ears |  |  |  |  |  | -0.071 |  |  |
| 1HISP25 | Hispanic Interaction Of PAGEISLN |  |  |  |  |  | 0.037 |  |  |
| 1HISP26 | Hispanic Interaction Of PAGE18QU |  |  |  |  |  | 0.330 |  |  |
| IHISP27 | Hispanic Interaction Of PAGEEIXCU |  |  |  |  |  | 0.272 |  |  |
| IHISP28 | Hispanic Interaction Of PAGE18QR |  |  |  |  |  | 0.225 |  |  |
| PSCHI2LN PSCH12QU | I: Linear: Percent 9-12 Years \& No High School Diploma <br> T: Quadratic: Percent 9-12 Years \& No High School Diploma |  | $\begin{aligned} & -0.486 \\ & -0.404 \end{aligned}$ |  |  |  | $\begin{array}{r} 0.128 \\ -0.801 \end{array}$ |  |  |
| IFEM60 <br> IFEM61 | Female Interaction Of PSCH12LN Female Interaction Of PSCH12QU |  |  |  |  |  | $\begin{array}{r} -0.170 \\ 0.760 \end{array}$ |  |  |
| $\begin{aligned} & \text { IHISP60 } \\ & \text { IHISP61 } \end{aligned}$ | Hispanic Interaction Of PSCH12LN Hispanic Interaction Of PSCH12QU |  |  |  |  |  | $\begin{aligned} & 0.270 \\ & 0.727 \end{aligned}$ |  |  |
| PSCHCOLN PSCHCOQU PSCHCOCU PSCHCOQR | I: Linear: Bachelors, Graduate, Or Professional Degree <br> T: Quadratic: Bachelors, Graduate, Or Professional Degree <br> T: Cubic: Bachelors, Graduate, Or Professional Degree <br> T: Quartic: Bachelors, Graduate, Or Professional Degree |  |  |  |  |  |  | -0.219 -0.192 | 0.172 -0.006 0.388 0.081 |
| PSCHSCLN | T: Linear: Percent Some College And No Degree | 0.548 |  |  |  | -0.093 |  |  |  |
| PSCHSCQU | T: Quadratic: Percent Some College And No Degree | -0.093 |  |  |  | 0.180 |  |  |  |
| PSCHSCCU | T: Cubic: Percent Some College And No Degree |  |  |  |  | -0.177 |  |  |  |
| IHISP80 <br> IHISP81 | Hispanic Interaction Of PSCHSCLN Hispanic Interaction Of PSCHSCQU | $\begin{array}{r} -0.393 \\ 0.491 \end{array}$ |  |  |  |  |  |  |  |
| PPOVERLN | T: Linear: Percent Families Below Poverty Level | -0.246 |  |  |  | 0.255 |  |  |  |
| PPOVERQU | T: Quadratic: Percent Families Below Poverty Level | -0.410 |  |  |  | -0.247 |  |  |  |
| PPOVERCU | T: Cubic: Percent Families Below Poverty Level |  |  |  |  | -0.473 |  |  |  |
| PPUBASLN | T: Linear: Percent Households With Public Assist Income |  | -0.549 |  |  |  | 0.317 |  |  |
| PPUBASQU PPUBASCU | T: Quadratic: Percent Households With Public Assist Income T: Cubic: Percent Households With Public Assist Income |  | 0.118 0.288 |  |  |  | 0.185 |  |  |
| $\begin{aligned} & \text { IHISP90 } \\ & \text { IHISP91 } \end{aligned}$ | Hispanic Interaction Of PPUBASLN Hispanic Interaction Of PPUBASQU |  | 0.603 |  |  |  | $\begin{aligned} & -0.253 \\ & -0.712 \end{aligned}$ |  |  |
| PBLACKLN <br> PBLACKQU | T: Linear: Percent Black Nonhispanic <br> T: Quadratic: Percent Black Nonhispanic |  |  |  |  |  |  |  | $\begin{aligned} & -0.066 \\ & -0.303 \end{aligned}$ |
| POTHLN <br> POTHOU | T: Linear: Percent Other Race/Hispanicity T: Quadratic: Percent Other Race/Hispanicity |  |  |  |  |  | 0.062 -0.087 |  |  |
| POTHCU | T: Cubic: Percent Other Race/Hispanicity |  |  |  |  |  | -0.235 |  |  |
| IFEM110 | Female Interaction Of POTHLN |  |  |  |  |  | 0.249 |  |  |
| IFEM111 | Female Interaction Of POTHQU |  |  |  |  |  | 0.146 |  |  |
| IFEM112 | Female Interaction Of POTHCU |  |  |  |  |  | 0.689 |  |  |
| PFNEVLN | T: Linear: Percent Females Never Married |  |  |  |  |  | 0.632 |  |  |
| PMNEVLN PMNEVOU | T: Linear: Percent Males Never Married T: Quadratic: Percent Males Never Married |  | 0.407 |  | -0.026 |  | -0.566 -0.213 |  | 0.288 0.037 |
| PMNEVCU | T: Cubic: Percent Males Never Married |  |  |  |  |  | 0.162 |  | -0.329 |
| IBLK140 | Black Interaction Of PMNEVLN |  |  |  |  |  | 0.028 |  | 0.120 |
| IBLK141 IBLK142 | Black Interaction Of PMNEVQU Black Interaction Of PMNEVCU |  |  |  |  |  | 0.135 -0.758 |  | -0.126 0.873 |
| IHISP140 | Hispanic Interaction Of PMNEVLN |  | -0.737 |  | -0.815 |  | -0.633 |  | -1.569 |
| PMLABLN | T: Linear: Percent Males $16+$ Years Old In Labor Force |  |  |  | -0.011 | -0.003 |  |  | 0.355 |
| PMLABQU | T: Quadratic: Percent Males $16+$ Years Old In Labor Force |  |  |  | 0.209 | 0.053 |  |  | 0.060 |
| PMLABCU PMLABQR | T: Cubic: Percent Males 16+ Years Old In Labor Force T: Quartic: Percent Males 16+ Years Old ln Labor Force |  |  |  |  | $\begin{array}{r} 0.038 \\ -0.108 \end{array}$ |  |  | 0.033 |
| IFEM145 | Female Interaction Of PMLABLN |  |  |  | 0.336 |  |  |  | -0.023 |
| IFEM146 | Female Interaction Of PMLABQU |  |  |  | -0.559 |  |  |  | 0.248 |
| IFEM147 | Female Interaction Of PMLABCU |  |  |  |  |  |  |  | 0.920 |
| POLDHULN | T: Linear: Percent Housing Units Built 1939 Or Earlier |  |  |  | 0.230 | 0.133 |  |  |  |
| POLDHUQU POLDHUCU | T: Quadratic: Percent Housing Units Built 1939 Or Earlier T: Cubic: Percent Housing Units Built 1939 Or Earlier |  |  |  |  | $\begin{aligned} & -0.229 \\ & -0.156 \end{aligned}$ |  |  |  |
| IFEM155 | Female Interaction Of POLDHULN |  |  |  | -0.578 | $-0.255$ |  |  |  |
| IFEM156 | Female Interaction Of POLDHUQU |  |  |  |  | 0.317 |  |  |  |
| IFEM157 | Female Interaction Of POLDHUCU |  |  |  |  | 0.480 |  |  |  |
| P40HULN | T: Linear: Percent Housing Units Built 1940-1949 |  |  |  |  |  |  |  | 0.320 |
| ADRATILN | C: Linear: Death Rate With Explicit Mention Of Alcohol |  |  | 0.026 -0.078 |  |  | -0.371 -0.360 |  |  |
| ADRATIQU ADRATICU | C: Quadratic: Death Rate With Explicit Mention Of Alcohol C: Cubic: Death Rate With Explicit Mention Of Alcohol |  |  | -0.078 0.134 -0.05 |  |  | $\begin{gathered} -0.360 \\ -0.551 \end{gathered}$ |  |  |
| ADRATIQR | C: Quartic: Death Rate With Explicit Mention Of Alcohol |  |  | -0.095 |  |  |  |  |  |
| $\begin{aligned} & \text { V18FLN } \\ & \text { V18FQU } \end{aligned}$ | C: Linear: Marijuana Posession Arrest Rate <br> C: Quadratic: Marijuana Posession Arrest Rate |  |  |  |  |  | $\begin{aligned} & -0.416 \\ & -0.311 \end{aligned}$ |  |  |
| $\begin{aligned} & \text { IBLKI85 } \\ & \text { IBLK186 } \end{aligned}$ | Black Interaction Of VI8FLN Black Interaction Of V18FQU |  |  |  |  |  | 0.381 0.519 |  |  |



| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| BINDIALN | B: Linear: Percent Pop: American Indian, Eskimo, Aleut |  |  | 0.045 | U.001 |  |  | -0.105 | 0.624 |
| BINDIAQU | B: Quadratic: Percent Pop: American Indian, Eskimo, Aleut |  |  | -0.052 | -0.167 |  |  | -0.155 | -0.291 |
| BINDIACU | B: Cubic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  | -0.112 |  |  |  | 0.509 |
| BINDIAQR | B: Quartic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  | -0.123 |  |  |  |  |
| IHISP300 | Hispanic Interaction Of BINDIALN |  |  | $0.070$ |  |  |  |  |  |
| IHISP301 | Hispanic Interaction Of BINDIAQU |  |  | $0.395$ |  |  |  | $0.614$ |  |
| BMNOTLN | B: Linear: Percent Males Separated, Divorced or Widowed | 0.082 |  |  |  | -0.041 |  |  |  |
| BMNOTQU | B: Quadratic: Percent Males Separated, Divorced or Widowed | -0.209 |  |  |  | -0.175 |  |  |  |
| BMNOTCU | B: Cubic: Percent Males Separated, Divorced or Widowed |  |  |  |  | 0.221 |  |  |  |
| BMNOTQR | B: Quartic: Percent Males Separated, Divorced or Widowed |  |  |  |  | -0.078 |  |  |  |
| IFEM305 | Female Interaction Of BMNOTLN | -0.304 |  |  |  | 0.115 |  |  |  |
| IFEM306 | Female Interaction Of BMNOTQU | 0.447 |  |  |  | 0.231 |  |  |  |
| IFEM307 | Female Interaction Of BMNOTCU |  |  |  |  | -0.008 |  |  |  |
| IFEM308 | Female Interaction Of BMNOTQR |  |  |  |  | 0.219 |  |  |  |
| BPOVERLN | B: Linear: Percent Families Below Poverty Level | 0.209 |  |  |  |  |  | 0.049 |  |
| BPOVERQU | B: Quadratic: Percent Families Below Poverty Level | 0.070 |  |  |  |  |  | $-0.024$ |  |
| BPOVERCU | B: Cubic: Percent Families Below Poverty Level | -0.022 |  |  |  |  |  |  |  |
| BPOVERQR | B: Quartic: Percent Families Below Poverty Level | -0.088 |  |  |  |  |  |  |  |
| BPRICALN | B: Linear: Percent Hispanics: Puerto Rican |  |  |  |  |  |  |  | 0.100 |
| BPRICAQU | B: Quadratic: Percent Hispanics: Puerto Rican |  |  |  |  |  |  | 0.098 |  |
| BPRICACU | B: Cubic: Percent Hispanics: Puerto Rican |  |  |  |  |  |  | -0.171 |  |
| BPRICAQR | B: Quartic: Percent Hispanics: Puerto Rican |  |  |  |  |  |  | -0.082 |  |
| IHISP315 | Hispanic Interaction Of BPRICALN |  |  |  |  |  |  | 0.033 | -0.866 |
| IHISP316 | Hispanic Interaction Of BPRICAQU |  |  |  |  |  |  | -0.564 |  |
| IHISP317 | Hispanic Interaction Of BPRICACU |  |  |  |  |  |  | 0.464 |  |
| IHISP318 | Hispanic Interaction Of BPRICAQR |  |  |  |  |  |  | 0.201 |  |
| BSCHASLN | B: Linear: Percent Associates Degree |  |  |  | 0.214 |  |  |  | 0.046 |
| BSCHASQU | B: Quadratic: Percent Associates Degree |  |  |  | -0.082 |  |  |  | 0.324 |
| BSCHASCU | B: Cubic: Percent Associates Degree |  |  |  | -0.092 |  |  |  | -0.289 |
| BSCHASQR | B: Quartic: Percent Associates Degree |  |  |  | 0.090 |  |  |  | -0.143 |
| IBLK320 | Black Interaction Of BSCHASLN |  |  |  | -1.164 |  |  |  | -0.180 |
| IBLK321 | Black Interaction Of BSCHASQU |  |  |  |  |  |  |  | -1.163 |
| PASIANLN | T: Linear: Percent Population: Asian, Pacific Islander |  |  |  | 0.284 |  |  | -0.276 | -0.328 |
| PASIANQU | T: Quadratic: Percent Population: Asian, Pacific Islander |  |  |  |  |  |  | -0.235 | -0.431 |
| PASIANCU | T: Cubic: Percent Population: Asian, Pacific Islander |  |  |  |  |  |  |  | -0.076 |
| PASIANQR | T: Quartic: Percent Population: Asian, Pacific Islander |  |  |  |  |  |  |  | 0.140 |
| IFEM325 | Female Interaction Of PASIANLN |  |  |  | -0.664 |  |  | 0.372 | 0.856 |
| IFEM326 | Female Interaction Of PASIANQU |  |  |  |  |  |  | 0.455 |  |
| IHISP325 | Hispanic Interaction Of PASIANLN |  |  |  |  |  |  | 0.625 |  |
| PCUBANLN | T: Linear: Percent Hispanics: Cuban |  |  |  |  |  | 0.068 | 0.426 |  |
| PCUBANQU | T: Quadratic: Percent Hispanics: Cuban |  |  |  |  |  | 0.395 | 0.195 |  |
| PCUBANCU | T: Cubic: Percent Hispanics: Cuban |  |  |  |  |  | -0.119 | -0.068 |  |
| PCUBANQR | T: Quartic: Percent Hispanics: Cuban |  |  |  |  |  | -0.102 | 0.135 |  |
| IFEM330 | Female Interaction Of PCUBANLN |  |  |  |  |  | -0.160 |  |  |
| IFEM331 | Female Interaction Of PCUBANQU |  |  |  |  |  | -0.334 |  |  |
| IFEM332 | Female Interaction Of PCUBANCU |  |  |  |  |  | -0.150 |  |  |
| IFEM333 | Female Interaction Of PCUBANQR |  |  |  |  |  | 0.236 |  |  |
| IBLK330 | Black Interaction Of PCUBANLN |  |  |  |  |  |  | -0.435 |  |
| PINDIALN | T: Linear: Percent Pop: American Indian, Eskimo, Aleut |  |  | 0.173 |  |  |  | 0.213 |  |
| PINDIAQU | T: Quadratic: Percent Pop: American Indian, Eskimo, Aleut |  |  | 0.100 |  |  |  |  |  |
| PINDIACU | T: Cubic: Percent Pop: American Indian, Eskimo, Aleut |  |  | -0.228 |  |  |  |  |  |
| PINDIAQK | 1: Quartic: Percent Pop: American Indian, Eskımo, Aleut |  |  | 0.121 |  |  |  |  |  |

E7. Coefficients of Model Parameters for Past Year Illicit Drug Use Treatment

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | $35+$ |
| DUMMY | O: Intercept Term | -5.043 | -4.773 | -4.581 | -6.415 | -5.359 | -4.595 | -4.979 | -7.462 |
| FEMALE | O : Female Indicator | 0.860 | -0.370 | -0.419 | -0.020 | 0.745 | -0.472 | -0.527 | -1.312 |
| FEMBLCK | O: Black Interaction Of FEMALE | 0.387 | 0.089 | -0.072 | -1.335 | -3.185 | -0.594 | -0.410 | 0.329 |
| FEMHISP | O: Hispanic Interaction Of FEMALE | -1.317 | -1.305 | $-0.844$ | $-0.362$ | -0.910 | $-0.367$ | -0.679 | -0.798 |
| FEMOTHR | O: Other Interaction Of FEMALE |  |  |  |  |  |  | -1.065 |  |
| RACEBLCK | O: Race/Black Indicator | $-3.492$ | -0.534 | 0.334 | 1.470 | -0.932 | -1.037 | 0.498 | 0.976 |
| RACEHISP <br> RACEOTHR | O: Race/Hispanic Indicator O: Race/Other Indicator | 0.091 | -0.029 -1.761 | -2.206 | -0.778 | $\begin{aligned} & -0.163 \\ & -2.205 \end{aligned}$ | -1.958 | $\begin{array}{r} -0.944 \\ 0.171 \end{array}$ | 0.648 1.545 |
| REGNOREA <br> REGSOUTH | O: Northeast Region Indicator O: South Region Indicator |  |  |  |  | $\begin{aligned} & -1.227 \\ & -0.207 \end{aligned}$ |  |  |  |
| $\begin{aligned} & \text { IHISP7 } \\ & \text { IHISP8 } \\ & \text { IHISP9 } \end{aligned}$ | Hispanic Interaction Of REGNOREA Hispanic Interaction Of REGSSOUTH Hispanic Interaction Of REGWEST |  |  | $\begin{aligned} & 2.957 \\ & 2.157 \\ & 1.724 \end{aligned}$ |  |  |  |  |  |
| PHHIPLN | T: Linear: Percent One Person Households |  |  |  |  |  |  | 0.262 | 0.202 |
| PHH1PQU | T: Quadratic: Percent One Person Households |  |  |  |  |  |  | 0.149 | -0.042 |
| PHHIPCU PHHIPQR | T: Cubic: Percent One Person Households |  |  |  |  |  |  | -0.118 0.085 | -0.090 -0.098 |
| POPRMLN | T: Linear: Average Persons Per Room |  |  |  |  |  |  | 0.347 |  |
| PAGE34LN | T: Linear: Percent Persons 25-34 Years |  |  |  |  | -0.111 |  |  |  |
| IFEM35 | Female Interaction Of PAGE34LN |  |  |  |  | 0.661 |  |  |  |
| PSCHI2LN <br> PSCHI2QU | I: Linear: Percent 9-12 Years \& No High School Diploma <br> T: Quadratic: Percent 9-12 Years \& No High School Diploma |  |  |  | -0.670 |  |  |  | -0.233 0.284 |
| PSCHSCLN PSCHSCQU | T: Linear: Percent Some College And No Degree T: Quadratic: Percent Some College And No Degree |  | 0.294 -0.123 |  |  |  | -0.152 -0.147 |  | 0.320 -0.381 |
| IFEM80 | Female Interaction Of PSCHSCLN |  | -0.355 |  |  |  |  |  | -0.277 |
| 1FEM81 | Female Interaction Of PSCHSCQU |  | 0.327 |  |  |  |  |  | 0.521 |
| $\begin{aligned} & \text { IHISP80 } \\ & \text { IHISP8 } \end{aligned}$ | Hispanic Interaction Of PSCHSCLN Hispanic Interaction Of PSCHSCQU |  |  |  |  |  | $\begin{aligned} & 0.381 \\ & 0.658 \end{aligned}$ |  |  |
| PPOVERLN | T: Linear: Percent Families Below Poverty Level |  |  |  | 0.807 |  |  |  | 0.806 |
| PBLACKLN <br> PBLACKQU | T: Linear: Percent Black Nonhispanic <br> T: Quadratic: Percent Black Nonhispanic |  |  |  |  |  |  | -0.214 -0.170 |  |
| PHISPLN | T: Linear: Percent Hispanic |  |  | 0.003 |  |  |  | 0.037 |  |
| PHISPQU | T: Quadratic: Percent Hispanic |  |  | 0.116 |  |  |  | 0.173 |  |
| PHISPCU | T: Cubic: Percent Hispanic |  |  | -0.172 |  |  |  | 0.241 |  |
| PHISPQR | T: Quartic: Percent Hispanic |  |  | 0.062 |  |  |  | 0.058 |  |
| POTHLN | T: Linear: Percent Other Race/Hispanicity |  |  |  |  |  | -0.075 |  |  |
| POTHQU | T: Quadratic: Percent Other Race/Hispanicity |  |  |  |  |  | -0.042 |  |  |
| POTHCU | T: Cubic: Percent Other Race/Hispanicity |  |  |  |  |  | -0.165 |  |  |
| IHISP110 | Hispanic Interaction Of POTHLN |  |  |  |  |  | -0.156 |  |  |
| IHISP111 | Hispanic Interaction Of POTHQU |  |  |  |  |  | 0.614 |  |  |
| IHISP112 | Hispanic Interaction Of POTHCU |  |  |  |  |  | 0.498 |  |  |
| PHHF18LN | T: Linear: \% Female-Headed HH W/No Spouse \& Chid Under 18 |  |  |  |  | 0.136 |  |  |  |
| PHHF18QU | T: Quadratic: \% Female-Headed HH W/No Spouse \& Chld Under 18 |  |  |  |  | -0.035 |  |  |  |
| PHHF18CU | T: Cubic: \% Female-Headed HH W/No Spouse \& Chld Under 18 |  |  |  |  | -0.150 |  |  |  |
| PHHF18QR | T: Quartic: \% Female-Headed HH W/No Spouse \& Chld Under 18 |  |  |  |  | -0.105 |  |  |  |
| PFLABLN | T: Linear: Percent Females 16+ Years Old In Labor Force | 0.029 |  |  |  | -0.196 |  |  |  |
| PFLABQU | T: Quadratic: Percent Females 16+ Years Old In Labor Force | $-0.204$ |  |  |  | 0.050 |  |  |  |
| PFLABCU | T: Cubic: Percent Females 16+ Years Old In Labor Force |  |  |  |  | 0.027 |  |  |  |
| PFLABQR | T: Quartic: Percent Females 16+ Years Old In Labor Force |  |  |  |  | 0.140 |  |  |  |
| PFNEVLN | T: Linear: Percent Females Never Married |  |  | 0.203 |  |  |  | -0.032 |  |
| PFNEVQU | T: Quadratic: Percent Females Never Married |  |  |  |  |  |  | 0.074 |  |
| PFNEVCU | T: Cubic: Percent Females Never Married |  |  |  |  |  |  | $-0.052$ |  |
| PFNEVQR | T: Quartic: Percent Females Never Married |  |  |  |  |  |  | -0.089 |  |
| PMNEVLN | T: Linear: Percent Males Never Married |  |  |  |  |  | 0.263 |  | 0.115 |
| PMNEVQU | T: Quadratic: Percent Males Never Married |  |  |  |  |  |  |  | 0.354 |
| IBLK140 | Black Interaction Of PMNEVLN |  |  |  |  |  | -0.707 |  |  |
| PMLABLN | T: Linear: Percent Males 16+ Years Old In Labor Force |  |  |  |  |  |  |  | 0.075 |
| PMLABQU | T: Quadratic: Percent Males $16+$ Years Old In Labor Force |  |  |  |  |  |  |  | 0.042 |
| PMLABCU PMLABQR | T: Cubic: Percent Males 16+ Years Old In Labor Force T: Quartic: Percent Males 16+ Years Old In Labor Force |  |  |  |  |  |  |  | -0.091 -0.0136 |
| ADRATELN | C: Linear: Death Rate For All Alcohol-Related Cases |  |  |  |  |  | -0.032 |  |  |
| ADRATEQU | C: Quadratic: Death Rate For All Alcohol-Related Cases |  |  |  |  |  | 0.245 |  |  |
| VIBFLN | C: Linear: Marijuana Posession Arrest Rate |  |  |  | -0.856 |  | 0.072 |  | -0.829 |
| V18FQU | C: Quadratic: Marijuana Posession Arrest Rate |  |  |  |  |  | 0.159 |  | -0.304 |
| V18FCU | C: Cubic: Marijuana Posession Arrest Rate |  |  |  |  |  | -0.088 |  | -0.300 |
| V18FQR | C: Quartic: Marijuana Posession Arrest Rate |  |  |  |  |  | -0.081 |  |  |
| IHISP185 | Hispanic Interaction Of V18FLN |  |  |  |  |  |  |  |  |
| IHISP186 | Hispanic Interaction Of V18FQU |  |  |  |  |  |  |  | 0.108 |
| IHISP187 | Hispanic Interaction Of V18FCU |  |  |  |  |  |  |  | 0.932 |
| V18BLN | C: Linear: Mariiuana Sale/Manutacture Arrest Rate |  | 0.239 |  |  |  | $-0.484$ |  |  |
| V18BQU | C: Quadratic: Marijuana Sale/Manufacture Arrest Rate |  |  |  |  |  | -0.322 |  |  |
| IBLK190 IBLK191 | Black Interaction Of V18BLN <br> Black Interaction Of V18BQU |  |  |  |  |  | $\begin{array}{r} -0.003 \\ 0.491 \end{array}$ |  |  |
| IHISP190 | Hispanic Interaction OfVI8BLN |  | -0.724 |  |  |  | 0.426 |  |  |
| IHISP191 | Hispanic Interaction Of V 18 BQQU |  |  |  |  |  | 0.590 |  |  |


| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | $35+$ | 12-17 | 18-25 | 26-34 | $35+$ |
| vireln | C: Linear: Upium/Cocane \& Deriv Posession Arrest Kate |  |  |  |  |  | u.s8u |  |  |
| V18LN | C: Linear: Total Drug Abuse Violations Arrest Rate |  |  |  | 0.774 |  |  |  | 0.484 |
| ARATELN | C: Linear: Mean A-Only Client Treatment Rate 1991 \& 1992 | -0.158 |  |  |  |  |  |  |  |
| ARATEQU | C: Quadratic: Mean A-Only Client Treatment Rate 1991 \& 1992 | 0.207 |  |  |  |  |  |  |  |
| ARATECU | C: Cubic: Mean A-Only Client Treatment Rate 1991 \& 1992 | -0.332 |  |  |  |  |  |  |  |
| B64DISLN | B: Linear: Percent Persons 16-64 With A Work Disability |  |  | 0.182 | 0.022 |  |  | 0.484 |  |
| B64DISQU | B: Quadratic: Percent Persons 16-64 With A Work Disability |  |  | 0.047 | 0.358 |  |  | -0.135 |  |
| B64DISCU | B: Cubic: Percent Persons 16-64 With A Work Disability |  |  | 0.015 |  |  |  | 0.009 |  |
| B64DISQR | B: Quartic: Percent Persons 16-64 With A Work Disability |  |  | 0.065 |  |  |  | -0.057 |  |
| IHISP260 | Hispanic Interaction Of B64DISLN |  |  |  |  |  |  | -0.142 |  |
| IHISP261 | Hispanic Interaction Of B64DISQU |  |  |  |  |  |  | 0.099 |  |
| IHISP262 | Hispanic Interaction Of B64DISCU |  |  |  |  |  |  | 0.681 |  |
| 1HISP263 | Hispanic Interaction Of B64DISQR |  |  |  |  |  |  | 0.183 |  |
| BAGE34LN | B: Linear: Percent Persons 25-34 Years |  |  |  |  | -0.080 |  |  |  |
| BAGE34QU | B: Quadratic: Percent Persons $25-34$ Years |  |  |  |  | -0.021 -0.007 |  |  |  |
| BAGE34CU | B: Cubic: Percent Persons 25-34 Years |  |  |  |  |  |  |  |  |
| BAGE44LN | B: Linear: Percent Persons 35-44 Years |  |  | -0.119 |  | ${ }^{-0.074}$ | 0.063 | ${ }^{-0.014}$ | 0.135 |
| BAGE44QU | B: Quadratic: Percent Persons 35-44 Years |  |  | 0.015 |  | -0.037 | 0.030 | -0.080 | -0.189 |
| BAGE44CU | B: Cubic: Percent Persons 35-44 Years |  |  | 0.159 |  | 0.196 | $-0.085$ | -0.109 | 0.473 |
| BAGE44QR | B: Quartic: Percent Persons 35-44 Years |  |  |  |  |  | $-0.044$ | 0.062 |  |
| IFEM270 | Female Interaction Of BAGE44LN |  |  |  |  |  | -0.008 |  |  |
| IFEM271 | Female Interaction Of BAGE44QU |  |  |  |  |  | -0.115 |  |  |
| LFEM272 | Female Interaction Of BAGE44CU |  |  |  |  |  | 0.381 0.117 |  |  |
| IFEM273 | Female Interaction Of BAGE44QR |  |  |  |  |  | 0.117 |  |  |
| BAGE54LN | B: Linear: Percent Persons 45-54 Years | -0.233 |  |  |  | 0.193 | 0.207 |  |  |
| IFEM275 | Female Interaction Of BAGE54LN |  |  |  |  |  | -0.499 |  |  |
| IBLK275 | Black Interaction Of BAGE54LN | 1.518 |  |  |  |  |  |  |  |
| BASIANLN | B: Linear: Percent Population: Asian, Pacific Islander |  | -0.269 | 0.288 |  |  | -0.235 |  |  |
| BASIANQU | B: Quadratic: Percent Population: Asian, Pacitic Islander |  |  | -0.202 |  |  | 0.039 |  |  |
| BASIANCU | B: Cubic: Percent Population: Asian, Pacitic Islander |  |  |  |  |  | -0.092 |  |  |
| BASIANQR | B: Quartic: Percent Population: Asian, Pacitic Islander |  |  |  |  |  | -0.045 |  |  |
| IFEM285 | Female Interaction Of BASIANLN |  |  |  |  |  | 0.226 |  |  |
| IFEM286 | Female Interaction Of BASIANQU |  |  |  |  |  | -0.276 |  |  |
| IFEM287 | Female Interaction Of BASIANCU |  |  |  |  |  | 0.077 |  |  |
| IFEM288 | Female Interaction Of BASIANQR |  |  |  |  |  | 0.201 |  |  |
| IBLK285 | Black Interaction Of BASIANLN |  | 0.470 |  |  |  | 1.131 |  |  |
| BCUBANLN | B: Linear: Percent Hispanics: Cuban | 0.419 |  |  |  |  | $-0.352$ |  |  |
| BCUBANQU | B: Quadratic: Percent Hispanics: Cuban | -0.071 |  |  |  |  | -0.140 |  |  |
| BCUBANCU | B: Cubic: Percent Hispanics: Cuban | 0.479 |  |  |  |  |  |  |  |
| IFEM290 | Female Interaction Of BCUBANLN |  |  |  |  |  | -0.175 |  |  |
| IFEM291 | Female Interaction Of BCUBANQU |  |  |  |  |  | 0.568 |  |  |
| IBLK290 | Black Interaction Of BCUBANLN | -1.371 |  |  |  |  |  |  |  |
| BFNOTLN | B: Linear: Percent Females Separated, Divorced or Widowed |  |  |  |  | 0.318 | 0.095 | -0.187 | $-0.325$ |
| BFNOTQU | B: Quadratic: Percent Females Separated, Divorced or Widowed |  |  |  |  |  | 0.009 | -0.019 | 0.216 |
| BFNOTCU | B: Cubic: Percent Females Separated, Divorced or Widowed |  |  |  |  |  | 0.211 | $0.057$ |  |
| BFNOTQR | B: Quartic: Percent Females Separated, Divorced or Widowed |  |  |  |  |  | 0.072 |  |  |
| IFEM295 | Female Interaction Of BFNOTLN |  |  |  |  | -0.419 |  |  | 0.193 |
| IFEM296 | Female Interaction Of BFNOTQU |  |  |  |  |  |  |  | -0.818 |
| IBLK295 | Black Interaction Of BFNOTLN |  |  |  |  |  | -0.107 |  |  |
| 1BLK297 | Black Interaction Of BFNOTCU |  |  |  |  |  | -0.225 |  |  |
| IBLK298 | Black Interaction Of BFNOTQR |  |  |  |  |  | -0.189 |  |  |
| BINDIALN | B: Linear: Percent Pop: American Indian, Eskimo, Aleut |  | 0.010 |  | -0.569 |  | 0.358 |  | 0.304 |
| BINDIAQU | B: Quadratic: Percent Pop: American Indian, Eskimo, Aleut |  | 0.097 |  | -0.540 |  | -0.064 |  | 0.642 |
| BINDIACU | B: Cubic: Percent Pop: American Indian, Eskimo, Aleut |  | 0.258 |  | -0.557 |  | 0.294 |  | -1.237 |
| BINDIAQR | B: Quartic: Percent Pop: American Indian, Eskimo, Aleut |  | -0.092 |  |  |  | -0.103 |  | 0.308 |
| IBLK300 | Black Interaction Of BINDIALN |  | 0.487 |  | 0.668 |  | -0.004 |  | 0.253 |
| ${ }^{18 L K} 301$ | Black Interaction Of BINDIAQU |  | -0.122 |  | ${ }^{0.686}$ |  | 0.419 |  | -0.353 |
| 1BLK302 | Black Interaction Of BINDIACU |  | 0.226 |  | 1.054 |  | 0.085 |  | 0.879 |
| IBLK303 | Black Interaction Of BINDIAQR |  | 0.139 |  |  |  | 0.246 |  | -0.373 |
| BMNOTLN | B: Linear: Percent Males Separated, Divorced or Widowed |  |  |  |  |  |  |  | 0.460 |
| BPOVERLN | B: Linear: Percent families Below Poverty Level |  | 0.053 |  |  |  |  |  | -0.488 |
| BPOVERQU | B: Quadratic: Percent Families Below Poverty Level |  | 0.132 |  |  |  |  |  | -0.336 |
| IOTH311 | Other Interaction Of BPOVERQU |  | -0.470 |  |  |  |  |  |  |
| BPRICALN | B: Linear: Percent Hispanics: Puerto Rican |  | -0.354 |  |  |  | 0.251 |  | 0.530 |
| BPRICAQU | B: Quadratic: Percent Hispanics: Puerto Rican |  |  |  |  |  | 0.104 |  |  |
| IHISP315 | Hispanic Interaction Of BPRICALN |  |  |  |  |  | 0.588 |  |  |
| $1 \mathrm{HISP316}$ | Hispanic Interaction Of BPRICAQU |  |  |  |  |  | -1.177 |  |  |
| BSCHASLN | B: Linear: Percent Associates Degree |  |  |  |  |  |  | 0.148 |  |
| BSCHASQU | B: Quadratic: Percent Associates Degree |  |  |  |  |  |  | -0.063 |  |
| BSCHASCU | B: Cubic: Percent Associates Degree |  |  |  |  |  |  | 0.150 |  |
| IBLK320 | Black Interaction Of BSCHASLN |  |  |  |  |  |  |  |  |
| IBLK321 | Black Interaction Of BSCHASQU |  |  |  |  |  |  | $-0.272$ |  |
| IBLK322 | Black Interaction Of BSCHASCU |  |  |  |  |  |  | -0.648 |  |
| PASIANLN | T: Linear: Percent Population: Asian, Pacific Islander |  |  |  |  | 0.122 |  | 0.016 |  |
| PASIANQU | T: Quadratic: Percent Population: Asian, Pacitic Islander |  |  |  |  |  |  | 0.131 |  |
| PASIANCU | T: Cubic: Percent Population: Asian, Pacitic Islander |  |  |  |  |  |  | -0.037 0.0082 |  |
| PASIANQR | T: Quartic: Percent Population: Asian, Pacitic Islander |  |  |  |  |  |  |  |  |
| PCUBANLN | T: Linear: Percent Hispanics: Cuban |  |  |  |  |  | -0.011 |  |  |
| PCUBANQU | T: Quadratic: Percent Hispanics: Cuban |  |  |  |  |  | 0.169 |  |  |
| PCUBANCU | T: Cubic: Percent Hispanics: Cuban |  |  |  |  |  | 0.024 |  |  |
| PCUBANQR | T: Quartic: Percent Hispanics: Cuban |  |  |  |  |  | -0.083 |  |  |
| IFEM330 | Female Interaction Of PCUBANLN |  |  |  |  |  | 0.682 |  |  |


|  | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Variable |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| IFEMS51 | remale Interaction Ut PCUBANQU |  |  |  |  |  | -0.235 |  |  |
| 1FEM332 | Female Interaction Of PCUBANCU Female Interaction Of PCUBANQR |  |  |  |  |  | $\begin{array}{r} -0.096 \\ 0.242 \end{array}$ |  |  |
| PINDIALN | T: Linear: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  |  | 0.254 |  |
| PINDIAQU | T: Quadratic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  |  | -0.115 |  |
| PINDIACU | T: Cubic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  |  | 0.301 |  |
| IBLK335 | Black Interaction Of PINDIALN |  |  |  |  |  |  | -0.108 |  |
| ${ }_{\text {IRLK336 }}$ | Black Interaction Of PINDIAQU |  |  |  |  |  |  | 0.093 |  |
| 1BLK33' | Black interaction Ot PINDIACU |  |  |  |  |  |  | -0.494 |  |

E8. Coefficients of Model Parameters for Past Year Dependency on Alcohol Only



| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| BFNOTLN | B: Linear: Percent Females Separated, Divorced or Widowed |  |  |  |  |  |  | 0.074 | -0.227 |
| BFNOTQU | B: Quadratic: Percent Females Separated, Divorced or Widowed |  |  |  |  |  |  | -0.002 | -0.015 |
| IFEM295 | Female Interaction Of BFNOTLN |  |  |  |  |  |  |  | 0.097 |
| IFEM296 | Female Interaction Of BFNOTQU |  |  |  |  |  |  |  | 0.236 |
| IOTH295 | Other Interaction Of BFNOTLN |  |  |  |  |  |  | 0.417 |  |
| IOTH296 | Other Interaction Of BFNOTQU |  |  |  |  |  |  | 0.721 |  |
| BINDIALN | B: Linear: Percent Pop: American Indian, Eskimo, Aleut |  |  | -0.214 |  | -0.053 |  | -0.093 | 0.069 |
| BINDIAQU BINDIACU | B: Quadratic: Percent Pop: American Indian, Eskimo, Aleut B: Cubic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  |  | 0.048 0.087 | 0.220 |
| IBLK300 | Black Interaction Of BINDIALN |  |  | 0.418 |  | 0.916 |  | 0.122 |  |
| IBLK301 | Black Interaction Of BINDIAQU |  |  |  |  |  |  | -0.070 |  |
| 1BLK302 | Black Interaction Of BINDIACU |  |  |  |  |  |  | -0.442 |  |
| IHISP300 | Hispanic Interaction Of BINDIALN |  |  | 0.309 |  |  |  | 0.160 |  |
| IHISP301 | Hispanic Interaction Of BINDIAQU |  |  |  |  |  |  | -0.268 |  |
| BMNOTLN | B: Linear: Percent Males Separated, Divorced or Widowed |  |  | 0.085 | -0.075 | -0.043 | -0.052 | -0.053 | -0.059 |
| BMNOTQU | B: Quadratic: Percent Males Separated, Divorced or Widowed |  |  |  | 0.097 | 0.091 | 0.021 | -0.094 | -0.064 |
| BMNOTCU | B: Cubic: Percent Males Separated, Divorced or Widowed |  |  |  | -0.004 | 0.009 |  |  | -0.175 |
| BMNOTQR | B: Quartic: Percent Males Separated, Divorced or Widowed |  |  |  | -0.045 | -0.050 |  |  | 0.006 |
| IBLK305 | Black Interaction Of BMNOTLN |  |  |  | 0.200 |  |  |  | 0.644 |
| IBLK306 | Black Interaction Of BMNOTQU |  |  |  | -0.200 |  |  |  | 0.040 |
| 1BLK307 | Black Interaction Of BMNOTCU |  |  |  | 0.308 |  |  |  | 0.312 |
| IBLK308 | Black Interaction Of BMNOTQR |  |  |  |  |  |  |  | -0.183 |
| 1HISP305 | Hispanic Interaction Of BMNOTLN |  |  |  |  | 0.299 |  |  |  |
| IHISP306 | Hispanic Interaction Of BMNOTQU |  |  |  |  | -0.128 |  |  |  |
| IHISP307 | Hispanic Interaction Of BMNOTCU |  |  |  |  | -0.048 |  |  |  |
| IHISP308 | Hispanic Interaction Of BMNOTQR |  |  |  |  | 0.169 |  |  |  |
| BPOVERLN | B: Linear: Percent Families Below Poverty Level |  |  |  |  |  |  |  | 0.093 |
| BPOVERQU | B: Quadratic: Percent Families Below Poverty Level |  |  |  | -0.061 |  |  |  |  |
| BPOVERCU | B: Cubic: Percent Families Below Poverty Level |  |  |  | 0.118 |  |  |  |  |
| 1HISP310 | Hispanic Interaction Of BPOVERLN |  |  |  |  |  |  |  | 0.408 |
| BPRICALN | B: Linear: Percent Hispanics: Puerto Rican |  | -0.229 | 0.089 |  |  | -0.173 | -0.112 |  |
| BPRICAQU | B: Quadratic: Percent Hispanics: Puerto Rican |  |  | -0.040 |  |  |  | -0.060 |  |
| BPRICACU | B: Cubic: Percent Hispanics: Puerto Rican |  |  | -0.140 |  |  |  | -0.062 |  |
| BPRICAQR | B: Quartic: Percent Hispanics: Puerto Rican |  |  |  |  |  |  | -0.079 |  |
| IBLK315 | Black Interaction Of BPRICALN |  |  |  |  |  |  | -0.265 |  |
| 1BLK316 | Black Interaction Of BPRICAQU |  |  |  |  |  |  | 0.090 |  |
| 1BLK317 | Black Interaction Of BPRICACU |  |  |  |  |  |  | -0.070 |  |
| 1BLK318 | Black Interaction Of BPRICAQR |  |  |  |  |  |  | 0.192 |  |
| PASIANLN | T: Linear: Percent Population: Asian, Pacific Islander |  |  |  |  |  |  |  |  |
| PASIANQU | T: Quadratic: Percent Population: Asian, Pacitic Islander | 0.157 |  |  |  | 0.147 | -0.032 |  | -0.048 |
| PASIANCU | T: Cubic: Percent Population: Asian, Pacitic Islander | -0.145 |  |  |  | 0.075 | -0.076 |  | -0.204 |
| PASIANQR | T: Quartic: Percent Population: Asian, Pacitic Islander |  |  |  |  | -0.041 |  |  |  |
| IFEM325 | Female Interaction Of PASIANLN | -0.009 |  |  |  | -0.287 |  |  |  |
| IFEM326 | Female Interaction Of PASIANQU | -0.242 |  |  |  | -0.119 |  |  |  |
| IFEM327 | Female Interaction Of PASIANCU | 0.249 |  |  |  | 0.033 |  |  |  |
| IFEM328 | Female Interaction Of PASIANQR |  |  |  |  | 0.137 |  |  |  |
| IBLK325 | Black Interaction Of PASIANLN |  |  |  |  |  | 0.151 |  |  |
| IBLK326 | Black Interaction Of PASIANQU |  |  |  |  |  | 0.072 |  |  |
| 1BLK327 | Black Interaction Of PASIANCU |  |  |  |  |  | 0.415 |  |  |
| PCUBANLN | T: Linear: Percent Hispanics: Cuban | -0.057 | -0.185 |  | 0.036 | 0.032 | 0.069 |  | -0.142 |
| PCUBANQU | T: Quadratic: Percent Hispanics: Cuban |  |  |  | -0.065 |  | 0.006 |  | $-0.037$ |
| PCUBANCU | T: Cubic: Percent Hispanics: Cuban |  |  |  |  |  |  |  |  |
| IBLK330 | Black Interaction Of PCUBANLN | 0.519 |  |  | 0.197 | 0.696 |  |  |  |
| IBLK331 | Black Interaction Of PCUBANQU |  |  |  | 0.296 |  |  |  | $-0.301$ |
| 1BLK332 | Black Interaction Of PCUBANCU |  |  |  |  |  |  |  |  |
| 10TH330 | Other Interaction Of PCUBANLN |  |  |  |  |  | 0.535 |  |  |
| IOTH331 | Other Interaction Of PCUBANQU |  |  |  |  |  | 0.515 |  |  |
| PINDIALN | T: Linear: Percent Pop: American Indian, Eskimo, Aleut | 0.055 |  |  | -0.179 | -0.064 |  |  |  |
| PINDIAQU | T: Quadratic: Percent Pop: American Indian, Eskimo, Aleut | -0.062 |  |  | 0.114 | 0.159 |  |  |  |
| PINDIACU | T: Cubic: Percent Pop: American Indian, Eskimo, Aleut | 0.015 |  |  | -0.057 | 0.154 |  |  |  |
| PINDIAQR | T: Quartic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  | 0.042 |  |  |  |  |
| IFEM335 | Female Interaction Of PINDIALN | 0.134 |  |  |  | 0.007 |  |  |  |
| 1FEM336 | Female Interaction Of PINDIAQU | 0.168 |  |  |  | -0.264 |  |  |  |
| IFEM337 | Female Interaction Of PINDIACU | -0.275 |  |  |  | -0.319 |  |  |  |
| IHISP335 | Hispanic Interaction Of PINDIALN |  |  |  | 0.282 |  |  |  |  |
| IHISP336 | Hispanic Interaction Of PINDIAQU |  |  |  | -0.091 |  |  |  |  |
| IHISP337 | Hispanic Interaction Of PINDIACU |  |  |  | 0.151 |  |  |  |  |
| IHISP338 | Hispanic Interaction Of PINDIAQR |  |  |  | -0.115 |  |  |  |  |
| IOTH335 | Other Interaction OfPINDIALN |  |  |  | 0.359 |  |  |  |  |
| 101H336 | Uther Interaction Ut PINDIAQU |  |  |  | -0.98\% |  |  |  |  |

## E9. Coefficients of Model Parameters for Past Year Illicit Dependency

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| DUMMY | O : Intercept Term | -4.381 | -3.268 | -4.208 | -5.485 | -4.057 | -3.268 | -4.618 | -6.476 |
| female | O: Female Indicator | 0.449 | -0.684 | -0.706 | -0.607 | -0.320 | -0.878 | -0.774 | -0.071 |
| FEMBLCK | O: Black Interaction Of FEMALE | -0.149 | 0.076 | 0.230 | -0.177 | 0.859 | 0.533 | -0.178 | -0.466 |
| FEMHISP | O: Hispanic Interaction Of FEMALE | -0.388 | 0.306 | 0.913 | -0.262 | 0.637 | 0.240 | 0.094 | -0.306 |
| RACEBLCK RACEHISP | O: Race/Black Indicator | -1.289 0.150 | -0.503 <br> -1.149 | 0.181 -1.313 | 0.696 -0.980 | -1.851 -0.302 | -0.864 -0.585 | 0.220 -0.778 | 0.884 -0.234 |
| RACEHISP | O: Race/Other Indicator |  | -1.1719 |  |  |  | -0.585 -1.661 |  |  |
| Reginorea REGSOUTH | O: Northeast Region Indicator O: South Region Indicator |  |  |  |  |  |  | 0.349 0.286 |  |
| REGWEST | O: West Region Indicator |  |  |  |  |  |  | 0.840 |  |
| PHHIPLN | T: Linear: Percent One Person Households |  |  |  |  |  | 0.258 |  |  |
| POPRMLN | T: Linear: Average Persons Per Room |  |  | -0.156 |  |  |  | -0.232 |  |
| POPRMQU | T: Quadratic: Average Persons Per Room |  |  | $-0.130$ |  |  |  | 0.040 |  |
| POPRMCU POPRMQR | T: Cubic: Average Persons Per Room T: Quartic: Average Persons Per Room |  |  |  |  |  |  | 0.082 0.074 |  |
| PAGEI8LN | T: Linear: Percent Persons 0-18 Years |  | 0.051 |  |  |  | 0.248 |  |  |
| PAGE18QU | T: Quadratic: Percent Persons 0-18 Years |  | -0.067 |  |  |  | 0.108 |  |  |
| PAGE18CU | T: Cubic: Percent Persons 0-18 Years |  | -0.072 |  |  |  | 0.078 |  |  |
| PAGE18QR | T: Quartic: Percent Persons 0-18 Years |  | 0.044 |  |  |  | 0.067 |  |  |
| IFEM25 | Female Interaction Of PAGE18LN |  | -0.201 |  |  |  | -0.128 |  |  |
| ${ }^{\text {IFEM26 }}$ | Female Interaction Of PAGE18QU |  | 0.084 |  |  |  | 0.036 |  |  |
| IFEM28 | Female Interaction Of PAGE18CU Female Interaction Of PAGE18QR |  | 0.158 -0.135 |  |  |  | -0.085 -0.096 |  |  |
| PAGE34LN | T: Linear: Percent Persons 25-34 Years |  | 0.072 |  |  | -0.183 |  | 0.127 |  |
| PAGE34QU | T: Quadratic: Percent Persons 25-34 Years |  |  |  |  | -0.202 |  | -0.187 |  |
| IBLK35 | Black Interaction Of PAGE34LN |  |  |  |  |  |  | -0.691 |  |
| 1HISP35 | Hispanic Interaction Of PAGE34LN |  | -0.416 |  |  |  |  |  |  |
| PAGE44LN <br> PAGE44QU | T: Linear: Percent Persons 35-44 Years <br> T: Quadratic: Percent Persons 35-44 Years |  |  |  |  |  |  |  | 0.381 0.267 |
| PAGE54LN | T: Linear: Percent Persons 45-54 Years |  |  |  | -0.073 | 0.057 |  |  |  |
| PAGE54QU | T: Quadratic: Percent Persons 45-54 Years |  |  |  | 0.146 | 0.040 |  |  |  |
| PAGE54CU | T: Cubic: Percent Persons 45-54 Years |  |  |  | -0.299 | -0.158 |  |  |  |
| IHISP45 | Hispanic Interaction Of PAGE54LN |  |  |  | -0.761 |  |  |  |  |
| 1HISP46 | Hispanic Interaction Of PAGE54QU |  |  |  | -0.915 |  |  |  |  |
| PSCH12LN | T: Linear: Percent 9-12 Years \& No High School Diploma | -0.109 |  |  |  |  |  |  |  |
| PSCHI2QU | T: Quadratic: Percent 9-12 Years \& No High School Diploma | 0.111 |  |  |  |  |  |  |  |
| IFEM60 | Female Interaction Of PSCHI2LN | 0.011 |  |  |  |  |  |  |  |
| IFEM61 | Female Interaction Of PSCHI2QU | -0.248 |  |  |  |  |  |  |  |
| PPOVERLN | T: Linear: Percent Families Below Poverty Level |  |  |  | -0.112 |  |  |  |  |
| PPOVERQU | T: Quadratic: Percent Families Below Poverty Level |  |  |  | -0.011 |  |  |  |  |
| PPOVERCU | T: Cubic: Percent Families Below Poverty Level |  |  |  | -0.220 |  |  |  |  |
| PMNEVLN | T: Linear: Percent Males Never Married |  |  | 0.159 |  |  |  |  |  |
| PMNEVQU | T: Quadratic: Percent Males Never Married |  |  | -0.057 |  |  |  |  |  |
| PMNEVCU | T: Cubic: Percent Males Never Married |  |  | 0.141 |  |  |  |  |  |
| PMLABLN | T: Linear: Percent Males 16+ Years Old In Labor Force |  | 0.140 |  |  |  |  |  |  |
| PMLABQU | T: Quadratic: Percent Males $16+$ Years Old In Labor Force |  | -0.073 |  |  |  |  |  |  |
| PMLABCU | T: Cubic: Percent Males 16+ Years Old In Labor Force |  | 0.145 |  |  |  |  |  |  |
| IHISP145 | Hispanic Interaction Of PMLABLN |  | -0.275 |  |  |  |  |  |  |
| IHISP146 | Hispanic Interaction Of PMLABQU |  | -0.006 |  |  |  |  |  |  |
| 1HISP147 | Hispanic Interaction Of PMLABCU |  | -0.492 |  |  |  |  |  |  |
| PMNOTLN | T: Linear: Percent Males Separated, Divorced Or Widowed |  |  |  |  |  |  |  | 0.033 |
| PMNOTQU | T: Quadratic: Percent Males Separated, Divorced Or Widowed |  |  |  |  |  |  |  | 0.184 |
| PRENTLN | T: Linear: Percent Housing Rented |  |  |  |  |  |  | 0.178 | 0.617 |
| PRENTQU | T: Quadratic: Percent Housing Rented |  |  |  |  |  |  | 0.164 |  |
| ADRATELN | C: Linear: Death Rate For All Alcohol-Related Cases |  |  |  |  |  |  | 0.062 |  |
| ADRATEQU | C: Quadratic: Death Rate For All Alcohol-Related Cases |  |  |  |  |  |  | 0.193 |  |
| VI8FLN | C: Linear: Marijuana Posession Arrest Rate |  |  | -0.374 |  |  |  |  |  |
| V18ELN | C: Linear: Opium/Cocaine \& Deriv Posession Arrest Rate |  |  | 0.560 |  |  |  | -0.056 |  |
| V18EQU | C: Quadratic: Opium/Cocaine \& Deriv Posession Arrest Rate |  |  | -0.143 |  |  |  | -0.078 |  |
| V18ECU V18EQR | C: Cubic: Opium/Cocaine \& Deriv Posession Arrest Rate C: Quartic: Opium/Cocaine \& Deriv Posession Arrest Rate |  |  | 0.113 0.059 |  |  |  | -0.070 -0.068 |  |
| IHISP195 | Hispanic Interaction Of V18ELN |  |  | -0.211 |  |  |  |  |  |
| IHISP196 | Hispanic Interaction Of V18EQU |  |  | 0.098 |  |  |  |  |  |
| IHISP197 IHISP198 | Hispanic Interaction Of V18ECU Hispanic Interaction Of V 18EQR |  |  | -0.420 0.187 |  |  |  |  |  |
| V18LN | C: Linear: Total Drug Abuse Violations Arrest Rate C: Quadratic: Total Drug Abuse Violations Arrest Rate |  |  |  |  |  | $0.013$ |  |  |
| VIOLLN | C: Linear: Total Violent Offenses Arrest Rate |  |  |  |  |  |  |  |  |
| VIOLQU | C: Quadratic: Total Violent Offenses Arrest Rate |  |  |  |  |  |  |  | -0.238 |
| VIOLCU | C: Cubic: Total Violent Offenses Arrest Rate |  |  |  |  |  |  |  | -0.404 |
| RP80ALN | T: Linear: Recoded Median Household Income |  |  |  |  | -0.124 |  |  |  |
| RPPVAQU RP80ACU | T: Quadratic: Recoded Median Household Income T: Cubic: Recoded Median Household Income |  |  |  |  | 0.259 |  |  | $\begin{aligned} & -0.005 \\ & -0.234 \end{aligned}$ |
| IFEM250 | Female Interaction Of RP80ALN |  |  |  |  | -0.068 |  |  |  |
| IFEM251 | Female Interaction Of RP80AQU |  |  |  |  | -0.224 |  |  |  |
| ARATELN | C: Linear: Mean A-Only Client Treatment Rate 1991 \& 1992 |  |  |  |  |  | 0.118 |  |  |

NOTE:
T : Indicates a tract-level variable, C : Indicates a county-level variable, B : Indicates a block-level variable, O : Other


NOTE:
T : Indicates a tract-level variable, C : Indicates a county-level variable, B : Indicates a block-level variable, O : Other

|  | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Variable |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| IFEM330 | Female Interaction Of PCUBANLN | 0.333 |  |  |  |  |  |  |  |
| IBLK330 | Black Interaction Of PCUBANLN | 0.103 -0.800 |  |  |  |  |  |  | -0.102 <br> -0.366 |
| IBLK332 | Black Interaction Of PCUBANCU |  |  |  |  |  |  |  | -0.366 -0.242 |
| 1BLK333 | Black Interaction Of PCUBANQR |  |  |  |  |  |  |  | 0.480 |

E10. Coefficients of Model Parameters for Past Year Arrested

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| DUMMY | O: Intercept Term | -3.028 | -3.002 | -3.690 | -4.853 | -2.878 | -2.294 | -4.243 | -5.665 |
| FEMALE | O: Female Indicator | -1.145 | -1.322 | -0.960 | -1.385 | -1.128 | -1.634 | -1.813 | -2.582 |
| FEMBLCK | O: Black Interaction Of FEMALE | -0.180 | -0.571 | -0.083 | -1.057 | 0.256 | 0.361 | 0.296 | 0.692 |
| FEMHISP | O: Hispanic Interaction Of FEMALE | 0.260 | -1.209 | -0.578 | -0.624 | 0.246 | -0.382 | -0.074 | -1.022 |
| RACEBLCK | O: Race/Black Indicator | 0.228 | 0.537 | 0.299 | 0.410 | 0.136 | -0.746 | 0.333 | 0.006 |
| RACEHISP RACEOTHR | O: Race/Hispanic Indicator O: Race/Other Indicator | 0.185 -1.490 | 0.050 -1.138 | 0.249 | 0.099 | 0.369 -0.380 | -0.214 -0.543 | -0.315 | 0.722 |
| REGNOREA | O: Northeast Region Indicator |  |  |  |  | -0.208 |  |  | -1.114 |
| REGSOUTH | O: South Region Indicator |  |  |  |  | $-0.434$ |  |  | $-0.679$ |
| REGWEST | O: West Region Indicator |  |  |  |  | 0.193 |  |  | -0.372 |
| PDENLEV1 PDENLEV2 | O: Large MSA |  |  |  |  |  | -0.214 -0.162 | 0.594 |  |
| PDENLEV3 | O: Small MSA |  |  |  |  |  | -0.102 | 0.676 1.159 |  |
| PDENLEV4 | O: NonMSA, Urban |  |  |  |  |  | -0.154 | 1.026 |  |
| IBLK10 | Black Interaction Of PDENLEV1 Black Interaction Of PDENLEV2 |  |  |  |  |  | 0.515 0.547 |  |  |
| IBLK11 | Black Interaction Of PDENLEV2 Black Interaction Of PDENLEV3 |  |  |  |  |  | 0.547 1.799 |  |  |
| 1BLK13 | Black Interaction Of PDENLEV4 |  |  |  |  |  | 0.850 |  |  |
| PHHIPLN | T: Linear: Percent One Person Households |  | -0.106 |  |  |  | -0.088 |  |  |
| PHH1PQU | T: Quadratic: Percent One Person Households |  | 0.032 |  |  |  | 0.049 |  |  |
| PHH1PCU | T: Cubic: Percent One Person Households |  | -0.020 |  |  |  | -0.155 |  |  |
| PHHIPQR | T: Quartic: Percent One Person Households |  | -0.034 |  |  |  | -0.039 |  |  |
| IBLK15 | Black Interaction Of PHH1PLN |  | 0.016 |  |  |  | 0.232 |  |  |
| 1BLK16 | Black Interaction Of PHHIPQU |  | 0.009 |  |  |  | 0.043 |  |  |
| $1 \mathrm{BLK17}$ | Black Interaction Of PHHIPCU |  | 0.110 |  |  |  | 0.240 |  |  |
| 1BLK18 | Black Interaction Of PHHIPQR |  | 0.089 |  |  |  | 0.076 |  |  |
| POPRMLN | T: Linear: Average Persons Per Room |  | -0.053 |  |  |  | -0.143 |  |  |
| PAGE34LN | T: Linear: Percent Persons 25-34 Years |  |  |  |  |  |  |  | 0.501 |
| PAGE54LN | T: Linear: Percent Persons 45-54 Years |  |  |  |  |  |  | -0.063 |  |
| $\begin{aligned} & \text { PAGE54QU } \\ & \text { PAGE54CU } \end{aligned}$ | T: Quadratic: Percent Persons 45-54 Years T: Cubic: Percent Persons 45-54 Years |  |  |  |  |  |  | $\begin{array}{r} 0.045 \\ -0.257 \end{array}$ |  |
| 1HISP45 | Hispanic Interaction Of PAGE54LN |  |  |  |  |  |  | -0.196 |  |
| IHISP46 | Hispanic Interaction Of PAGE54QU |  |  |  |  |  |  | -0.221 |  |
| IHISP47 | Hispanic Interaction Of PAGE54CU |  |  |  |  |  |  | 0.396 |  |
| PAGE64LN | T: Linear: Percent Persons 55-64 Years |  |  |  |  | 0.205 |  |  |  |
| PSCH8LN | T: Linear: Percent 0-8 Years Of School | -0.100 |  |  |  |  |  |  |  |
| PSCH8QU | T: Quadratic: Percent 0-8 Years Of School | -0.017 |  |  |  |  |  |  |  |
| IOTH55 IOTH56 | Other Interaction Of PSCH8LN | -0.661 -0.773 |  |  |  |  |  |  |  |
| 10TH56 | Other Interaction Of PSCH8QU | -0.773 |  |  |  |  |  |  |  |
| PSCH12LN | T: Linear: Percent 9-12 Years \& No High School Diploma |  | 0.187 |  |  |  | 0.157 |  |  |
| PSCH12QU | T: Quadratic: Percent 9-12 Years \& No High School Diploma |  |  |  |  |  | 0.061 |  |  |
| PSCHI2CU | T: Cubic: Percent 9-12 Years \& No High School Diploma |  |  |  |  |  | -0.092 |  |  |
| IHISP60 | Hispanic Interaction Of PSCH12LN |  |  |  |  |  | -0.351 |  |  |
| PSCHCOLN | T: Linear: Bachelors, Graduate, Or Professional Degree |  |  |  |  |  |  |  | 0.222 |
| PSCHCOQU | T: Quadratic: Bachelors, Graduate, Or Protessional Degree |  |  |  |  |  |  |  | 0.027 |
| PSCHCOCU | T: Cubic: Bachelors, Graduate, Or Professional Degree |  |  |  |  |  |  |  | -0.315 |
| IBLK75 | Black Interaction Of PSCHCOLN |  |  |  |  |  |  |  | -0.227 |
| 1BLK76 | Black Interaction Of PSCHCOQU |  |  |  |  |  |  |  | 0.076 |
| 1BLK77 | Black Interaction Of PSCHCOCU |  |  |  |  |  |  |  | 0.608 |
| PPUBASLN | T: Linear: Percent Households With Public Assist Income |  |  |  |  |  | 0.199 |  |  |
| P64DISLN | T: Linear: Percent 16-64 With A Work Disability |  |  | 0.200 |  |  |  | 0.261 |  |
| PBLACKLN | T: Linear: Percent Black Nonhispanic |  | -0.070 |  |  |  |  |  |  |
| PBLACKQU | T: Quadratic: Percent Black Nonhispanic |  | -0.094 |  |  |  |  |  |  |
| POTHLN | T: Linear: Percent Other Race/Hispanicity |  |  |  | 0.071 |  |  |  |  |
| IHISP110 | Hispanic Interaction Of POTHLN |  |  |  | 0.287 |  |  |  |  |
| PFLABLN PFLABQU | I: Linear: Percent Females 16+ Years Old In Labor Force <br> T: Quadratic: Percent Females 16+ Years Old In Labor Force |  |  |  | 0.284 |  |  |  | $\begin{array}{r} 0.066 \\ -0.333 \end{array}$ |
| IFEM125 | Female Interaction Of PFLABLN |  |  |  | 0.444 |  |  |  |  |
| PFNOTLN PFNOTQU | T: Linear: Percent Females Separated, Divorced Or Widowed <br> T: Quadratic: Percent Females Separated, Divorced Or Widowed |  |  |  |  |  |  | $\begin{aligned} & 0.112 \\ & 0.169 \end{aligned}$ |  |
| PMLABLN <br> PMLABQU | T: Linear: Percent Males 16+ Years Old In Labor Force <br> T: Quadratic: Percent Males 16+ Years Old In Labor Force |  |  |  | -0.038 |  | $\begin{array}{r} 0.137 \\ -0.088 \end{array}$ |  | -0.424 |
| IFEM145 | Female Interaction Of PMLABLN |  |  |  | -0.636 |  |  |  |  |
| PMNOTLN | T: Linear: Percent Males Separated, Divorced Or Widowed |  |  |  |  |  | $-0.020$ |  |  |
| PMNOTQU | T: Quadratic: Percent Males Separated, Divorced Or Widowed |  |  |  |  |  | -0.052 |  |  |
| PMNOTCU | T: Cubic: Percent Males Separated, Divorced Or Widowed |  |  |  |  |  | -0.037 |  |  |
| PMNOTQR | T: Quartic: Percent Males Separated, Divorced Or Widowed |  |  |  |  |  | 0.040 |  |  |
| POLDHULN | T: Linear: Percent Housing Units Built 1939 Or Earlier | -0.145 |  |  |  |  |  |  |  |
| POLDHUQU | T: Quadratic: Percent Housing Units Built 1939 Or Earlier |  |  |  |  | -0.027 |  |  |  |
| POLDHUCU | T: Cubic: Percent Housing Units Built 1939 Or Earlier |  |  |  |  | -0.119 |  |  |  |
| P40HULN | T: Linear: Percent Housing Units Built 1940-1949 | 0.201 |  |  |  |  |  |  |  |
| P40HUQU | T: Quadratic: Percent Housing Units Built 1940-1949 |  |  |  |  |  |  | -0.152 |  |
| PRENTLN | T: Linear: Percent Housing Rented |  |  |  |  | 0.362 |  |  |  |

NOTE:
T : Indicates a tract-level variable, C : Indicates a county-level variable, B : Indicates a block-level variable, O : Other

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | $35+$ | 12-17 | 18-25 | 26-34 | $35+$ |
| ADKAIILN | C: Linear: Death Kate With Explicit Mention Ut Alconol |  | -0.012 | -0.190 |  |  |  |  |  |
| IFEM180 | Female Interaction Of ADRATILN |  | 0.434 |  |  |  |  |  |  |
| V18FLN V18FQU | C: Linear: Marijuana Posession Arrest Rate C: Quadratic: Mariiuana Posession Arrest Rate |  |  | -0.359 |  |  |  | $\begin{aligned} & -0.201 \\ & -0.136 \end{aligned}$ |  |
| VIBELN <br> VI8EQU | C: Linear: Opium/Cocaine \& Deriv Posession Arrest Rate C: Quadratic: Opium/Cocaine \& Deriv Posession Arrest Rate |  |  | 0.414 | $\begin{aligned} & 0.052 \\ & 0.218 \end{aligned}$ |  |  | 0.383 | $\begin{array}{r} -0.015 \\ 0.080 \end{array}$ |
| IFEM195 <br> IFEM196 | Female Interaction Of V18ELN Female Interaction Of V18EQU |  |  |  |  |  |  |  | $\begin{aligned} & -0.540 \\ & -0.968 \end{aligned}$ |
| VİALN | C: Linear: Opium/Cocaine \& Deriv Sale/Manuf Arrest Rate |  |  |  |  |  |  | -0.219 |  |
| DRATELN DRATEQU DRATECU | C: Linear: Mean Drug Client Treatment Rate 1991 \& 1992 C: Quadratic: Mean C: Cubic: Mean Drug Client Treatment Rate 1991 \& 1992 | -0.091 -0.005 0.146 |  |  |  |  |  |  |  |
| DRATECU | C: Cubic: Mean Drug Client Treatment Rate 1991 \& 1992 | 0.146 |  |  |  |  |  |  |  |
| RH43ALN | T: Linear: Recoded Median Rents For Rental Units |  |  |  | -0.254 |  |  | -0.055 | -0.700 |
| RH33AQU | T: Quadratic: Recoded Median Rents For Rental Units |  |  |  |  |  |  | -0.031 |  |
| RH43ACU RH43AQR | T: Cubic: Recoded Median Rents For Rental Units T: Quartic: Recoded Median Rents For Rental Units |  |  |  |  |  |  | 0.053 0.056 |  |
| RH61ALN | T: Linear: Recoded Median Value Of Owner Occupied HUs |  | -0.007 | -0.147 -0.100 |  |  | 0.059 | 0.029 -0.000 |  |
| RH61AQU RH61ACU | T: Quadratic: Recoded Median Value Of Owner Occupied HUs T: Cubic: Recoded Median Value Of Owner Occupied HUs |  |  | -0.100 |  |  | -0.061 -0.099 | -0.000 0.132 |  |
| IHISP245 | Hispanic Interaction Of RH61ALN |  |  |  |  |  |  | 0.155 |  |
| 1HISP246 | Hispanic Interaction Of RH61AQU |  |  |  |  |  |  | 0.166 |  |
| IHISP247 | Hispanic Interaction Of RH61ACU |  |  |  |  |  |  | -0.282 |  |
| ARATELN | C: Linear: Mean A-Only Client Treatment Rate 1991 \& 1992 |  |  |  |  |  |  |  | 0.010 |
| ARATEQU | C: Quadratic: Mean A-Only Client Treatment Rate 1991 \& 1992 |  |  |  |  |  |  |  | 0.050 |
| ARATECU ARATEQR | C: Cubic: Mean A-Only Client Treatment Rate 1991 \& 1992 C: Quartic: Mean A-Only Client Treatment Rate 1991 \& 1992 |  |  |  |  |  |  |  | -0.175 -0.036 |
| IBLK255 | Black Interaction Of ARATELN |  |  |  |  |  |  |  | -0.037 |
| 1BLK256 | Black Interaction Of ARATEQU |  |  |  |  |  |  |  | -0.264 -0.289 0 |
| IBLK257 | Black Interaction Of ARATECU |  |  |  |  |  |  |  | 0.089 |
| 1BLK258 | Black Interaction Of ARATEQR |  |  |  |  |  |  |  | 0.155 |
| B64DISLN | B: Linear: Percent Persons 16-64 With A Work Disability |  |  |  |  |  |  |  | 0.086 |
| B64DISQU | B: Quadratic: Percent Persons 16-64 With A Work Disability |  |  |  |  |  |  |  | 0.025 0.085 |
| B64DISCU | B: Cubic: Percent Persons 16-64 With A Work Disability |  |  |  |  |  |  |  | 0.085 |
| B64DISQR | B: Quartic: Percent Persons 16-64 With A Work Disability |  |  |  |  |  |  |  | -0.076 |
| BAGE34LN | B: Linear: Percent Persons 25-34 Y ears |  |  |  | 0.128 |  | -0.012 |  |  |
| BAGE34QU | B: Quadratic: Percent Persons 25-34 Years |  |  |  | 0.024 |  | 0.046 |  |  |
| BAGE34CU BAGE34QR | B: Cubic: Percent Persons 25-34 Years B: Quartic: Percent Persons 25-34 Years |  |  |  |  |  | 0.098 0.012 |  |  |
| IFEM265 | Female Interaction Of BAGE34LN |  |  |  |  |  | 0.114 |  |  |
| IFEM266 | Female Interaction Of BAGE34QU |  |  |  |  |  | -0.132 |  |  |
| IFEM267 | Female Interaction Of BAGE34CU |  |  |  |  |  | 0.001 |  |  |
| IFEM268 | Female Interaction Of BAGE34QR |  |  |  |  |  | -0.101 |  |  |
| IHISP265 | Hispanic Interaction Of BAGE34LN |  |  |  | -0.008 |  |  |  |  |
| 1HISP266 | Hispanic Interaction Of BAGE34QU |  |  |  | -0.388 |  |  |  |  |
| BAGE44LN | B: Linear: Percent Persons 35-44 Years |  |  |  |  |  | -0.080 | 0.002 |  |
| BAGE44QU | B: Quadratic: Percent Persons $35-44$ Years |  |  |  |  |  | $-0.086$ | ${ }^{0.006}$ |  |
| BAGE44CU | B: Cubic: Percent Persons 35-44 Years |  |  |  |  |  | $-0.035$ | -0.110 |  |
| BAGE44QR | B: Quartic: Percent Persons 35-44 Years |  |  |  |  |  | 0.042 |  |  |
| IBLK270 | Black Interaction Of BAGE44LN |  |  |  |  |  | 0.094 |  |  |
| IBLK271 | Black Interaction Of BAGE44QU |  |  |  |  |  | 0.093 |  |  |
| IBLK272 IBLK273 | Black Interaction Of BAGE44CU Black Interaction Of BAGE44QR |  |  |  |  |  | -0.075 -0.127 |  |  |
| IHISP270 | Hispanic Interaction Of BAGGE44LN |  |  |  |  |  |  |  |  |
| IHISP271 | Hispanic Interaction Of BAGE44QU |  |  |  |  |  |  | -0.323 |  |
| BAGE54LN | B: Linear: Percent Persons 45-54 Years |  |  |  |  |  | -0.126 |  |  |
| BAGE54QU | B: Quadratic: Percent Persons 45-54 Years |  |  |  |  |  | $-0.030$ |  |  |
| BAGE54CU BAGE540R | B: Cubic: Percent Persons 45-54 Years B: Quartic: Percent Persons $45-54$ Years |  |  |  |  |  |  |  |  |
| BAGE54QR | B: Quartic: Percent Persons 45-54 Years |  |  |  |  |  |  |  |  |
| BAGE64LN BAGE64OU | B: Linear: Percent Persons 55-64 Years B: |  | -0.139 |  |  | -0.186 | -0.040 -0.057 -0.056 |  |  |
| BAGE64QU BAGE64CU | B: Quadratic: Percent Persons $55-64$ Years B: Cubic: Percent Persons $55-64$ Years |  |  |  |  |  | -0.046 |  |  |
| IHISP280 | Hispanic Interaction Of BAGE64LN |  | 0.298 |  |  |  | -0.033 |  |  |
| IHISP281 | Hispanic Interaction Of BAGE64QU |  |  |  |  |  | $-0.086$ |  |  |
| 1HISP282 | Hispanic Interaction Of BAGE64CU |  |  |  |  |  | -0.240 |  |  |
| BINDIALN | B: Linear: Percent Pop: American Indian, Eskimo, Aleut |  | -0.005 |  |  | 0.170 |  |  |  |
| BINDIAQU BINDIACU | B: Quadratic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  | -0.046 0.184 |  |  |  |
| BINDIACU | B: Cubic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  | 0.184 |  |  |  |
| 10th300 | Other Interaction Of BINDIALN |  | 0.671 |  |  |  |  |  |  |
| BMNOTLN BMNOTQU | B: Linear: Percent Males Separated, Divorced or Widowed <br> B: Quadratic: Percent Males Separated, Divorced or Widowed | $\begin{array}{r} 0.043 \\ -0.139 \end{array}$ |  |  |  |  |  |  |  |
| BPOVERLN | B: Linear: Percent Families Below Poverty Level |  |  |  |  |  |  | 0.057 |  |
| BPOVERQU | B: Quadratic: Percent Families Below Poverty Level |  |  |  |  |  |  | 0.049 |  |
| BPOVERCU | B: Cubic: Percent Families Below Poverty Level |  |  |  |  |  |  | -0.171 |  |
| BPRICALN | B: Linear: Percent Hispanics: Puerto Rican |  |  |  |  | 0.120 |  |  |  |
| BPRICAQU | B: Quadratic: Percent Hispanics: Puerto Rican |  |  |  |  | 0.167 |  |  |  |
| BPRICACU | B: Cubic: Percent Hispanics: Puerto Rican |  |  |  |  | -0.174 |  |  |  |
| IFEM315 | Female Interaction OfBPRICALN |  |  |  |  | -0.283 |  |  |  |
| IFEM316 | Female Interaction Of BPRICAQU |  |  |  |  | -0.125 |  |  |  |
| IFEM317 | Female Interaction Of BPRICACU |  |  |  |  | 0.403 |  |  |  |
| BSCHASLN | B: Linear: Percent Associates Degree |  |  | -0.168 |  | -0.041 |  | 0.001 |  |
| BSCHASQU | B: Quadratic: Percent Associates Degree |  |  |  |  | 0.018 |  | 0.018 |  |
| BSCHASCU | B: Cubic: Percent Associates Degree |  |  |  |  | 0.172 |  | 0.023 |  |
| BSCHASQR | B: Quartic: Percent Associates Degree |  |  |  |  |  |  | -0.059 |  |
| PASIANLN | T: Linear: Percent Population: Asian, Pacitic Islander | -0.083 |  |  |  | 0.061 |  |  |  |

NOTE:


## E11. Coefficients of Model Parameters for Past Year Treatment Needed for Drug Abuse



[^14]

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | $35+$ | 12-17 | 18-25 | 26-34 | 35+ |
| BFNOTLN | B: Linear: Percent Females Separated, Divorced or Widowed | 0.033 | 0.076 |  |  | 0.044 | 0.061 | 0.064 |  |
| BFNOTQU | B: Quadratic: Percent Females Separated, Divorced or Widowed |  | 0.010 |  |  | -0.062 | -0.054 | -0.097 |  |
| BFNOTCU | B: Cubic: Percent Females Separated, Divorced or Widowed |  |  |  |  | 0.011 | 0.042 | -0.051 |  |
| BFNOTQR | B: Quartic: Percent Females Separated, Divorced or Widowed |  |  |  |  | 0.028 | 0.005 | 0.007 |  |
| IBLK295 | Black Interaction Of BFNOTLN |  |  |  |  |  | -0.144 |  |  |
| IBLK296 | Black Interaction Of BFNOTQU |  |  |  |  |  | 0.204 |  |  |
| 1BLK297 | Black Interaction Of BFNOTCU |  |  |  |  |  | -0.085 |  |  |
| IBLK298 | Black Interaction Of BFNOTQR |  |  |  |  |  | -0.070 |  |  |
| IHISP295 | Hispanic Interaction Of BFNOTLN |  | -0.123 |  |  |  | -0.187 |  |  |
| IHISP296 | Hispanic Interaction Of BFNOTQU |  | 0.118 |  |  |  | -0.162 |  |  |
| 1HISP297 | Hispanic Interaction Of BFNOTCU |  |  |  |  |  | -0.185 |  |  |
| IOTH295 | Other Interaction Of BFNOTLN | 0.657 |  |  |  |  |  | 0.544 |  |
| 10TH296 | Other Interaction Of BFNOTQU |  |  |  |  |  |  | 0.523 |  |
| IOTH297 | Other Interaction Of BFNOTCU |  |  |  |  |  |  | 0.228 |  |
| IOTH298 | Other Interaction Of BFNOTQR |  |  |  |  |  |  | 0.352 |  |
| BINDIALN | B: Linear: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  | 0.137 |  | -0.024 |
| BINDIAQU | B: Quadratic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  | -0.094 |  | 0.253 |
| IFEM300 | Female Interaction Of BINDIALN |  |  |  |  |  | -0.061 |  |  |
| IFEM301 | Female Interaction Of BINDIAQU |  |  |  |  |  | 0.127 |  |  |
| IHISP300 | Hispanic Interaction Of BINDIALN |  |  |  |  |  |  |  | -0.160 |
| IHISP301 | Hispanic Interaction Of BINDIAQU |  |  |  |  |  |  |  | -0.371 |
| BMNOTLN | B: Linear: Percent Males Separated, Divorced or Widowed |  |  |  |  |  |  | -0.045 |  |
| BMNOTQU | B: Quadratic: Percent Males Separated, Divorced or Widowed |  |  |  |  |  |  | 0.011 |  |
| BMNOTCU | B: Cubic: Percent Males Separated, Divorced or Widowed |  |  |  |  |  |  | -0.021 |  |
| BMNOTQR | B: Quartic: Percent Males Separated, Divorced or Widowed |  |  |  |  |  |  | 0.021 |  |
| IHISP305 | Hispanic Interaction Of BMNOTLN |  |  |  |  |  |  | 0.081 |  |
| 1HISP306 | Hispanic Interaction Of BMNOTQU |  |  |  |  |  |  | 0.009 |  |
| IHISP307 | Hispanic Interaction Of BMNOTCU |  |  |  |  |  |  | 0.236 |  |
| IHISP308 | Hispanic Interaction Of BMNOTQR |  |  |  |  |  |  | -0.092 |  |
| BPOVERLN | B: Linear: Percent Families Below Poverty Level |  | 0.134 |  | 0.256 |  | $-0.051$ |  |  |
| BPOVERQU | B: Quadratic: Percent Families Below Poverty Level |  | 0.106 |  | 0.104 |  |  |  | -0.194 |
| BPOVERCU BPOVERQR | B: Cubic: Percent Families Below Poverty Level B: Quartic: Percent Families Below Poverty Level |  |  |  |  |  |  |  | -0.034 -0.042 |
| BPOVERQR | B: Quartic: Percent Families Below Poverty Level |  |  |  |  |  |  |  | -0.042 |
| IFEM310 | Female Interaction Of BPOVERLN |  |  |  | -0.040 |  | 0.192 |  | 0.034 |
| IFEM311 | Female Interaction Of BPOVERQU |  |  |  | -0.199 |  |  |  | 0.233 |
| IFEM312 | Female Interaction Of BPOVERCU |  |  |  |  |  |  |  | -0.165 |
| IFEM313 | Female Interaction Of BPOVERQR |  |  |  |  |  |  |  | 0.102 |
| 1BLK310 | Black Interaction Of BPOVERLN |  | -0.299 |  |  |  |  |  |  |
| 1BLK311 | Black Interaction Of BPOVERQU |  | -0.123 |  |  |  |  |  |  |
| BPRICALN |  |  |  |  |  |  | $0.231$ |  |  |
| BPRICAQU | B: Quadratic: Percent Hispanics: Puerto Rican |  |  |  |  |  | $0.036$ |  |  |
| IBLK315 | Black Interaction Of BPRICALN |  |  |  |  |  |  |  |  |
| IBLK316 | Black Interaction Of BPRICAQU |  |  |  |  |  | $0.479$ |  |  |
| BSCHASLN | B: Linear: Percent Associates Degree |  |  | 0.029 |  |  |  | 0.069 | 0.144 |
| BSCHASQU | B: Quadratic: Percent Associates Degree |  |  |  |  |  |  | 0.016 |  |
| BSCHASCU | B: Cubic: Percent Associates Degree |  |  |  |  |  |  | 0.074 |  |
| BSCHASQR | B: Quartic: Percent Associates Degree |  |  |  |  |  |  | -0.037 |  |
| IFEM320 | Female Interaction Of BSCHASLN |  |  |  |  |  |  | -0.001 |  |
| IFEM321 | Female Interaction Of BSCHASQU |  |  |  |  |  |  | 0.018 |  |
| IFEM322 | Female Interaction Of BSCHASCU |  |  |  |  |  |  | 0.047 |  |
| IFEM323 | Female Interaction Of BSCHASQR |  |  |  |  |  |  | 0.059 |  |
| IBLK320 | Black Interaction Of BSCHASLN |  |  | -0.279 |  |  |  |  |  |
| IOTH320 | Other Interaction Of BSCHASLN |  |  |  |  |  |  | -0.410 |  |
| IOTH321 | Other Interaction Of BSCHASQU |  |  |  |  |  |  | 0.971 |  |
| PASIANLN | T: Linear: Percent Population: Asian, Pacitic Islander |  |  |  | -0.032 |  |  | 0.101 |  |
| PASIANQU | T: Quadratic: Percent Population: Asian, Pacitic Islander |  |  |  |  |  |  | 0.034 |  |
| PASIANCU | T: Cubic: Percent Population: Asian, Pacific Islander |  |  |  |  |  |  | -0.085 |  |
| IBLK325 | Black Interaction Of PASIANLN |  |  |  |  |  |  | -0.083 |  |
| 1BLK326 | Black Interaction Of PASIANQU |  |  |  |  |  |  | 0.104 |  |
| 1BLK327 | Black Interaction Of PASIANCU |  |  |  |  |  |  | 0.321 |  |
| IOTH325 | Other Interaction Of PASIANLN |  |  |  |  |  |  |  | -0.664 |
| PCUBANLN | T: Linear: Percent Hispanics: Cuban |  |  | -0.021 |  |  |  | 0.022 |  |
| PCUBANQU | T: Quadratic: Percent Hispanics: Cuban |  |  | 0.127 |  |  |  | 0.139 |  |
| PCUBANCU | T: Cubic: Percent Hispanics: Cuban |  |  | 0.100 |  |  |  | -0.093 |  |
| PCUBANQR | T: Quartic: Percent Hispanics: Cuban |  |  |  |  |  |  | 0.037 |  |
| PINDIALN | T: Linear: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  | 0.064 | 0.096 | 0.061 |  |
| PINDIAQU | T: Quadratic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  | -0.084 | 0.093 | 0.026 |  |
| PINDIACU | T: Cubic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  | 0.097 |  | 0.113 |  |
| IFEM335 | Female Interaction Of PINDIALN |  |  |  |  |  | -0.047 |  |  |
| IFEM336 | Female Interaction Of PINDIAQU |  |  |  |  |  | -0.110 |  |  |
| 1OTH335 | Other Interaction Of PINDIALN |  |  |  |  |  |  | -0.255 |  |
| IOTH336 | Other Interaction Of PINDIAQU |  |  |  |  |  |  | 0.425 |  |
| IOTH337 | Other Interaction Of PINDIACU |  |  |  |  |  |  | -0.934 |  |

## Appendix F: SignificanceProbabilities for Fixed Effect <br> Coefficients

## F1. Significance Probabilities for Fixed Effect Coefficients for Past Month Alcohol Use by Age

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| DUMMY | 0 : Intercept Term | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Female | O : Female Indicator | 29.20 | 0.00 | 0.00 | 0.00 | 0.12 | 0.00 | 0.00 | 0.00 |
| FEMBLCK | O: Black Interaction Of FEMALE | 15.10 | 5.21 | 0.00 | 0.00 | 46.56 | 27.70 | 4.71 | 0.00 |
| FEMHISP | O : Hispanic Interaction Of FEMALE | 0.36 | 0.00 | 0.00 | 0.00 | 98.60 | 0.04 | 0.04 | 0.00 |
| FEMOTHR | O : Other Interaction Of FEMALE | 41.04 | 30.60 | 0.00 | 0.00 | 2.09 | 95.46 | 44.24 | 0.00 |
| Raceblck | O: Race/Black Indicator | 0.00 | 0.00 | 0.00 | 0.00 | 5.11 | 0.00 | 0.00 | 0.00 |
| RACEHISP RACEOTHR | O: Race/Hispanic Indicator O: Race/Other Indicator | 95.35 0.00 | 0.00 0.00 | 66.62 0.00 | 58.11 0.00 | 99.80 0.03 | 37.20 0.00 | 43.40 0.00 | 0.53 0.00 |
|  |  |  |  |  |  |  |  |  |  |
| REGNOREA | O: Northeast Region Indicator |  |  |  |  |  | 32.62 |  | 30.40 |
| REGSOUTH REGWEST | O: South Region Indicator O: West Region Indicator |  |  |  |  |  | 2.01 50.63 |  | 0.06 39.18 |
| IOTH7 | Other Interaction Of REGNOREA |  |  |  |  |  | 0.00 |  | 0.00 |
| IOTH8 | Other Interaction Of REGSOUTA |  |  |  |  |  | 0.00 |  | 0.00 |
| IOTH9 | Other Interaction Of REGWEST |  |  |  |  |  | 0.00 |  | 0.00 |
| UCLASS9 | T: Underclass Indicator ${ }^{\text {T: }}$ Linear: Percent Persons 0-18 Years |  |  |  | 0.00 |  |  |  | 0.00 0.19 |
| PAGEIPQU | T: Quadratic: Percent Persons 0-18 Years |  |  |  |  |  |  |  | 0.00 |
| 10TH25 | Other Interaction Of PAGEI8LN |  |  |  |  |  |  |  | 0.00 |
| IOTH26 | Other Interaction Of PAGEIBQU |  |  |  |  |  |  |  | 0.00 |
| $\begin{aligned} & \text { PAGE24LN } \\ & \text { PAGE24QU } \end{aligned}$ | T: Linear: Percent Persons 19-24 Years <br> T: Quadratic: Percent Persons 19-24 Years |  |  |  |  |  | 7.83 0.00 |  |  |
| IFEM30 | Female Interaction Of PAGE24LN |  |  |  |  |  | 69.15 |  |  |
| IFEM31 | Female Interaction Of PAGE24QU |  |  |  |  |  | 0.00 |  |  |
| PAGE34LN | T: Linear: Percent Persons 25-34 Years | 0.01 |  |  |  |  |  |  |  |
| PAGE44LN | T: Linear: Percent Persons $35-44$ Years |  |  |  | 0.00 |  |  |  | 0.00 |
| PAGE44QU PAGE44CU | T: Quadratic: Percent Persons 35-44 Years |  |  |  |  |  |  |  | 0.00 15.17 |
| PAGE44QR | T: Quartic: Percent Persons 35-44 Years |  |  |  |  |  |  |  | 0.00 |
| PAGE64LN | T: Linear: Percent Persons 55-64 Years | 1.90 |  |  |  |  |  |  |  |
| PSCH8LN | T: Linear: Percent 0-8 Years Of School |  | 0.00 |  |  |  |  |  |  |
| PSCHCOLN | T: Linear: Bachelors, Graduate, Or Protessional Degree |  | 0.00 |  |  |  | 0.00 | 0.00 |  |
| IBLK75 | Black Interaction Of PSCHCOLN |  |  |  |  |  | 0.00 | 0.01 |  |
| PSCHSCLN | T: Linear: Percent Some College And No Degree |  | 0.00 |  |  |  |  |  |  |
| PPOVERLN | T: Linear: Percent Families Below Poverty Level |  |  |  |  | 2.48 |  |  |  |
| PPOVERQU | T: Quadratic: Percent Families Below Poverty Level |  |  |  |  | 22.11 |  |  |  |
| PPOVERCU PPOVERQR | T: Cubic: Percent Families Below Poverty Level |  |  |  |  | 0.00 0.27 |  |  |  |
| IBLK85 | Black Interaction Of PPOVERLN |  |  |  |  | 2.49 |  |  |  |
| ${ }^{\text {1BLK886 }}$ | Black Interaction Of PPOVERQU |  |  |  |  | 50.49 |  |  |  |
| ${ }^{13 L K 878}$ | Black Interaction Of PPOVERECU |  |  |  |  | 36.10 3.40 |  |  |  |
| IBLK88 | Black Interaction Of PPOVERQR |  |  |  |  |  |  |  |  |
| PBLACKLN | T: Linear: Percent Black Nonhispanic |  | 0.00 |  |  |  |  |  |  |
| POTHLN POTHQU | T: Linear: Percent Other Race/Hispanicity |  |  |  |  |  | 7.76 0.00 |  |  |
| POTHQU | T: Quadratic: Percent Other Race/Hispanicity |  |  |  |  |  | 0.00 |  |  |
| PFLABLN <br> PFLABQU | I: Linear: Percent Females $16+$ Years Old In Labor Force <br> I: Quadratic: Percent Females 16+ Years Old In Labor Force | $\begin{aligned} & 6.05 \\ & 0.07 \end{aligned}$ |  |  |  |  |  |  |  |
| PFNEVLN | T: Linear: Percent Females Never Married |  |  |  |  |  | 0.00 |  |  |
| PFNOTLN PFNOTQU PFNOTCU PFNOTQR | T: Linear: Percent Females Separated, Divorced Or Widowed <br> I: Quadratic: Percent Females Separated, Divorced Or Widowed <br> T: Cubic: Percent Females Separated, Divorced Or Widowed <br> T: Quartic: Percent Females Separated, Divorced Or Widowed |  |  |  | $\begin{array}{r}0.00 \\ 20.07 \\ 0.07 \\ 0.00 \\ \hline\end{array}$ |  |  |  |  |
| PMNEVLN | T: Linear: Percent Males Never Married |  |  | 0.00 |  | 0.22 |  | 0.21 | 0.00 |
| PMNEVQU | T: Quadratic: Percent Males Never Married |  |  |  |  |  |  | 6.51 | 0.00 |
| PMNEVCU | T: Cubic: Percent Males Never Married |  |  |  |  |  |  | 0.94 | 54.64 |
| PMNEVQR | T: Quartic: Percent Males Never Married |  |  |  |  |  |  |  | 0.00 |
| IFEM140 | Female Interaction Of PMNEVLN Female Interaction Of PMNEVQU |  |  |  |  |  |  |  | ${ }_{0}^{0.00}$ |
| IFEM141 | Female Interaction Of PMNEVQU |  |  |  |  |  |  |  | 0.00 |
| IBLK140 | Black Interaction Of PMNEVLN |  |  |  |  | 0.53 |  |  |  |
| IHISP140 | Hispanic Interaction Of PMNEVLN |  |  | 0.00 |  |  |  |  |  |
| IOTH140 IOTH141 | Other Interaction Of PMNEVLN Other Interaction Of PMNEVQU |  |  | 0.00 |  |  |  | 24.42 42.50 |  |
| IOTH142 | Other Interaction Ot PMNEVCU |  |  |  |  |  |  | 0.00 |  |
| P40HULN | T: Linear: Percent Housing Units Built 1940-1949 |  |  |  |  | 0.01 |  |  |  |
| IFEM160 | Female Interaction Of P40HULN |  |  |  |  | 0.04 |  |  |  |
| PRENTLN | T: Linear: Percent Housing Rented |  |  | 0.48 |  | 80.55 |  |  |  |
| IBLK165 | Black Interaction Of PRENTLN |  |  | 0.01 |  |  |  |  |  |

NOTE: T : Indicates a tract-level variable, C : Indicates a county-level variable, B : Indicates a block-level variable, O : Other


NOTE: $\mathrm{T}:$ Indicates a tract-level variable, C : Indicates a county-level variable, B: Indicates a block-level variable, O : Other


[^15]
## F2. Significance Probabilities for Fixed Effect Coefficients for Past Month Any Illicit Drug Use by Age

| Varibable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | $35+$ | 12-17 | 18-25 | 26-34 | 35+ |
| dummy | O: Intercept Term | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| UCLASS9 | T: Underclass Indicator |  |  |  |  |  | 0.55 |  |  |
| FEmale | O: Female Indicator | 64.64 | 0.00 | 0.00 | 0.00 | 48.67 | 0.00 | 0.00 | 0.00 |
| FEmblCK | O: Black Interaction Of FEMALE | 0.41 | 0.00 | 0.01 | 9.18 | 88.02 | 31.63 | 43.68 | 1.24 |
| FEMHISP | O: Hispanic Interaction Of FEMALE | 10.40 | 27.91 | 0.00 | 0.00 |  | 28.86 | 40.07 | 59.64 |
| FEMOTHR | O: Other Interaction Of FEMALE | 23.94 | 69.98 | 0.09 |  |  | 56.72 | 0.00 | 0.01 |
| RACEBLCK RACEHISP | O: Race/Black Indicator O: $\mathrm{Race/Hispanic}$ Indicator | 59.06 4.56 | 4.39 0.00 | 0.00 0.00 | 0.00 0.00 | 18.51 48.56 | 0.31 0.14 | 90.64 24.39 | 0.00 0.15 |
| RACEOTHR | O: Race/Other Indicator | 0.02 | 0.00 | 0.00 | 0.00 |  | 0.20 | ${ }_{0.00}$ | 0.00 |
| Regnorea REGSOUTH | O: Northeast Region Indicator O: South Region Indicator |  |  |  |  |  | 4.96 12.14 | 1.92 22.19 |  |
| REGWEST | 0 O: West Region Indicator |  |  |  |  |  | 0.01 | ${ }_{0.00}$ |  |
| PDENLEV1 | O: Large MSA |  |  |  |  | 72.37 | 0.13 | 51.18 |  |
| PDENLEV2 PDENLEV3 | O: Medium MSA O: Small MSA |  |  |  |  | 29.66 16.25 | 1.67 0.88 | 97.05 84.57 |  |
| PDENLEV4 | O: NonMSA, Urban |  |  |  |  | 53.05 | 0.39 | 64.75 |  |
| IBLK10 | Black Interaction Of PDENLEV1 |  |  |  |  |  | 4.41 |  |  |
| IBLK11 | Black Interaction Of PDENLEV2 |  |  |  |  |  | 17.62 |  |  |
| ${ }_{\text {IBLK12 }}{ }_{\text {IBLK13 }}$ | Black Interaction Of PDENLEV3 Black Interaction Of PDENLEV4 |  |  |  |  |  | 1.87 0.98 |  |  |
| IHISP 10 | Hispanic Interaction Of PDENLEV1 |  |  |  |  |  |  | 2.08 |  |
| 1 HISP 11 | Hispanic Interaction Of PDENLEV2 |  |  |  |  |  |  | 0.38 |  |
| 1HISP12 | Hispanic Interaction Of PDENLEV3 |  |  |  |  |  |  | 12.70 |  |
| $1 \mathrm{HISP13}$ | Hispanic Interaction Of PDENLEV4 |  |  |  |  |  |  | 13.06 |  |
| PHH1PLN PHHIPQU | T: Linear: Percent One Person Households <br> T: Quadratic: Percent One Person Households |  |  |  |  |  | $\begin{aligned} & 9.71 \\ & 0.03 \end{aligned}$ |  |  |
| POPRMLN POPRMQU | T: Linear: Average Persons Per Room T: Quadratic: Average Persons Per Room |  |  | 38.68 |  |  |  | 0.00 0.00 |  |
| IFEM20 <br> IFEM21 | Female Interaction Of POPRMLN |  |  |  |  |  |  | 0.93 0.04 |  |
| PAGE18LN PAGE180U | T: Linear: Percent Persons 0-18 Years T: Quadratic: Percent Persons $0-18$ Years |  |  |  |  |  | 4.17 37 |  |  |
| PAGE18CU | T: Cubic: Percent Persons 0-18 Years |  |  |  |  |  | 0.00 |  |  |
| IFEM25 | Female Interaction Of PAGEIELN |  |  |  |  |  | 0.09 |  |  |
| IFEM26 | Female Interaction Of PAGE18QU Female Interaction Of PAGE18CU |  |  |  |  |  | 98.64 0.01 |  |  |
| PAGE24LN | T: Linear: Percent Persons 19-24 Years |  |  |  |  |  |  | 0.00 |  |
| PAGE24QU | T: Quadratic: Percent Persons 19-24 Years |  |  |  |  |  |  | 4.50 |  |
| PAGE24CU | T: Cubic: Percent Persons 19-24 Years |  |  |  |  |  |  | 0.00 |  |
| PAGE24QR | T: Quartic: Percent Persons 19-24 Years |  |  |  |  |  |  | 37.40 |  |
| IHISP30 | Hispanic Interaction Of PAGE24LN |  |  |  |  |  |  | 66.58 |  |
| IHISP31 | Hispanic Interaction Of PAGE24QU |  |  |  |  |  |  | 64.69 |  |
| IHISP32 | Hispanic Interaction Of PAGE24CU |  |  |  |  |  |  | 81.90 62.74 |  |
| 1HISP33 | Hispanic Interaction Of PAGE24QR |  |  |  |  |  |  |  |  |
| PAGE34LN PAGE34QU | T: Linear: Percent Persons 25-34 Years |  |  |  |  | 96.79 0.02 | 41.91 2.16 |  |  |
| IHISP35 | Hispanic Interaction Of PAGE34LN |  |  |  |  |  | $\begin{array}{r} 48.67 \\ 1.50 \end{array}$ |  |  |
| PAGE44LN | T: Linear: Percent Persons 35-44 Years |  |  |  |  |  |  | 0.63 |  |
| PAGE54LN | T: Linear: Percent Persons 45-54 Years |  |  |  | 0.00 |  | 0.00 |  | 0.00 |
| PAGE54QU PAGE54CU | T: Quadratic: Percent Persons 45-54 Years |  |  |  | 0.68 |  | 6.44 0.16 |  | 0.00 |
| IBLK45 | Black Interaction Of PAGE54LN |  |  |  | 0.00 |  |  |  |  |
| 1BLK46 | Black Interaction Of PAGE54QU |  |  |  | 0.00 |  |  |  |  |
| 1HISP45 | Hispanic Interaction Of PAGE54LN |  |  |  |  |  | 1.71 |  |  |
| PSCH8LN PSCH8QU | T: Linear: Percent 0-8 Years Of School <br> T: Quadratic: Percent 0-8 Years Of School |  |  |  |  |  |  | 2.32 14.81 |  |
| IBLK55 | Black Interaction Of PSCH8LN |  |  |  |  |  |  | 0.16 |  |
| 1BLK56 | Black Interaction Of PSCH8QU |  |  |  |  |  |  | 0.03 |  |
| PSCHI2LN | T: Linear: Percent 9-12 Years \& No High School Diploma | 95.60 |  |  | 0.00 | 18.22 |  |  | 4.37 |
| PSCHI2QU | T: Quadratic: Percent 9-12 Years \& No High School Diploma | 0.46 |  |  |  | 0.64 |  |  | 0.00 |
| PSCH12CU | T: Cubic: Percent $9-12$ Years \& No High School Diploma T: Quartic: Percent 9-12 Years \& No High School Diploma | 18.91 0.48 |  |  |  |  |  |  |  |
| $\begin{aligned} & \text { IFEM60 } \\ & \text { IFEM61 } \end{aligned}$ | Female Interaction Of PSCH12LN <br> Female Interaction Of PSCH12QU |  |  |  |  | $\begin{array}{r} 35.76 \\ 1.18 \end{array}$ |  |  |  |
| PSCHASLN PSCHASQU | I: Linear: Percent Associates Degree <br> T: Quadratic: Percent Associates Degree |  |  |  |  |  |  | 44.93 0.00 |  |
| IBLK65 IBLK66 | Black Interaction Of PSCHASLN Black Interaction Of PSCHASQU |  |  |  |  |  |  | $\begin{array}{r} 30.45 \\ 0.80 \end{array}$ |  |
| PSCHCOLN | T: Linear: Bachelors, Graduate, Or Professional Degree |  |  |  |  | 11.51 |  |  | 87.93 |



NOTE: $\quad \mathrm{T}:$ Indicates a tract-level variable, $\mathrm{C}:$ Indicates a county-level variable, B: Indicates a block-level variable, O: Other


NOTE: $\quad \mathrm{T}:$ Indicates a tract-level variable, $\mathrm{C}:$ Indicates a county-level variable, $\mathrm{B}:$ Indicates a block-level variable, $\mathrm{O}:$ Other


|  | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Varibable |  | 12-17 | 18-25 | 26-34 | $35+$ | 12-17 | 18-25 | 26-34 | 35+ |
| PINDIAQR | T: Quartic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  |  |  | 0.00 |
| IFEM335 | Female Interaction Of PINDIALN |  |  |  |  |  |  |  |  |
| IFEM336 | Female Interaction Of PINDIAQU |  |  |  |  |  |  |  | 0.18 |
| IFEM338 | Female Interaction Of PINDIACU Female Interaction Of PINDIAQR |  |  |  |  |  |  |  | 1.03 0.00 |
| IHISP335 IHISP336 | ( Hispanic Interaction Of PINDIALN | $\begin{aligned} & 0.11 \\ & 0.00 \end{aligned}$ |  |  |  |  |  |  |  |

## F3. Significance Probabilities for Fixed Effect Coefficients for Past Month Cigarette Use by Age

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| DUMMY | O: Intercept Term | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| FEMALE | O: Female Indicator | 18.66 | 0.00 | 0.00 | 0.00 | 69.46 | 10.47 | 0.01 | 0.00 |
| FEMBLCK | O: Black Interaction Of FEMALE | 0.08 | 22.30 | 0.00 | 0.00 | 95.57 | 12.13 | 0.24 | 6.07 |
| FEMHISP | O: Hispanic Interaction Of FEMALE | 22.71 | 0.00 | 0.00 | 0.00 |  |  | 0.00 | 0.26 |
| FEMOTHR | O: Other Interaction Of FEMALE | 61.50 | 0.00 | 0.00 | 0.00 | 63.05 | 0.00 | 0.00 | 33.73 |
| RACEBLCK RACEHISP | O: Race/Black Indicator O: Race/Hispanic Indicator | 0.00 0.01 | 0.00 0.00 | 16.43 0.00 | 0.00 0.00 | 0.01 | 0.00 | 42.15 51.45 | 0.00 14.68 |
| RACEOTHR | O: Race/Other Indicator | 0.00 | 0.00 | 26.30 | 0.00 | 0.04 | 96.08 | 12.02 | 0.00 |
| REGNOREA REGSOUTH REGWEST | O: Northeast Region Indicator <br> O: South Region Indicator <br> O : West Region Indicator |  |  |  |  |  | 0.69 45.28 62.65 |  |  |
| PDENLEV1 | O: Large MSA |  |  |  |  | 27.60 | 18.67 | 10.88 |  |
| PDENLEV2 | O: Medium MSA |  |  |  |  | 0.35 | 32.48 | 4.90 |  |
| PDENLEV3 | O: Small MSA |  |  |  |  | 4.30 | 26.97 | 88.49 |  |
| PDENLEV4 | O: NonMSA, Urban |  |  |  |  | 0.50 | 95.89 | 83.20 |  |
| IHISP10 IHISP11 | Hispanic Interaction Of PDENLEV1 Hispanic Interaction Of PDENLEV2 |  |  |  |  |  |  | 22.94 40.45 |  |
| POPRMLN POPRMQU POPRMCU | T: Linear: Average Persons Per Room <br> T: Quadratic: Average Persons Per Room <br> T: Cubic: Average Persons Per Room |  |  | 0.00 |  | $\begin{array}{r} 79.47 \\ 26.43 \\ 3.06 \end{array}$ |  | 48.67 |  |
| IFEM20 | Female Interaction Of POPRMLN |  |  |  |  |  |  | 0.09 |  |
| IBLK20 IBLK21 | Black Interaction Of POPRMLN Black Interaction Of POPRMQU |  |  |  |  | 58.00 65.78 |  |  |  |
| 1BLK22 | Black Interaction Of POPRMCU |  |  |  |  | 2.41 |  |  |  |
| $\begin{aligned} & \text { IOTH20 } \\ & \text { IOTH22 } \end{aligned}$ | Other Interaction Of POPRMLN Other Interaction Of POPRMQU |  |  |  |  | 1.82 57.88 |  |  |  |
| 10TH22 | Other Interaction Of POPRMCU |  |  |  |  | 0.33 |  |  |  |
| PAGE18LN <br> PAGEI8OU | T: Linear: Percent Persons 0-18 Years T: Quadratic: Percent Persons 0-18 Years |  | 0.00 |  |  |  | 0.00 27.41 |  |  |
| PAGEI8CU | T: Cubic: Percent Persons 0-18 Years |  |  |  |  |  | 0.00 |  |  |
| IFEM25 | Female Interaction Of PAGEL18LN |  | 0.00 |  |  |  | 0.88 |  |  |
| IFEM26 | Female Interaction Of PAGE18QU |  |  |  |  |  | 2.96 |  |  |
| IFEM27 | Female Interaction Of PAGE18CU |  |  |  |  |  | 0.00 |  |  |
| PAGE24LN | T: Linear: Percent Persons 19-24 Years |  |  |  |  | 6.32 |  | 20.06 | 21.56 |
| PAGE24QU | T: Quadratic: Percent Persons 19-24 Years |  |  |  |  | 0.62 |  | 0.15 | 0.00 |
| PAGE24CU | T: Cubic: Percent Persons 19-24 Years |  |  |  |  |  |  | 0.95 | 0.17 |
| PAGE24QR | T: Quartic: Percent Persons 19-24 Years |  |  |  |  |  |  | 5.18 | 0.00 |
| IHISP30 | Hispanic Interaction Of PAGE24LN |  |  |  |  |  |  | 1.23 |  |
| IHISP31 | Hispanic Interaction Of PAGE24QU |  |  |  |  |  |  | 8.94 |  |
| IHISP32 | Hispanic Interaction Of PAGE24CU |  |  |  |  |  |  | 85.50 |  |
| 1 HISP 33 | Hispanic Interaction Of PAGE24QR |  |  |  |  |  |  | 36.06 |  |
| IOTH30 | Other Interaction Of PAGE24LN |  |  |  |  |  |  |  | 0.00 |
| IOTH31 | Other Interaction Of PAGE24QU |  |  |  |  |  |  |  | 0.02 |
| 10TH32 <br> 1OTH33 | Other Interaction Of PAGE24CU Other Interaction Of PAGE24QR |  |  |  |  |  |  |  | 0.42 0.00 |
| PAGE44LN | T: Linear: Percent Persons 35-44 Years |  |  |  |  |  |  | 14.74 |  |
| PAGE54LN | T: Linear: Percent Persons 45-54 Years |  |  |  | 0.00 | 51.19 |  |  | 0.00 |
| PAGE54QU | T: Quadratic: Percent Persons 45-54 Years |  |  |  | 72.44 | 1.40 |  |  | 0.00 |
| IBLK45 | Black Interaction Of PAGE54LN |  |  |  | 0.00 | 91.08 |  |  |  |
| IBLK46 | Black Interaction Of PAGE54QU |  |  |  | 0.00 | 6.12 |  |  |  |
| PAGE64LN | T: Linear: Percent Persons 55-64 Y ears |  |  |  |  | 15.22 |  |  |  |
| PAGE64QU | T: Quadratic: Percent Persons 55-64 Years |  |  |  |  | 41.91 |  |  |  |
| PAGE64CU | T: Cubic: Percent Persons 55-64 Years |  |  |  |  | 74.00 |  |  |  |
| PAGE64QR | T: Quartic: Percent Persons 55-64 Years |  |  |  |  | 0.18 |  |  |  |
| PSCH8LN | T: Linear: Percent 0-8 Years Of School |  |  |  |  | 47.40 |  |  |  |
| IOTH55 | Other Interaction Of PSCH8LN |  |  |  |  | 0.24 |  |  |  |
| PSCHI2LN PSCH12QU PSCH12CU | I: Linear: Percent 9-12 Years \& No High School Diploma <br> T: Quadratic: Percent 9-12 Years \& No High School Diploma <br> T: Cubic: Percent 9-12 Years \& No High School Diploma |  |  |  |  | $\begin{aligned} & 55.63 \\ & 30.15 \\ & 10.93 \end{aligned}$ |  |  |  |
| PSCHASLN | T: Linear: Percent Associates Degree |  |  |  |  | 56.16 |  | 53.02 |  |
| PSCHASQU | T: Quadratic: Percent Associates Degree |  |  |  |  | 22.97 |  | 77.20 |  |
| PSCHASCU | T: Cubic: Percent Associates Degree |  |  |  |  | 41.91 |  |  |  |
| PSCHASQR | T: Quartic: Percent Associates Degree |  |  |  |  | 0.00 |  |  |  |
| IFEM65 | Female Interaction Of PSCHASLN |  |  |  |  | 35.64 |  |  |  |
| IFEM66 | Female Interaction Of PSCHASQU |  |  |  |  | 8.51 |  |  |  |
| IFEM67 | Female Interaction Of PSCHASCU |  |  |  |  | 91.64 |  |  |  |
| IFEM68 | Female Interaction Of PSCHASQR |  |  |  |  | 0.02 |  |  |  |
| PSCHCOLN | T: Linear: Bachelors, Graduate, Or Professional Degree |  |  |  |  | 14.46 |  |  | 0.00 |
| PSCHCOQU | T: Quadratic: Bachelors, Graduate, Or Professional Degree |  |  |  |  | 18.11 |  |  | 0.00 |
| IFEM75 <br> IFEM76 | Female Interaction Of PSCHCOLN Female Interaction Of PSCHCOQU |  |  |  |  | $\begin{aligned} & 6.27 \\ & 0.82 \end{aligned}$ |  |  |  |




NOTE: $\quad \mathrm{T}:$ Indicates a tract-level variable, $\mathrm{C}:$ Indicates a county-level variable, $\mathrm{B}:$ Indicates a block-level variable, O : Other

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| IFEM267 | Female Interaction Of BAGE34CU |  |  |  |  |  |  |  | 0.00 |
| IBLK265 | Black Interaction Of BAGE34LN |  |  |  |  |  |  |  | 0.00 |
| IOTH265 | Other Interaction Of BAGE34LN |  |  |  |  | 1.63 |  | 0.00 |  |
| IOTH266 | Other Interaction Of BAGE34QU |  |  |  |  | 0.50 |  | 0.00 |  |
| IOTH267 | Other Interaction Of BAGE34CU |  |  |  |  |  |  | 0.00 |  |
| BAGE44LN | B: Linear: Percent Persons 35-44 Years |  |  |  |  |  |  | 5.70 |  |
| BAGE44QU | B: Quadratic: Percent Persons 35-44 Years |  |  |  |  |  |  | 0.00 |  |
| IHISP270 | Hispanic Interaction Of BAGE44LN |  |  |  |  |  |  | 25.74 |  |
| 1 HISP271 | Hispanic Interaction Of BAGE44QU |  |  |  |  |  |  | 1.72 |  |
| BAGE54LN | B: Linear: Percent Persons 45-54 Y ears |  |  |  |  | ${ }^{64.51}$ | 95.57 | 0.00 | 1.65 |
| BAGE54QU | B: Quadratic: Percent Persons 45-54 Years |  |  |  |  | 90.79 | 0.17 | 0.88 | ${ }_{0}^{0.00}$ |
| BAGE54CU BAGE54QR | B: Cubic: Percent Persons 45-54 Years B: Quartic: Percent Persons $45-54$ Years |  |  |  |  | 14.56 | 0.00 | 5.08 7.17 | 0.00 |
| IFEM275 | Female Interaction Of BAGE54LN |  |  |  |  |  | 37.51 |  | 85.96 |
| IFEM276 | Female Interaction Of BAGE54QU |  |  |  |  |  | 2.09 |  | 0.00 |
| IFEM277 | Female Interaction Of BAGE54CU |  |  |  |  |  | 0.00 |  | 14.88 |
| IBLK275 | Black Interaction Of BAGE54LN |  |  |  |  |  | 94.22 |  |  |
| IBLK276 | Black Interaction Of BAGE54QU |  |  |  |  |  | 80.74 |  |  |
| 10TH275 | Other Interaction Of BAGE54LN |  |  |  |  | 16.67 |  | 38.98 |  |
| IOTH276 | Other Interaction Of BAGE54QU |  |  |  |  | 80.34 |  | 36.63 |  |
| IOTH277 | Other Interaction Of BAGE54CU |  |  |  |  | 0.77 |  | 0.10 |  |
| IOTH278 | Other Interaction Of BAGE54QR |  |  |  |  |  |  | 0.00 |  |
| BAGE64LN | B: Linear: Percent Persons 55-64 Years |  | 36.79 | 56.55 | 0.00 | 0.91 | 29.28 |  | 0.00 |
| BAGE64QU | B: Quadratic: Percent Persons 55-64 Years |  | 0.00 | 19.32 | 0.00 |  | 62.11 |  | 68.56 |
| BAGE64CU | B: Cubic: Percent Persons 55-64 Years |  | 49.19 | 58.04 |  |  | 5.82 |  | 0.00 |
| BAGE64QR | B: Quartic: Percent Persons 55-64 Years |  |  |  |  |  | 11.28 |  |  |
| IFEM280 | Female Interaction Of BAGE64LN |  |  |  | 0.00 |  |  |  | 0.00 |
| IFEM281 | Female Interaction Of BAGE64QU |  |  |  | 24.61 |  |  |  | 0.00 |
| IFEM282 | Female Interaction Of BAGE64CU |  |  |  |  |  |  |  | 92.42 |
| 1BLK280 | Black Interaction Of BAGE64LN |  |  |  |  |  |  |  | 1.21 |
| 1BLK281 | Black Interaction Of BAGE64QU |  |  |  |  |  |  |  | 0.76 |
| IHISP280 | Hispanic Interaction Of BAGE64LN |  | 89.38 | 0.00 |  |  |  |  |  |
| IHISP281 | Hispanic Interaction Of BAGE64QU |  | 67.45 | 1.13 |  |  |  |  |  |
| 1HISP282 | Hispanic Interaction Of BAGE64CU |  | 2.47 | 53.65 |  |  |  |  |  |
| BASIANLN | B: Linear: Percent Population: Asian, Pacitic Islander |  | 0.08 | 69.16 |  |  | 95.06 | 0.00 | 0.00 |
| BASIANQU | B: Quadratic: Percent Population: Asian, Pacitic Islander |  | 9.72 | 32.30 |  |  | 1.60 | 91.23 | 7.44 |
| BASIANCU | B: Cubic: Percent Population: Asian, Pacitic Islander |  |  | 35.49 |  |  | 0.05 | 1.46 | 0.00 |
| BASIANQR | B: Quartic: Percent Population: Asian, Pacific Islander |  |  | 30.23 |  |  | 17.13 | 0.00 |  |
| IFEM285 | Female Interaction Of BASIANLN |  |  |  |  |  | 34.28 |  | 0.07 |
| IFEM286 | Female Interaction Of BASIANQU |  |  |  |  |  | 33.07 |  | 45.23 |
| IFEM287 | Female Interaction Of BASIANCU |  |  |  |  |  | 12.38 |  | 0.00 |
| IFEM288 | Female Interaction Of BASIANQR |  |  |  |  |  | 0.03 |  |  |
| 1HISP285 | Hispanic Interaction Of BASIANLN |  |  | 86.33 |  |  |  | 1.20 |  |
| IHISP286 | Hispanic Interaction Of BASIANQU |  |  | 0.00 |  |  |  |  |  |
| 1HISP287 | Hispanic Interaction Of BASIANCU |  |  | 86.51 |  |  |  |  |  |
| 1HISP288 | Hispanic Interaction Of BASIANQR |  |  | 0.00 |  |  |  |  |  |
| BCUBANLN | B: Linear: Percent Hispanics: Cuban |  |  |  |  |  | ${ }^{12.06}$ | 20.62 |  |
| BCUBANQU | B: Quadratic: Percent Hispanics: Cuban |  |  |  |  |  | 37.38 |  |  |
| BCUBANCU | B: Cubic: Percent Hispanics: Cuban |  |  |  |  |  | 7.35 |  |  |
| IFEM290 | Female Interaction Of BCUBANLN |  |  |  |  |  |  | 7.19 |  |
| BFNOTLN | B: Linear: Percent Females Separated, Divorced or Widowed |  |  |  |  | 62.65 |  | 79.84 |  |
| BFNOTQU BFNOTCU | B: Quadratic: Percent Females Separated, Divorced or Widowed B: Cubic: Percent Females Separated, Divorced or Widowed |  |  |  |  | $\begin{aligned} & 82.60 \\ & 10.60 \end{aligned}$ |  | 0.00 |  |
| IFEM295 | Female Interaction Of BFNOTLN |  |  |  |  |  |  | 21.84 |  |
| IFEM296 | Female Interaction Of BFNOTQU |  |  |  |  | 35.85 |  | 0.00 |  |
| IFEM297 | Female Interaction Of BFNOTCU |  |  |  |  | 0.08 |  |  |  |
| BINDIALN | B: Linear: Percent Pop: American Indian, Eskimo, Aleut |  | 0.00 | 80.41 |  |  | 1.26 |  |  |
| BINDIAQU | B: Quadratic: Percent Pop: American Indian, Eskimo, Aleut |  |  | 0.77 |  |  | 42.08 |  |  |
| BINDIACU | B: Cubic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  | 85.33 |  |  |
| BINDIAQR | B: Quartic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  | 45.55 |  |  |
| IBLK300 | Black Interaction Of BINDIALN |  |  |  |  |  | 5.29 |  |  |
| IHISP300 | Hispanic Interaction Of BINDIALN |  |  | 0.00 |  |  |  |  |  |
| 1HISP301 | Hispanic Interaction Of BINDIAQU |  |  | 0.00 |  |  |  |  |  |
| IOTH300 | Other Interaction Of BINDIALN |  |  |  |  |  | 0.01 |  |  |
| IOTH301 | Other Interaction Of BINDIAQU |  |  |  |  |  | 0.00 |  |  |
| BMNOTLN | B: Linear: Percent Males Separated, Divorced or Widowed |  |  | 0.00 | 0.00 | 64.82 | 0.38 |  | 0.00 |
| BMNOTQU | B: Quadratic: Percent Males Separated, Divorced or Widowed |  |  | 0.63 | 0.00 | 0.18 | 98.04 |  | 0.00 |
| BMNOTCU | B: Cubic: Percent Males Separated, Divorced or Widowed |  |  | 3.27 | 0.00 |  | 8.19 |  |  |
| BMNOTQR | B: Quartic: Percent Males Separated, Divorced or Widowed |  |  | 0.00 |  |  |  |  |  |
| IFEM305 | Female Interaction Of BMNOTLN |  |  |  | 0.00 | 68.58 |  |  |  |
| 1FEM306 | Female Interaction Of BMNOTQU |  |  |  | 0.00 | 0.15 |  |  |  |
| IFEM307 | Female Interaction Of BMNOTCU |  |  |  | 0.29 |  |  |  |  |
| IHISP305 | Hispanic Interaction Of BMNOTLN |  |  | 56.38 |  |  |  |  | 11.40 |
| IHISP306 | Hispanic Interaction Of BMNOTQU |  |  | 42.61 |  |  |  |  | 0.00 |
| IHISP307 | Hispanic Interaction Of BMNOTCU |  |  | 6.37 |  |  |  |  |  |
| IHISP308 | Hispanic Interaction Of BMNOTQR |  |  | 0.00 |  |  |  |  |  |
| BPOVERLN | B: Linear: Percent Families Below Poverty Level |  | 0.00 |  |  | 91.59 | 10.32 |  | 0.00 |
| BPOVERQU | B: Quadratic: Percent Families Below Poverty Level |  | 0.15 |  |  | 64.98 | 23.28 |  | 0.00 |
| BPOVERCU | B: Cubic: Percent Families Below Poverty Level |  | 0.00 |  |  | 19.25 | 0.13 |  | 0.00 |
| BPOVERQR | B: Quartic: Percent Families Below Poverty Level |  | 0.98 |  |  |  | 43.51 |  |  |



F4. Significance Probabilities for Fixed Effect Coefficients for Past Month Cocaine Use by Age

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| DUMMY | O: Intercept Term | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| FEMALE | O: Female Indicator | 1.88 | 0.00 | 0.00 | 0.00 | 68.84 | 0.00 | 10.68 | 47.23 |
| FEMBLCK | O: Black Interaction Of FEMALE | 0.25 | 64.10 | 0.98 | 0.00 | 88.15 | 44.96 | 30.22 | 0.00 |
| FEMHISP | O: Hispanic Interaction Of FEMALE | 28.95 | 31.40 | 21.27 | 0.01 | 76.91 | 48.80 | 31.16 | 1.47 |
| RACEBLCK | O: Race/Black Indicator | 30.25 | 10.25 0 | 6.69 0.00 | 0.00 0.00 | 61.05 8.08 | 47.58 36.90 | 51.66 | 0.00 0.00 |
| RACEOTHR | O: Race/Other Indicator | 17.11 | 0.00 |  |  |  | 46.97 | 88.74 |  |
| PDENLEV1 | O: Large MSA |  |  |  |  |  | 51.01 | 62.66 |  |
| PDENLEV2 | O: Medium MSA |  |  |  |  |  | 28.49 | 28.80 |  |
| PDENLEV3 | O: Small MSA |  |  |  |  |  | 9.48 | 29.55 |  |
| PDENLEV4 | O: NonMSA, Urban |  |  |  |  |  | 0.14 | 22.58 |  |
| POPRMLN | T: Linear: Average Persons Per Room |  |  | 0.00 |  |  |  | 0.00 |  |
| IFEM20 | Female Interaction Of POPRMLN |  |  |  |  |  |  | 0.00 |  |
| PAGE24LN | T: Linear: Percent Persons 19-24 Years |  |  |  |  |  |  | 6.30 |  |
| PAGE24QU | T: Quadratic: Percent Persons 19-24 Years |  |  |  |  |  |  | 95.50 |  |
| PAGE24CU | T: Cubic: Percent Persons 19-24 Years |  |  |  |  |  |  | 0.00 |  |
| PAGE24QR | T: Quartic: Percent Persons 19-24 Years |  |  |  |  |  |  | 0.00 |  |
| IHISP30 | Hispanic Interaction Of PAGE24LN |  |  |  |  |  |  | 56.68 |  |
| 1HISP31 | Hispanic Interaction Of PAGE24QU |  |  |  |  |  |  | 95.46 |  |
| IHISP32 | Hispanic Interaction Of PAGE24CU |  |  |  |  |  |  | 5.38 |  |
| $1 \mathrm{HISP33}$ | Hispanic Interaction Of PAGE24QR |  |  |  |  |  |  | 7.99 |  |
| PAGE44LN | T: Linear: Percent Persons 35-44 Years |  |  |  |  |  |  | 0.00 |  |
| PAGE54LN | T: Linear: Percent Persons 45-54 Y ears |  |  |  | 0.00 |  |  |  | 17.83 |
| PAGE54QU | T: Quadratic: Percent Persons 45-54 Years |  |  |  | 0.00 |  |  |  | 0.00 |
| IBLK45 | Black Interaction Of PAGE54LN |  |  |  | 0.00 |  |  |  |  |
| IBLK46 | Black Interaction Of PAGE54QU |  |  |  | 0.00 |  |  |  |  |
| PSCHASLN <br> PSCHASQU | I: Linear: Percent Associates Degree <br> T: Quadratic: Percent Associates Degree |  |  |  |  |  |  | $\begin{array}{r} 53.87 \\ 0.00 \end{array}$ |  |
| PSCHCOLN | T: Linear: Bachelors, Graduate, Or Professional Degree |  |  |  |  | 52.13 |  |  | 1.98 |
| PSCHCOQU | T: Quadratic: Bachelors, Graduate, Or Professional Degree |  |  |  |  | 5.87 |  |  | 0.00 |
| IFEM75 | Female Interaction Of PSCHCOLN |  |  |  |  | 15.29 |  |  |  |
| IFEM76 | Female Interaction Of PSCHCOQU |  |  |  |  | 3.00 |  |  |  |
| PBLACKLN | T: Linear: Percent Black Nonhispanic |  |  | 0.00 |  |  |  | 7.45 |  |
| PBLACKQU | T: Quadratic: Percent Black Nonhispanic |  |  | 9.18 |  |  |  | 22.48 |  |
| PBLACKCU | T: Cubic: Percent Black Nonhispanic |  |  | 0.00 |  |  |  | 0.00 |  |
| PHISPLN | T: Linear: Percent Hispanic |  |  |  |  |  |  |  | 10.76 |
| PHISPQU | T: Quadratic: Percent Hispanic |  |  |  |  |  |  |  | 1.98 |
| PHISPCU | T: Cubic: Percent Hispanic |  |  |  |  |  |  |  | 18.05 0.00 |
| PHISPQR | T: Quartic: Percent Hispanic |  |  |  |  |  |  |  | 0.00 |
| POTHLN | T: Linear: Percent Other Race/Hispanicity |  |  |  |  | 81.78 |  |  |  |
| POTHQU | T: Quadratic: Percent Other Race/Hispanicity |  |  |  |  | 27.78 |  |  |  |
| POTHCU | T: Cubic: Percent Other Race/Hispanicity |  |  |  |  | 13.38 |  |  |  |
| PHHF18LN | T: Linear: \% Female-Headed HH W/No Spouse \& Chld Under 18 |  |  |  |  | 31.22 |  |  | 0.00 |
| PHHF18QU | T: Quadratic: \% Female-Headed HH W/No Spouse \& Chld Under 18 |  |  |  |  | 65.13 |  |  |  |
| $\begin{aligned} & \text { PHHF18CU } \\ & \text { PHHF18OR } \end{aligned}$ | T: Cubic: \% Female-Headed HH W/No Spouse \& Chld Under 18 T: Quartic: \% Female-Headed HH W/No Spouse \& Chld Under 18 |  |  |  |  | $\begin{array}{r} 47.40 \\ 2.90 \end{array}$ |  |  |  |
| IFEM120 | Female Interaction Of PHHF18LN |  |  |  |  |  |  |  | 0.00 |
| PFNOTLN | T: Linear: Percent Females Separated, Divorced Or Widowed |  |  | 0.00 |  |  |  | 0.74 |  |
| PFNOTQU | T: Quadratic: Percent Females Separated, Divorced Or Widowed |  |  |  |  |  |  | 0.00 |  |
| IHISP135 <br> IHISP136 | Hispanic Interaction Of PFNOTLN Hispanic Interaction Of PFNOTQU |  |  |  |  |  |  | 21.71 3.36 |  |
| PMNOTLN | T: Linear: Percent Males Separated, Divorced Or Widowed |  |  |  |  |  | 2.29 | 34.05 |  |
| PMNOTQU | T: Quadratic: Percent Males Separated, Divorced Or Widowed |  |  |  |  |  | 0.04 | 0.32 |  |
| IFEM150 | Female Interaction Of PMNOTLN |  |  |  |  |  | 0.00 |  |  |
| IFEM151 | Female Interaction Of PMNOTQU |  |  |  |  |  | 0.06 |  |  |
| IHISP150 | Hispanic Interaction Of PMNOTLN |  |  |  |  |  |  | 82.93 |  |
| 1HISP151 | Hispanic Interaction Of PMNOTQU |  |  |  |  |  |  | 7.03 |  |
| PRENTLN | T: Linear: Percent Housing Rented |  |  |  |  |  |  |  | 0.00 |
| PRENTQU | T: Quadratic: Percent Housing Rented |  |  |  |  |  |  |  | 0.00 |
| PRENTCU | T: Cubic: Percent Housing Rented |  |  |  |  |  |  |  | 0.00 |
| PRENTQR | T: Quartic: Percent Housing Rented |  |  |  |  |  |  |  | 0.00 |
| V18BLN | C: Linear: Mariiuana Sale/Manufacture Arrest Rate |  |  |  |  |  |  | 7.03 |  |
| V18BQU | C: Quadratic: Marijuana Sale/Manutacture Arrest Rate |  |  |  |  |  |  | 65.75 |  |
| V18BCU | C: Cubic: Marijuana Sale/Manufacture Arrest Rate |  |  |  |  |  |  | 0.00 |  |
| V18ELN | C: Linear: Opium/Cocaine \& Deriv Posession Arrest Rate |  |  |  |  |  |  |  | 0.50 |
| V18EQU | C: Quadratic: Opium/Cocaine \& Deriv Posession Arrest Rate |  |  |  |  |  |  |  | 0.00 |
| V18ECU | C: Cubic: Opium/Cocaine \& Deriv Posession Arrest Rate |  |  |  |  |  |  |  | 10.98 |
| V18EQR | C: Quartic: Opium/Cocaine \& Deriv Posession Arrest Rate |  |  |  |  |  |  |  | 0.00 |
| V18ALN | C: Linear: Opium/Cocaine \& Deriv Sale/Manuf Arrest Rate |  | 0.00 |  |  |  |  | 0.33 |  |
| IHISP200 | Hispanic Interaction Of V18ALN |  | 0.01 |  |  |  |  |  |  |

NOTE: $\mathrm{T}:$ Indicates a tract-level variable, $\mathrm{C}:$ Indicates a county-level variable, $\mathrm{B}:$ Indicates a block-level variable, O : Other


NOTE: $\quad \mathrm{T}:$ Indicates a tract-level variable, $\mathrm{C}:$ Indicates a county-level variable, $\mathrm{B}:$ Indicates a block-level variable, O : Other

|  | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Variable |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| IBLK320 | Black Interaction Of BSCHASLN |  |  |  |  |  |  | 35.71 |  |
| IBLK321 | Black Interaction Of BSCHASQU |  |  |  |  |  |  | 28.54 |  |
| IBLK322 | Black Interaction Of BSCHASCU |  |  |  |  |  |  | 2.37 |  |
| PCUBANLN | T: Linear: Percent Hispanics: Cuban | 6.13 |  | 0.00 |  |  |  | 21.02 |  |
| PCUBANQU | T: Quadratic: Percent Hispanics: Cuban | 3.78 |  | 0.00 |  |  |  | 25.58 |  |
| PCUBANCU | T: Cubic: Percent Hispanics: Cuban | 21.45 |  |  |  |  |  | 5.33 |  |
| PCUBANQR | T: Quartic: Percent Hispanics: Cuban |  |  |  |  |  |  | 0.00 |  |
| IBLK330 | Black Interaction Of PCUBANLN | 60.28 |  |  |  |  |  |  |  |
| 1BLK331 | Black Interaction Of PCUBANQU | 5.32 |  |  |  |  |  |  |  |
| 1BLK332 | Black Interaction Of PCUBANCU | 4.58 |  |  |  |  |  |  |  |

F5. Significance Probabilities for Fixed Effect Coefficients for
Past Month Any Illicit Drug But Marijuana by Age

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| DUMMY | O: Intercept Term | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| FEMALE | O: Female Indicator | 29.69 | 0.00 | 0.00 | 0.00 | 19.09 | 0.00 | 0.05 | 15.97 |
| FEMBLCK | O: Black Interaction Of FEMALE | 7.24 | 27.46 | 16.55 | 0.00 | 15.03 | 42.92 | 27.75 | 0.00 |
| FEMHISP | O: Hispanic Interaction Of FEMALE | 71.27 | 0.24 | 0.02 | 0.00 |  | 99.81 | 92.54 | 77.59 |
| FEMOTHR | O: Other Interaction Of FEMALE | 48.96 | 0.00 | 95.28 |  | 37.39 | 23.59 |  | 0.00 |
| RACEBLCK RACEHISP | O: Race/Black Indicator O: Race/Hispanic Indicator | 5.49 90.88 | 0.00 0.00 | 0.00 0.00 | 0.00 0.00 | 6.81 | 2.52 17.13 | 11.62 30.45 | 0.00 13.65 |
| RACEOTHR | O: Race/Other Indicator | 1.31 | 0.00 | 0.00 |  | 33.65 | 0.00 | 0.04 | 0.00 |
| REGNOREA REGSOUTH | O: Northeast Region Indicator O: South Region Indicator |  |  |  |  |  |  | 0.05 0.54 |  |
| REGWEST | O: West Region Indicator |  |  |  |  |  | 0.02 | 0.00 |  |
| PDENLEV1 | O: Large MSA |  |  |  |  |  |  |  | 0.00 |
| PDENLEV2 | O: Medium MSA |  |  |  |  |  |  |  | 62.05 |
| PDENLEV3 PDENLEV4 | O: Small MSA O: NonMSA, Urban |  |  |  |  |  |  |  | 0.00 76.27 |
| PHHIPLN | T: Linear: Percent One Person Households |  |  |  |  | 0.22 |  |  |  |
| PAGE24LN | T: Linear: Percent Persons 19-24 Y ears |  |  |  |  |  |  | 0.70 | 0.00 |
| PAGE24QU | T: Quadratic: Percent Persons 19-24 Years |  |  |  |  |  |  |  | 0.00 |
| PAGE24CU PAGE24QR | T: Cubic: Percent Persons 19-24 Years T: Quartic: Percent Persons 19-24 Years |  |  |  |  |  |  | 0.00 0.00 |  |
| PAGE34LN | T: Linear: Percent Persons 25-34 Years |  |  |  |  | 27.92 |  |  |  |
| PAGE34QU | T: Quadratic: Percent Persons 25-34 Years |  |  |  |  | 0.04 |  |  |  |
| PAGE44LN | T: Linear: Percent Persons 35-44 Years |  |  |  |  | 60.65 |  |  |  |
| PAGE44QU | T: Quadratic: Percent Persons 35-44 Years |  |  |  |  | 95.50 |  |  |  |
| PAGE54LN | T: Linear: Percent Persons 45-54 Y ears |  |  |  |  |  |  |  | 0.00 |
| PAGE54QU | T: Quadratic: Percent Persons 45-54 Years |  |  |  |  |  |  |  | 0.00 |
| IFEM45 | Female Interaction Of PAGE54LN |  |  |  |  |  |  |  | 70.27 |
| IFEM46 | Female Interaction Of PAGE54QU |  |  |  |  |  |  |  | 0.00 |
| PSCH8LN | T: Linear: Percent 0-8 Years Of School |  |  |  |  |  |  | 0.00 |  |
|  | T: Linear: Percent 9-12 Years \& No High School Diploma |  |  |  |  |  |  |  |  |
| PSCHI2QU | T: Quadratic: Percent 9-12 Y ears \& No High School Diploma | 1.30 |  |  |  | 9.49 |  |  |  |
| PSCH12CU | T: Cubic: Percent 9-12 Years \& No High School Diploma | 90.69 |  |  |  | 83.93 |  |  |  |
| PSCH12QR | T: Quartic: Percent 9-12 Years \& No High School Diploma | 0.02 |  |  |  | 1.53 |  |  |  |
| IFEM60 | Female Interaction Of PSCH12LN | 11.21 |  |  |  | 14.46 |  |  |  |
| IFEM61 | Female Interaction Of PSCH12QU | 0.10 |  |  |  | 1.89 |  |  |  |
| PSCHASLN | T: Linear: Percent Associates Degree |  |  |  |  | 41.46 |  |  |  |
| PSCHASQU | T: Quadratic: Percent Associates Degree |  |  |  |  | 8.40 |  |  |  |
| IBLK65 | Black Interaction Of PSCHASLN |  |  |  |  | 19.76 |  |  |  |
| IBLK66 | Black Interaction Of PSCHASQU |  |  |  |  | 1.30 |  |  |  |
| PSCHSCLN | T: Linear: Percent Some College And No Degree |  |  |  |  | 87.11 |  |  |  |
| PSCHSCQU | T: Quadratic: Percent Some College And No Degree |  |  |  |  | 0.96 |  |  |  |
| PPOVERLN | T: Linear: Percent Families Below Poverty Level |  |  |  |  |  |  | 9.97 |  |
| PPOVERQU | T: Quadratic: Percent Families Below Poverty Level |  |  |  |  |  |  | 14.90 |  |
| PPOVERCU PPOVERQR | T: Cubic: Percent Families Below Poverty Level |  |  |  |  |  |  | 89.27 0.00 |  |
| PPOVERQR | T: Quartic: Percent Families Below Poverty Level |  |  |  |  |  |  | 0.00 |  |
| P64DISLN | T: Linear: Percent 16-64 With A Work Disability | 18.53 |  |  |  | 16.27 |  |  |  |
| P64DISQU | T: Quadratic: Percent 16-64 With A Work Disability | 11.22 |  |  |  | 8.68 |  |  |  |
| P64DISCU | T: Cubic: Percent 16-64 With A Work Disability | 3.37 |  |  |  | 12.12 |  |  |  |
| IBLK95 | Black Interaction Of P64DISLN | 2.12 |  |  |  | 68.77 |  |  |  |
| IBLK96 | Black Interaction Of P64DISQU | 92.69 |  |  |  | 18.19 |  |  |  |
| IBLK97 | Black Interaction Of P64DISCU | 0.14 |  |  |  | 1.25 |  |  |  |
| PBLACKLN | T: Linear: Percent Black Nonhispanic |  |  | 0.24 |  |  |  | 0.39 |  |
| PBLACKQU | T: Quadratic: Percent Black Nonhispanic |  |  | 78.57 |  |  |  | 60.13 |  |
| PBLACKCU | T: Cubic: Percent Black Nonhispanic |  |  | 0.00 |  |  |  | 0.00 |  |
| PFNOTLN | T: Linear: Percent Females Separated, Divorced Or Widowed |  |  | 0.00 |  |  |  | 0.00 |  |
| PMNEVLN | T: Linear: Percent Males Never Married |  |  |  |  | 1.85 |  |  |  |
| PMNOTLN | T: Linear: Percent Males Separated, Divorced Or Widowed |  |  |  |  | 84.60 |  |  |  |
| PMNOTQU | T: Quadratic: Percent Males Separated, Divorced Or Widowed |  |  |  |  | 93.42 |  |  |  |
| PMNOTCU | T: Cubic: Percent Males Separated, Divorced Or Widowed |  |  |  |  | 46.88 |  |  |  |
| PMNOTQR | T: Quartic: Percent Males Separated, Divorced Or Widowed |  |  |  |  | 4.29 |  |  |  |
| P40HULN | T: Linear: Percent Housing Units Built 1940-1949 |  |  |  |  | 2.32 |  | 0.00 |  |
| P40HUQU | T: Quadratic: Percent Housing Units Built 1940-1949 |  |  |  |  |  |  | 11.39 |  |
| P40HUCU | T: Cubic: Percent Housing Units Built 1940-1949 |  |  |  |  |  |  | 0.07 |  |
| P40HUQR | T: Quartic: Percent Housing Units Built 1940-1949 |  |  |  |  |  |  | 0.00 |  |
| PRENTLN | T: Linear: Percent Housing Rented |  |  |  |  |  |  | 7.03 | 0.00 |
| PRENTQU | T: Quadratic: Percent Housing Rented |  |  |  |  |  |  | 0.00 |  |
| ADRATEQR | C: Quartic: Death Rate For All Alcohol-Related Cases |  |  |  |  |  | 0.00 |  |  |
| ADRAT1LN | C: Linear: Death Rate With Explicit Mention Of Alcohol |  |  |  |  |  | 0.00 |  |  |
| V18FLN | C: Linear: Marijuana Posession Arrest Rate |  |  |  |  | 20.21 |  | 0.04 |  |

NOTE:


| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| BPRICALN | B: Linear: Percent Hispanics: Puerto Rican | 0.42 |  |  |  | 24.31 |  | 12.64 |  |
| BPRICAQU | B: Quadratic: Percent Hispanics: Puerto Rican |  |  |  |  | 6.37 |  | 0.06 |  |
| BPRICACU | B: Cubic: Percent Hispanics: Puerto Rican |  |  |  |  | 26.72 |  | 0.00 |  |
| BPRICAQR | B: Quartic: Percent Hispanics: Puerto Rican |  |  |  |  | 65.32 |  |  |  |
| IFEM315 | Female Interaction Of BPRICALN |  |  |  |  | 90.15 |  | 2.46 |  |
| IFEM316 | Female Interaction Of BPRICAQU |  |  |  |  | 3.78 |  | 26.43 |  |
| IFEM317 | Female Interaction Of BPRICACU |  |  |  |  | 50.82 |  | 0.01 |  |
| IFEM318 | Female Interaction Of BPRICAQR |  |  |  |  | 0.18 |  |  |  |
| BSCHASLN | B: Linear: Percent Associates Degree | 61.98 | 0.00 |  |  | 63.54 | 88.36 | 0.73 |  |
| BSCHASQU | B: Quadratic: Percent Associates Degree | 38.21 |  |  |  | 2.16 | 0.03 | 81.98 |  |
| BSCHASCU | B: Cubic: Percent Associates Degree | 5.57 |  |  |  | 15.09 |  | 0.00 |  |
| BSCHASQR | B: Quartic: Percent Associates Degree | 0.18 |  |  |  | 9.29 |  |  |  |
| IFEM320 | Female Interaction Of BSCHASLN |  |  |  |  | 74.76 |  |  |  |
| IFEM321 | Female Interaction Of BSCHASQU |  |  |  |  | 0.11 |  |  |  |
| IFEM322 | Female Interaction Of BSCHASCU |  |  |  |  | 3.39 |  |  |  |
| IFEM323 | Female Interaction Of BSCHASQR |  |  |  |  | 6.10 |  |  |  |
| PASIANLN | T: Linear: Percent Population: Asian, Pacitic Islander |  |  |  |  |  |  |  | 0.00 |
| PASIANQU | T: Quadratic: Percent Population: Asian, Pacitic Islander |  |  |  |  |  | $19.27$ | 7.88 |  |
| PASIANCU | T: Cubic: Percent Population: Asian, Pacitic Islander |  |  |  |  |  | 0.01 | 0.00 |  |
| IHISP325 | Hispanic Interaction Of PASIANLN |  |  |  |  |  | 24.64 |  |  |
| IHISP326 | Hispanic Interaction Of PASIANQU |  |  |  |  |  | 42.91 |  |  |
| IHISP327 | Hispanic Interaction Of PASIANCU |  |  |  |  |  | 8.42 |  |  |
| IOTH325 | Other Interaction Of PASIANLN |  |  |  |  |  | 0.01 |  |  |
| PINDIALN | T: Linear: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  | 7.72 | 0.03 |  |
| IHISP335 | Hispanic Interaction Of PINDIALN |  |  |  |  |  |  | 1.37 |  |
| IOTH335 | Other Interaction Of PINDIALN |  |  |  |  |  | 0.00 |  |  |

F6. Significance Probabilities for Fixed Effect Coefficients for Past Year Alcohol Treatment by Age


NOTE:

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| 1HISPLzo | Hispanic interaction Ut BADIANUU |  |  |  |  |  |  |  | 0.11 |
| BCUBANLN | B: Linear: Percent Hispanics: Cuban |  |  |  | 0.00 |  |  |  | 8.21 |
| BCUBANQU | B: Quadratic: Percent Hispanics: Cuban |  |  |  |  |  |  |  | 0.00 |
| IHISP290 | Hispanic Interaction Of BCUBANLN |  |  |  | 0.00 |  |  |  | 16.37 |
| IHISP291 | Hispanic Interaction Of BCUBANQU |  |  |  |  |  |  |  | 1.55 |
| BFNOTLN | B: Linear: Percent Females Separated, Divorced or Widowed |  |  |  | 0.00 | 78.51 |  |  | 0.20 |
| BFNOTQU | B: Quadratic: Percent Females Separated, Divorced or Widowed |  |  |  |  | 66.11 |  |  | 76.24 |
| BFNOTCU | B: Cubic: Percent Females Separated, Divorced or Widowed |  |  |  |  | 0.25 |  |  | 0.00 |
| BFNOTQR | B: Quartic: Percent Females Separated, Divorced or Widowed |  |  |  |  |  |  |  | 0.00 |
| BINDIALN | B: Linear: Percent Pop: American Indian, Eskimo, Aleut |  |  | 40.17 | 98.08 |  |  | 3.98 | 0.00 |
| BINDIAQU | B: Quadratic: Percent Pop: American Indian, Eskimo, Aleut |  |  | 19.35 | 0.00 |  |  | 0.56 | 0.00 |
| BINDIACU | B: Cubic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  | 0.00 |  |  |  | 0.00 |
| BINDIAQR | B: Quartic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  | 0.00 |  |  |  |  |
| IHISP300 | Hispanic Interaction Of BINDIALN |  |  | 38.45 |  |  |  | 96.34 |  |
| IHISP301 | Hispanic Interaction Of BINDIAQU |  |  | 0.00 |  |  |  | 2.61 |  |
| BMNOTLN | B: Linear: Percent Males Separated, Divorced or Widowed | 69.97 |  |  |  | 86.27 |  |  |  |
| BMNOTQU | B: Quadratic: Percent Males Separated, Divorced or Widowed | 18.54 |  |  |  | 31.79 |  |  |  |
| BMNOTCU | B: Cubic: Percent Males Separated, Divorced or Widowed |  |  |  |  | 18.19 |  |  |  |
| BMNOTQR | B: Quartic: Percent Males Separated, Divorced or Widowed |  |  |  |  | 24.53 |  |  |  |
| IFEM305 | Female Interaction Of BMNOTLN | 23.89 |  |  |  | 70.83 |  |  |  |
| IFEM306 | Female Interaction Of BMNOTQU | 3.24 |  |  |  | 31.76 |  |  |  |
| IFEM307 | Female Interaction Of BMNOTCU |  |  |  |  | 97.78 |  |  |  |
| IFEM308 | Female Interaction Of BMNOTQR |  |  |  |  | 2.40 |  |  |  |
| BPOVERLN | B: Linear: Percent Families Below Poverty Level | 32.43 |  |  |  |  |  | 46.73 |  |
| BPOVERQU | B: Quadratic: Percent Families Below Poverty Level | 60.68 |  |  |  |  |  | 60.11 |  |
| BPOVERCU | B: Cubic: Percent Families Below Poverty Level | 84.12 |  |  |  |  |  | 0.00 |  |
| BPOVERQR | B: Quartic: Percent Families Below Poverty Level | 5.34 |  |  |  |  |  |  |  |
|  | B: Linear: Percent Hispanics: Puerto Rican |  |  |  |  |  |  |  | 7.43 |
| BPRICAQU | B: Quadratic: Percent Hispanics: Puerto Rican |  |  |  |  |  |  | 25.91 |  |
| BPRICACU | B: Cubic: Percent Hispanics: Puerto Rican |  |  |  |  |  |  | 4.87 |  |
| BPRICAQR | B: Quartic: Percent Hispanics: Puerto Rican |  |  |  |  |  |  | 4.47 |  |
| IHISP315 | Hispanic Interaction Of BPRICALN |  |  |  |  |  |  |  | 0.73 |
| IHISP316 | Hispanic Interaction Of BPRICAQU |  |  |  |  |  |  | 12.72 |  |
| IHISP317 | Hispanic Interaction Of BPRICACU |  |  |  |  |  |  | 30.37 |  |
| IHISP318 | Hispanic Interaction Of BPRICAQR |  |  |  |  |  |  | 14.08 |  |
| BSCHASLN | B: Linear: Percent Associates Degree |  |  |  | 0.00 |  |  |  | 14.87 |
| BSCHASQU | B: Quadratic: Percent Associates Degree |  |  |  | 0.00 |  |  |  | 0.00 |
| BSCHASCU | B: Cubic: Percent Associates Degree |  |  |  | 0.00 |  |  |  | 0.00 |
| BSCHASQR | B: Quartic: Percent Associates Degree |  |  |  | 0.00 |  |  |  | 0.00 |
| IBLK320 | Black Interaction Of BSCHASLN |  |  |  | 0.00 |  |  |  | 21.52 |
| IBLK321 | Black Interaction Of BSCHASQU |  |  |  |  |  |  |  | 0.00 |
| PASIANLN | T: Linear: Percent Population: Asian, Pacitic Islander |  |  |  | 0.00 |  |  | 0.03 0.00 | 0.00 0.00 |
| PASIANCU | T: Cubic: Percent Population: Asian, Pacific Islander |  |  |  |  |  |  |  | 0.00 3.07 |
| PASIANQR | T: Quartic: Percent Population: Asian, Pacific Islander |  |  |  |  |  |  |  | 0.00 |
| IFEM325 | Female Interaction Of PASIANLN |  |  |  | 0.00 |  |  | 0.37 | 0.00 |
| IFEM326 | Female Interaction Of PASIANQU |  |  |  |  |  |  | 0.00 |  |
| IHISP325 | Hispanic Interaction Of PASIANLN |  |  |  |  |  |  | 5.15 |  |
| PCUBANLN | T: Linear: Percent Hispanics: Cuban |  |  |  |  |  | 69.17 | 0.00 |  |
| PCUBANQU | T: Quadratic: Percent Hispanics: Cuban |  |  |  |  |  | 1.46 | 0.56 |  |
| PCUBANCU | T: Cubic: Percent Hispanics: Cuban |  |  |  |  |  | 42.87 | 50.48 |  |
| PCUBANQR | T: Quartic: Percent Hispanics: Cuban |  |  |  |  |  | 18.70 | 0.00 |  |
| IFEM330 | Female Interaction Of PCUBANLN |  |  |  |  |  | 64.02 |  |  |
| IFEM331 | Female Interaction Of PCUBANQU |  |  |  |  |  | 18.59 |  |  |
| IFEM332 | Female Interaction Of PCUBANCU |  |  |  |  |  | 59.22 |  |  |
| IFEM333 | Female Interaction Of PCUBANQR |  |  |  |  |  | 1.97 |  |  |
| 1BLK330 | Black Interaction Of PCUBANLN |  |  |  |  |  |  | 28.02 |  |
| PINDIALN | T: Linear: Percent Pop: American Indian, Eskimo, Aleut |  |  | 0.00 |  |  |  | 0.03 |  |
| PINDIAQU | T: Quadratic: Percent Pop: American Indian, Eskimo, Aleut |  |  | 0.04 |  |  |  |  |  |
| PINDIACU | T: Cubic: Percent Pop: American Indian, Eskimo, Aleut |  |  | 0.00 |  |  |  |  |  |
| PINDIAQR | T: Quartic: Percent Pop: American Indian, Eskimo, Aleut |  |  | 0.00 |  |  |  |  |  |

## F7. Significance Probabilities for Fixed Effect Coefficients for Past Year Illicit Drug Use Treatment by Age

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| DUMMY | O: Intercept Term | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Female | O: Female Indicator | 0.14 | 4.25 | 0.00 | 68.27 | 3.58 | 0.79 | 0.01 | 0.00 |
| FEMBLCK | O: Black Interaction Of FEMALE | 63.75 | 76.89 | 64.53 | 0.00 | 44.15 | 46.19 | 42.27 | 14.83 |
| FEMHISP | O: Hispanic Interaction Of FEMALE | 1.08 | 0.19 | 0.01 | 0.12 | 54.30 | 70.89 | 46.50 | 25.73 |
| FEMOTHR | O: Other Interaction Of FEMALE |  |  |  |  |  |  | 12.59 |  |
| RACEBLCK RACEHISP | O: Race/Black Indicator | 0.17 80.64 | 0.84 88.44 | 0.16 1.06 | 0.00 0.00 | 37.33 85.61 | 9.46 5.98 | 25.89 23.33 | 0.00 16.68 |
| RACEOTHR | O: Race/Other Indicator |  | 0.02 |  |  | 21.58 |  | 60.38 | 0.00 |
| REGNOREA REGSOUTH | O: Northeast Region Indicator O: South Region Indicator |  |  |  |  | $\begin{array}{r} 3.15 \\ 51.98 \end{array}$ |  |  |  |
| IHISP7 IHISP8 | Hispanic Interaction Of REGNOREA Hispanic Interaction Of REGSOUTH |  |  | 0.07 1.33 |  |  |  |  |  |
| 1HISP9 | Hispanic Interaction Of REGWEST |  |  | 4.74 |  |  |  |  |  |
| PHHIPLN | T: Linear: Percent One Person Households |  |  |  |  |  |  | 0.01 | 0.00 |
| PHH1PQU | T: Quadratic: Percent One Person Households |  |  |  |  |  |  | 0.01 | 11.18 |
| PHHIPCU | T: Cubic: Percent One Person Households |  |  |  |  |  |  | 1.33 | 0.01 |
| PHHIPQR | T: Quartic: Percent One Person Households |  |  |  |  |  |  | 0.00 | 0.00 |
| POPRMLN | T: Linear: Average Persons Per Room |  |  |  |  |  |  | 0.00 |  |
| PAGE34LN | T: Linear: Percent Persons 25-34 Years |  |  |  |  | 61.80 |  |  |  |
| IFEM35 | Female Interaction Of PAGE34LN |  |  |  |  | 0.61 |  |  |  |
| $\begin{aligned} & \text { PSCH12LN } \\ & \text { PSCH12QU } \end{aligned}$ | T: Linear: Percent 9-12 Years \& No High School Diploma I: Quadratic: Percent 9-12 Years \& No High School Diploma |  |  |  | 0.00 |  |  |  | 0.00 0.00 |
| PSCHSCLN PSCHSCQU | T: Linear: Percent Some College And No Degree T: Quadratic: Percent Some College And No Degree |  | 0.00 0.78 |  |  |  | 2.09 0.19 |  | 0.00 0.00 |
| IFEM80 IFEM81 | Female Interaction Of PSCHSCLN Female Interaction Of PSCHSCQU |  | $\begin{aligned} & 0.02 \\ & 0.00 \end{aligned}$ |  |  |  |  |  | 0.00 0.00 |
| $\begin{aligned} & \text { IHISP80 } \\ & \text { IHISP81 } \end{aligned}$ | Hispanic Interaction Of PSCHSCLN Hispanic Interaction Of PSCHSCQU |  |  |  |  |  | 38.73 8.65 |  |  |
| PPOVERLN | T: Linear: Percent Families Below Poverty Level |  |  |  | 0.00 |  |  |  | 0.00 |
| PBLACKLN PBLACKQU | T: Linear: Percent Black Nonhispanic T: Quadratic: Percent Black Nonhispanic |  |  |  |  |  |  | 0.64 |  |
| PHISPLN | T: Linear: Percent Hispanic |  |  | 93.38 |  |  |  | 64.08 |  |
| ${ }^{\text {PHISPPQ }}$ | T: Quadratic: Percent Hispanic |  |  | 0.00 |  |  |  | 0.03 |  |
| PHISPCU | T: Cubic: Percent Hispanic |  |  | 0.00 |  |  |  | 0.00 |  |
| PHISPQR | T: Quartic: Percent Hispanic |  |  | 0.00 |  |  |  | 0.16 |  |
| POTHLN | T: Linear: Percent Other Race/Hispanicity |  |  |  |  |  | 34.18 |  |  |
| POTHQU | T: Quadratic: Percent Other Race/Hispanicity |  |  |  |  |  | 42.63 |  |  |
| POTHCU | T: Cubic: Percent Other Race/Hispanicity |  |  |  |  |  | 0.17 |  |  |
| IHISP110 | Hispanic Interaction Of POTHLN |  |  |  |  |  | 77.49 |  |  |
| 1HISP111 | Hispanic Interaction Of POTHQU |  |  |  |  |  | 15.30 |  |  |
| IHISP112 | Hispanic Interaction Of POTHCU |  |  |  |  |  | 24.84 |  |  |
| PHHF18LN PHHF18QU | T: Linear: \% Female-Headed HH W/No Spouse \& Chld Under 18 T: Quadratic: \% Female-Headed HH W/No Spouse \& Chld Under 18 |  |  |  |  | 42.41 78.22 |  |  |  |
| PHHFICCU | T: Cubic: \% Female-Headed HH W/No Spouse \& Chld Under 18 |  |  |  |  | 16.55 |  |  |  |
| PHHF18QR | T: Quartic: \% Female-Headed HH W/No Spouse \& Chld Under 18 |  |  |  |  | 0.82 |  |  |  |
| PFLABLN | T: Linear: Percent Females 16+ Years Old In Labor Force | 76.03 |  |  |  | 16.18 |  |  |  |
| PFLABQU | T: Quadratic: Percent Females 16+ Years Old In Labor Force | 0.29 |  |  |  | 56.85 |  |  |  |
| PFLABCU | T: Cubic: Percent Females 16+ Years Old In Labor Force |  |  |  |  | 83.02 |  |  |  |
| PFLABQR | T: Quartic: Percent Females 16+ Years Old In Labor Force |  |  |  |  | 0.05 |  |  |  |
| Prnevin | T: Linear: Percent Females Never Married |  |  | 0.00 |  |  |  |  |  |
| PFNEVQU | T: Quadratic: Percent Females Never Married |  |  |  |  |  |  | 11.79 |  |
| PFNEVCU PFNEVQR | T: Cubic: Percent Females Never Married T: Quartic: Percent Females Never Married |  |  |  |  |  |  | 24.54 0.00 |  |
| PMNEVLN | T: Linear: Percent Males Never Married |  |  |  |  |  | 0.00 |  | 0.15 |
| PMNEVQU | T: Quadratic: Percent Males Never Married |  |  |  |  |  |  |  | 0.00 |
| IBLK140 | Black Interaction Of PMNEVLN |  |  |  |  |  | 2.39 |  |  |
| PMLABLN PMLABOU | T: Linear: Percent Males $16+$ Years Old In Labor Force T: Quadratic: Percent Males $16+$ Years Old In Labor Force |  |  |  |  |  |  |  | 2.51 9.23 |
| ${ }^{\text {PMLABCU }}$ | T: Cubic: Percent Males 16+ Years Old In Labor Force |  |  |  |  |  |  |  | ${ }_{0.00}$ |
| PMLABQR | T: Quartic: Percent Males 16+ Years Old In Labor Force |  |  |  |  |  |  |  | 0.00 |
| ADRATELN ADRATEQU | C: Linear: Death Rate For All Alcohol-Related Cases <br> C: Quadratic: Death Rate For All Alcohol-Related Cases |  |  |  |  |  | $\begin{array}{r} 59.54 \\ 0.00 \end{array}$ |  |  |
| V18FLN | C: Linear: Mariuana Posession Arrest Rate |  |  |  | 0.00 |  | 42.28 |  | 0.00 |
| V18FQU V18FCu | C: Quadratic: Marijuana Posession Arrest Rate C: Cubic: Marijuana Posession Arrest Rate |  |  |  |  |  | 1.06 9.02 |  | 0.00 0.00 |
| V18FQR | C: Quartic: Marijuana Posession Arrest Rate |  |  |  |  |  | 0.11 |  |  |
| IHISP185 | Hispanic Interaction Of V18FLN |  |  |  |  |  |  |  | 9.25 |
| IHISP187 | Hispanic Interaction Of V18FCU |  |  |  |  |  |  |  | 0.06 |
| VI8BLN | C: Linear: Marijuana Sale/Manufacture Arrest Rate |  | 0.12 |  |  |  | 0.00 |  |  |

NOTE: T: Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other


NOTE: $\quad \mathrm{T}:$ Indicates a tract-level variable, $\mathrm{C}:$ Indicates a county-level variable, $\mathrm{B}:$ Indicates a block-level variable, O : Other

|  | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Variable |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| 1BLKSL2 | Black interaction Ut BSCHASCU |  |  |  |  |  |  | 0.42 |  |
| PASIANLN | T: Linear: Percent Population: Asian, Pacitic Islander |  |  |  |  | 34.34 |  | 76.52 |  |
| PASIANQU | T: Quadratic: Percent Population: Asian, Pacitic Islander |  |  |  |  |  |  | 0.09 |  |
| PASIANCU | T: Cubic: Percent Population: Asian, Pacitic Islander |  |  |  |  |  |  | 48.88 |  |
| PASIANQR | T: Quartic: Percent Population: Asian, Pacific Islander |  |  |  |  |  |  | 0.00 |  |
| PCUBANLN | T: Linear: Percent Hispanics: Cuban |  |  |  |  |  | 94.41 |  |  |
| PCUBANQU | T: Quadratic: Percent Hispanics: Cuban |  |  |  |  |  | 14.84 |  |  |
| PCUBANCU | T: Cubic: Percent Hispanics: Cuban |  |  |  |  |  | 81.24 |  |  |
| PCUBANQR | T: Quartic: Percent Hispanics: Cuban |  |  |  |  |  | 4.25 |  |  |
| IFEM330 | Female Interaction Of PCUBANLN |  |  |  |  |  | 0.58 |  |  |
| IFEM331 | Female Interaction Of PCUBANQU |  |  |  |  |  | 17.81 |  |  |
| IFEM332 | Female Interaction Of PCUBANCU |  |  |  |  |  | 62.35 |  |  |
| IFEM333 | Female Interaction Of PCUBANQR |  |  |  |  |  | 0.01 |  |  |
|  | T: Linear: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  |  |  |  |
| PINDIAQU | T: Quadratic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  |  | 2.07 |  |
| PINDIACU | T: Cubic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  |  | 0.00 |  |
| IBLK335 | Black Interaction Of PINDIALN |  |  |  |  |  |  | 69.10 |  |
| 1BLK336 | Black Interaction Of PINDIAQU |  |  |  |  |  |  | 63.35 |  |
| IBLK337 | Black Interaction Of PINDIACU |  |  |  |  |  |  | 1.95 |  |

## F8. Significance Probabilities for Fixed Effect Coefficients for Past Year Dependency on Alcohol Only by Age

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| DUMMY | O : Intercept Term | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| FEMALE | O: Female Indicator | 4.96 | 0.00 | 0.00 | 0.00 | 65.85 | 0.00 | 0.00 | 0.00 |
| Femblek | O: Black Interaction Of FEMALE | 0.74 | 89.92 | 50.43 | 0.00 | 25.55 | 84.93 | 94.45 | 20.97 |
| FEMHISP | O: Hispanic Interaction Of FEMALE | 95.05 | 0.00 | 0.00 | 0.00 | 86.83 | 83.81 | 26.07 | 0.52 |
| FEMOTHR | O: Other Interaction Of FEMALE | 64.23 | 19.71 | 32.50 | 0.00 |  | 0.00 | 50.36 |  |
| RACEBLCK RACEHISP | O: Race/Black Indicator O: Race/Hispanic Indicator | 54.46 1.90 | 0.00 35.01 | 0.00 0.06 | 0.00 52.63 | 23.20 91.23 | 0.41 25.78 | 87.95 0.75 | 0.00 4.51 |
| RACEOTHR | O: Race/Other Indicator | 0.73 | 0.00 | 0.00 | 0.00 |  | 0.00 | 0.99 | 15.38 |
| REGNOREA REGSOUTH | O: Northeast Region Indicator O: South Region Indicator |  |  |  |  | 70.41 45.32 |  |  |  |
| REGWEST | 0 : West Region Indicator |  |  |  |  | 51.64 |  |  |  |
| IBLK7 IBLK8 | Black Interaction Of ReGNOREA |  |  |  |  | 28.15 30.03 |  |  |  |
| IBLK9 | Black Interaction Of REGWEST |  |  |  |  | 18.21 |  |  |  |
| PDENLEV1 | O: Large MSA |  |  |  |  | 9.37 |  |  | 2.73 |
| PDENLEV2 | O: Medium MSA |  |  |  |  | 16.12 81.48 |  |  | 70.98 1.63 1 |
| PDENLEV4 | O: NonMSA, Urban |  |  |  |  | 53.42 |  |  | 0.00 |
| IBLK10 | Black Interaction Of PDENLEV1 |  |  |  |  | 66.79 |  |  | 0.00 |
| ${ }^{\text {IBLK11 }}$ | Black Interaction Of PDENLEV2 |  |  |  |  | 92.18 |  |  | 0.00 |
| IBLK12 | Black Interaction Of PDENLEV3 |  |  |  |  | 23.52 |  |  | 0.54 |
| IBLK13 | Black Interaction Of PDENLEV4 |  |  |  |  | 46.49 |  |  | 6.10 |
| $\begin{aligned} & \text { PHHIPLN } \\ & \text { PHHIPQU } \end{aligned}$ | T: Linear: Percent One Person Households |  |  |  |  |  |  |  | 0.00 0.00 |
| IFEM15 | Female Interaction Of PHH1PLN |  |  |  |  |  |  |  | 22.53 |
| IFEM16 | Female Interaction Of PHHIPQU |  |  |  |  |  |  |  | 0.00 |
| POPRMLN | T: Linear: Average Persons Per Room |  | 0.00 |  |  |  | 0.01 |  |  |
| POPRMQU | T: Quadratic: Average Persons Per Room |  |  |  |  |  | 0.01 |  |  |
| POPRMCU | T: Cubic: Average Persons Per Room |  |  |  |  |  | 0.00 |  |  |
| 1BLK21 | Black Interaction Of POPRMQU |  |  |  |  |  | 4.50 |  |  |
| PAGE44LN PAGE44()U | T: Linear: Percent Persons 35-44 Years |  |  |  |  | 95.95 3.94 |  |  |  |
| PSCHI2LN | T: Linear: Percent 9-12 Years \& No High School Diploma |  |  |  | 68.91 |  |  |  | 0.00 |
| PSCH12QU | T: Quadratic: Percent 9-12 Years \& No High School Diploma |  |  |  | 0.00 |  |  |  | 0.00 |
| PSCHI2CU | T: Cubic: Percent 9-12 Years \& No High School Diploma |  |  |  |  |  |  |  | 0.00 |
| PSCHCOLN | T: Linear: Bachelors, Graduate, Or Professional Degree |  |  |  |  |  |  |  | 0.00 |
| PSCHSCLN | T: Linear: Percent Some College And No Degree |  |  | 0.32 6396 |  |  |  |  |  |
| ${ }^{\text {PSCHSCOU }}$ | T: Quadratic: Percent Some College And No Degree T: Cubic: Percent Some College And No Degree |  |  | 63.96 0.00 |  |  |  | 1.01 73.54 |  |
| IFEM80 | Female Interaction Of PSCHSCLN |  |  |  |  |  |  | 29.01 |  |
| IFEM81 | Female Interaction Of PSCHSCQU |  |  |  |  |  |  | 63.88 |  |
| 1FEM82 | Female Interaction Of PSCHSCCU |  |  |  |  |  |  | 0.00 |  |
| PPOVERLN | T: Linear: Percent Families Below Poverty Level |  |  |  |  | 92.01 |  | 0.00 |  |
| PPOVERQU | T: Quadratic: Percent Families Below Poverty Level |  |  |  |  | 49.93 |  | 0.01 |  |
| PPOVERCU | T: Cubic: Percent Families Below Poverty Level |  |  |  |  | 34.87 |  | 23.15 |  |
| PPOVERQR | T: Quartic: Percent Families Below Poverty Level |  |  |  |  | 98.40 |  | 0.00 |  |
| IFEM85 | Female Interaction Of PPOVERLN |  |  |  |  | 78.71 |  |  |  |
| IFEM86 | Female Interaction Of PPOVERQU |  |  |  |  | 9.66 |  |  |  |
| IFEM87 | Female Interaction Of PPOVERCU |  |  |  |  | 51.85 |  |  |  |
| IFEM88 | Female Interaction Of PPOVERQR |  |  |  |  | 1.34 |  |  |  |
| IHISP85 | Hispanic Interaction Of PPOVERLN |  |  |  |  | 24.62 |  | 68.85 |  |
| IHISP86 | Hispanic Interaction Of PPOVERQU |  |  |  |  | 18.44 |  | 0.52 |  |
| P64DISLN | T: Linear: Percent 16-64 With A Work Disability |  | 0.35 |  |  |  | 0.01 |  |  |
| P64DISQU P64DISCU | T: Quadratic: Percent 16-64 With A Work Disability |  | 9.42 11.69 |  |  |  | $\stackrel{2.99}{1547}$ |  |  |
| P64DISCU P64DISQR | T: Cubic: Percent 16-64 With A Work Disability T: Quartic: Percent $16-64$ With A Work Disability |  | 11.69 15.40 |  |  |  | 15.47 0.00 |  |  |
| IBLK95 | Black Interaction Of P64DISLN |  | 3.64 |  |  |  | 12.94 |  |  |
| 1BLK96 | Black Interaction Of P64DISQU |  | 0.00 |  |  |  | 43.73 |  |  |
| IBLK97 | Black Interaction Of P64DISCU |  | 88.81 |  |  |  | 16.76 |  |  |
| 1BLK98 | Black Interaction Of P64DISQR |  | 0.00 |  |  |  | 2.58 |  |  |
| PHISPLN | T: Linear: Percent Hispanic |  |  |  |  |  |  |  | 0.00 |
| PHISPQU | T: Quadratic: Percent Hispanic |  |  |  |  |  |  |  | 0.00 |
| IBLK105 | Black Interaction Of PHISPLN |  |  |  |  |  |  |  | 33.38 |
| IBLK106 | Black Interaction Of PHISPQU |  |  |  |  |  |  |  | 0.00 |
| PFNOTLN PFNOTQU | T: Linear: Percent Females Separated, Divorced Or Widowed T. Quadratic: Percent Females Separated, Divorced Or Widowed |  |  |  |  |  | $36.75$ |  |  |
| IOTH135 <br> IOTH136 | Other Interaction Of PFNOTLN Other Interaction Of PFNOTOU |  |  |  |  |  | $\begin{array}{r} 41.02 \\ 0.28 \end{array}$ |  |  |
| PMNOTLN PMNOTQU PMNOTCU | T: Linear: Percent Males Separated, Divorced Or Widowed <br> T: Quadratic: Percent Males Separated, Divorced Or Widowed <br> T: Cubic: Percent Males Separated, Divorced Or Widowed |  |  |  |  |  |  |  | 0.07 0.00 0.00 |



NOTE: $\quad \mathrm{T}:$ Indicates a tract-level variable, $\mathrm{C}:$ Indicates a county-level variable, $\mathrm{B}:$ Indicates a block-level variable, $\mathrm{O}:$ Other

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | $35+$ | 12-17 | 18-25 | 26-34 | $35+$ |
| BCUBANLN | B: Linear: Percent Hispanics: Cuban |  | 0.00 | 0.00 |  |  | 32.91 |  |  |
| BCUBANQU | B: Quadratic: Percent Hispanics: Cuban |  | 0.00 | 3.38 |  |  | 20.78 |  |  |
| BCUBANCU | B: Cubic: Percent Hispanics: Cuban |  |  |  |  |  | 29.06 |  |  |
| BCUBANQR | B: Quartic: Percent Hispanics: Cuban |  |  |  |  |  | 0.00 |  |  |
| IFEM290 | Female Interaction Of BCUBANLN |  | 0.00 |  |  |  | 63.31 |  |  |
| IFEM291 | Female Interaction Of BCUBANQU |  | 0.00 |  |  |  | 49.55 |  |  |
| IFEM292 | Female Interaction Of BCUBANCU |  |  |  |  |  | 0.04 |  |  |
| IFEM293 | Female Interaction Of BCUBANQR |  |  |  |  |  | 0.00 |  |  |
| IBLK290 | Black Interaction Of BCUBANLN |  |  | 10.19 |  |  |  |  |  |
| IBLK291 | Black Interaction Of BCUBANQU |  |  | 0.00 |  |  |  |  |  |
| BFNOTLN | B: Linear: Percent Females Separated, Divorced or Widowed |  |  |  |  |  |  | 1.10 | 0.00 |
| BFNOTQU | B: Quadratic: Percent Females Separated, Divorced or Widowed |  |  |  |  |  |  | 92.94 | 24.93 |
| IFEM295 | Female Interaction Of BFNOTLN |  |  |  |  |  |  |  | 0.06 |
| IFEM296 | Female Interaction Of BFNOTQU |  |  |  |  |  |  |  | 0.00 |
| IOTH295 | Other Interaction Of BFNOTLN |  |  |  |  |  |  | 0.16 |  |
| IOTH296 | Other Interaction Of BFNOTQU |  |  |  |  |  |  | 0.00 |  |
| BINDIALN | B: Linear: Percent Pop: American Indian, Eskimo, Aleut |  |  | 0.00 |  | 60.23 |  | 0.92 | 0.01 |
| BINDIAQU | B: Quadratic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  |  | 10.17 | 0.00 |
| BINDIACU | B: Cubic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  |  |  |  | 1.09 |  |
| IBLK300 | Black Interaction Of BINDIALN |  |  | 0.00 |  | 2.59 |  | 50.83 |  |
| IBLK301 | Black Interaction Of BINDIAQU |  |  |  |  |  |  | 63.91 |  |
| IBLK302 | Black Interaction Of BINDIACU |  |  |  |  |  |  | 0.47 |  |
| IHISP300 | Hispanic Interaction Of BINDIALN |  |  | 0.00 |  |  |  | 35.26 |  |
| 1HISP301 | Hispanic Interaction Of BINDIAQU |  |  |  |  |  |  | 3.21 |  |
| BMNOTLN | B: Linear: Percent Males Separated, Divorced or Widowed |  |  | 0.00 | 0.00 | 55.18 | 9.17 | 8.02 | 0.14 |
| BMNOTQU | B: Quadratic: Percent Males Separated, Divorced or Widowed |  |  |  | 0.00 | 11.37 | 31.83 | 0.00 | 0.00 |
| BMNOTCU | B: Cubic: Percent Males Separated, Divorced or Widowed |  |  |  | 46.81 | 88.51 |  |  | 0.00 |
| BMNOTQR | B: Quartic: Percent Males Separated, Divorced or Widowed |  |  |  | 0.00 | 4.51 |  |  | 17.98 |
| IBLK305 | Black Interaction Of BMNOTLN |  |  |  | 0.00 |  |  |  | 0.00 |
| 1BLK306 | Black Interaction Of BMNOTQU |  |  |  | 0.00 |  |  |  | 53.28 |
| 1BLK307 | Black Interaction Of BMNOTCU |  |  |  | 0.00 |  |  |  | 0.00 |
| IBLK308 | Black Interaction Of BMNOTQR |  |  |  |  |  |  |  | 0.00 |
| IHISP305 | Hispanic Interaction Of BMNOTLN |  |  |  |  | 31.66 |  |  |  |
| IHISP306 | Hispanic Interaction Of BMNOTQU |  |  |  |  | 57.74 |  |  |  |
| IHISP307 | Hispanic Interaction Of BMNOTCU |  |  |  |  | 87.35 |  |  |  |
| 1HISP308 | Hispanic Interaction Of BMNOTQR |  |  |  |  | 7.17 |  |  |  |
| BPOVERLN | B: Linear: Percent Families Below Poverty Level |  |  |  |  |  |  |  | 0.00 |
| BPOVERQU | B: Quadratic: Percent Families Below Poverty Level |  |  |  | 0.00 |  |  |  |  |
| BPOVERCU | B: Cubic: Percent Families Below Poverty Level |  |  |  | 0.00 |  |  |  |  |
| IHISP310 | Hispanic Interaction Of BPOVERLN |  |  |  |  |  |  |  | 0.00 |
| BPricaln | B: Linear: Percent Hispanics: Puerto Rican |  | 0.00 | 0.02 |  |  | 0.13 | 3.05 |  |
| BPRICAQU | B: Quadratic: Percent Hispanics: Puerto Rican |  |  | 2.63 |  |  |  | 16.50 |  |
| BPRICACU | B: Cubic: Percent Hispanics: Puerto Rican |  |  | 0.00 |  |  |  | 12.62 |  |
| BPRICAQR | B: Quartic: Percent Hispanics: Puerto Rican |  |  |  |  |  |  | 0.00 |  |
| IBLK315 | Black Interaction Of BPRICALN |  |  |  |  |  |  | 14.04 |  |
| IBLK316 | Black Interaction Of BPRICAQU |  |  |  |  |  |  | 57.20 |  |
| IBLK317 | Black Interaction Of BPRICACU |  |  |  |  |  |  | 70.65 |  |
| IBLK318 | Black Interaction Of BPRICAQR |  |  |  |  |  |  | 0.87 |  |
| PASIANLN | T: Linear: Percent Population: Asian, Pacitic Islander | 78.78 |  |  |  | 47.49 | 26.45 |  | 0.00 |
| PASIANQU | T: Quadratic: Percent Population: Asian, Pacitic Islander | 0.77 |  |  |  | 11.47 | 16.96 |  | 0.00 |
| PASIANCU | T: Cubic: Percent Population: Asian, Pacitic Islander | 2.40 |  |  |  | 43.05 | 0.27 |  | 0.00 |
| PASIANQR | T: Quartic: Percent Population: Asian, Pacific Islander |  |  |  |  | 33.47 |  |  |  |
| IFEM325 | Female Interaction Of PASIANLN | 93.85 |  |  |  | 6.84 |  |  |  |
| IFEM326 | Female Interaction Of PASIANQU | 1.06 |  |  |  | 37.34 |  |  |  |
| IFEM327 | Female Interaction Of PASIANCU | 1.57 |  |  |  | 83.07 |  |  |  |
| IFEM328 | Female Interaction Of PASIANQR |  |  |  |  |  |  |  |  |
| IBLK325 | Black Interaction Of PASIANLN |  |  |  |  |  | 31.62 |  |  |
| 1BLK326 | Black Interaction Of PASIANQU |  |  |  |  |  | 55.41 |  |  |
| IBLK327 | Black Interaction Of PASIANCU |  |  |  |  |  | 0.22 |  |  |
| PCUBANLN | T: Linear: Percent Hispanics: Cuban | 56.65 | 0.00 |  | 0.03 | 82.30 | 26.17 |  | 0.00 |
| PCUBANQU | T: Quadratic: Percent Hispanics: Cuban |  |  |  | 0.00 |  | 89.19 |  | 6.12 |
| PCUBANCU | T: Cubic: Percent Hispanics: Cuban |  |  |  |  |  |  |  | 0.00 |
| IBLK330 | Black Interaction Of PCUBANLN | 1.54 |  |  | 0.00 | 14.80 |  |  | 7.06 |
| 1BLK331 | Black Interaction Of PCUBANQU |  |  |  | 0.00 |  |  |  | 0.69 |
| IBLK332 | Black Interaction Of PCUBANCU |  |  |  |  |  |  |  | 0.00 |
| IOTH330 | Other Interaction Of PCUBANLN |  |  |  |  |  | 8.87 |  |  |
| IOTH331 | Other Interaction Of PCUBANQU |  |  |  |  |  | 3.06 |  |  |
| PINDIALN | T: Linear: Percent Pop: American Indian, Eskimo, Aleut | 50.38 |  |  | 0.00 | 50.95 |  |  |  |
| PINDIAQU | T: Quadratic: Percent Pop: American Indian, Eskimo, Aleut | 32.08 |  |  | 0.00 | 5.07 |  |  |  |
| PINDIACU | T: Cubic: Percent Pop: American Indian, Eskimo, Aleut | 82.38 |  |  | 0.00 | 14.36 |  |  |  |
| PINDIAQR | T: Quartic: Percent Pop: American Indian, Eskimo, Aleut |  |  |  | 0.00 |  |  |  |  |
| TFEM335 | Female Interaction OfPINDIALN |  |  |  |  |  |  |  |  |
| IFEM336 | Female Interaction Of PINDIAQU | 10.17 |  |  |  | 1.57 |  |  |  |
| IFEM337 | Female Interaction Of PINDIACU | 1.88 |  |  |  | 2.55 |  |  |  |
| IHISP335 | Hispanic Interaction Of PINDIALN |  |  |  | 0.00 |  |  |  |  |
| 1HISP336 | Hispanic Interaction Of PINDIAQU |  |  |  | 0.00 |  |  |  |  |
| IHISP337 | Hispanic Interaction Of PINDIACU |  |  |  | 0.00 |  |  |  |  |
| 1HISP338 | Hispanic Interaction Of PINDIAQR |  |  |  | 0.00 |  |  |  |  |
| IOTH335 | Other Interaction Of PINDIALN |  |  |  | 0.00 |  |  |  |  |
| 10TH336 | Other Interaction Of PINDIAQU |  |  |  | 0.00 |  |  |  |  |

F9. Significance Probabilities for Fixed Effect Coefficients for Past Year Illicit Dependency by Age


NOTE:


|  | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Variable |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| BSCHASUU BSCHASCU | B: Uuadratic: Percent Associates Degree <br> B: Cubic: Percent Associates Degree |  |  |  | 13.20 0.00 |  |  |  |  |
| IHISP320 | Hispanic Interaction Of BSCHASLN |  |  |  | 0.00 |  |  |  |  |
| IHISP321 | Hispanic Interaction Of BSCHASQU |  |  |  | 0.00 |  |  |  |  |
| IHISP322 | Hispanic Interaction Of BSCHASCU |  |  |  | 0.00 |  |  |  |  |
| PASIANLN | T: Linear: Percent Population: Asian, Pacitic Islander |  | 0.00 |  |  |  | 0.00 |  |  |
| PCUBANLN | T: Linear: Percent Hispanics: Cuban | 57.23 |  | 11.78 |  |  |  | 5.25 | 0.00 |
| PCUBANQU | T: Quadratic: Percent Hispanics: Cuban | 87.26 |  | 0.00 |  |  |  | 0.25 | 0.00 |
| PCUBANCU | T: Cubic: Percent Hispanics: Cuban |  |  |  |  |  |  | 13.14 | 0.00 |
| PCUBANQR | T: Quartic: Percent Hispanics: Cuban |  |  |  |  |  |  | 0.00 | 0.00 |
| IFEM330 | Female Interaction Of PCUBANLN | 1.97 |  |  |  |  |  |  |  |
| 1BLK330 | Black Interaction Of PCUBANLN | 71.96 |  |  |  |  |  |  | 55.75 |
| 1BLK331 | Black Interaction Of PCUBANQU | 0.02 |  |  |  |  |  |  | 0.75 |
| IBLK332 | Black Interaction Of PCUBANCU |  |  |  |  |  |  |  | 24.02 |
| IBLK333 | Black Interaction Of PCUBANQR |  |  |  |  |  |  |  | 0.00 |

F10. Significance Probabilities for Fixed Effect Coefficients for Past Year Arrested by Age



NOTE:

| Variable | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 12-17 | 18-25 | 26-34 | 35+ | 12-17 | 18-25 | 26-34 | 35+ |
| BPKILAQU BPRICACU | B: Quadratic: Percent Hispanics: Puerto Kıcan <br> B: Cubic: Percent Hispanics: Puerto Rican | 4.73 0.00 |  |  |  | $\begin{array}{r} 9.86 \\ 12.75 \end{array}$ |  |  |  |
| IFEM315 | Female Interaction Of BPRICALN |  |  |  |  | 16.41 |  |  |  |
| IFEM316 | Female Interaction Of BPRICAQU |  |  |  |  | 49.28 |  |  |  |
| IFEM317 | Female Interaction Of BPRICACU |  |  |  |  | 4.19 |  |  |  |
| BSCHASLN | B: Linear: Percent Associates Degree |  |  |  |  | 44.93 |  | 97.97 50.87 |  |
| BSCHASQU | B: Quadratic: Percent Associates Degree B: Cubic: Percent Associates Degree |  |  |  |  | 65.53 0.03 |  | 50.87 40.06 |  |
| BSCHASCU | B: Cubic: Percent Associates Degree B: Quartic: Percent Associates Degree |  |  |  |  |  |  | 40.06 0.00 |  |
| PASIANLN PASIANOU | T: Linear: Percent Population: Asian, Pacific Islander T: Quadratic: Percent Population: Asian, Pacific Islander |  |  |  |  | 39.47 39.05 |  |  |  |
| PASIANCU | T: Cubic: Percent Population: Asian, Pacitic Islander |  |  |  |  | 39.05 1.23 |  |  |  |
| IFEM325 | Female Interaction Of PASIANLN |  |  |  |  | 31.71 |  |  |  |
| IFEM326 | Female Interaction Of PASIANQU |  |  |  |  | 77.29 |  |  |  |
| IFEM327 | Female Interaction Of PASIANCU |  |  |  |  | 0.43 |  |  |  |
|  | T: Linear: Percent Hispanics: Cuban |  |  |  |  | $\begin{array}{r} 70.18 \\ 66.99 \\ 0.00 \end{array}$ |  |  |  |
| PCUBANQU | T: Quadratic: Percent Hispanics: Cuban |  |  |  |  |  |  |  |  |
| PCUBANCU | T: Cubic: Percent Hispanics: Cuban |  |  |  |  |  |  |  |  |

F11. Significance Probabilities for Fixed Effect Coefficients for Past Year Treatment Needed for Drug Abuse by Age




NOTE:
T : Indicates a tract-level variable, C: Indicates a county-level variable, B: Indicates a block-level variable, O: Other

|  | Label | BIG CITY |  |  |  | REMAINDER |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Variable |  | 12-17 | 18-25 | 26-34 | $35+$ | 12-17 | 18-25 | 26-34 | $35+$ |
| IUIHsa/ | Uther interaction Ui PIINDIACU |  |  |  |  |  |  | u.vo |  |

## Appendix G: Details of Estimating <br> Variances

## Appendix G. Details of Estimating Variances

## G. 1 Derivation of Formulas

As discussed in Section 2.6, we want to estimate ${ }^{1}$

$$
\begin{equation*}
\mathrm{MSE}_{\mathrm{i}}=\mathrm{E}\left(\hat{\pi}_{i}^{W}-\pi_{i}\right)^{2} \tag{G.1}
\end{equation*}
$$

where $\pi_{i}$ is the sum of person-level propensities for area i. Expanding (G.1), we have that it is equal to

$$
\begin{align*}
\mathrm{MSE}_{\mathrm{i}} & =\mathrm{E}\left[\sum_{a} \sum_{d} \sum_{b} N_{i b}^{a d} \hat{\pi}_{i b}^{a d}-\sum_{a} \sum_{d} \sum_{b} N_{i b}^{a d} \pi_{i b}^{a d}\right]^{2}  \tag{G.2}\\
& =\sum_{a} \mathrm{E}\left[\sum_{d} \sum_{b} N_{i b}^{a d}\left(\hat{\pi}_{i b}^{a d}-\pi_{i b}^{a d}\right)\right]^{2}=\sum_{a} \mathrm{MSE}_{\mathrm{i}}^{\mathrm{a}}
\end{align*}
$$

This approximation ignores the covariances of the errors across the domains for which separate models were fit. Recall that there were four such domains, defined by age, as discussed in Section 2.5. We believe that these covariances are mostly positive since over- or underestimation of the substance abuse rate for one age domain in an area is probably accompanied by similar over- or underestimation of the rate for the other age domains in the same area, but the sizes and signs of the covariances are unknown. We were forced to ignore them by the computing constraints.

To simplify notation, we will now focus on a particular area $i$ and age group $a$, dropping the $a$ subscript since the age groups were modeled separately. We may then write the inner expectation in (G.2) as

$$
\begin{equation*}
\operatorname{MSE}_{\mathrm{i}}^{\mathrm{a}}=\mathrm{E}\left[\sum_{d} \sum_{b} N_{i b}^{d}\left(\hat{\pi}_{i b}^{d}-\pi_{i b}^{d}\right)\right]^{2}=\mathrm{E}\left[\tilde{N}^{t}(\hat{\pi}-\pi)\right]^{2} \tag{G.3}
\end{equation*}
$$

where $\tilde{N}$ is the column matrix of populations for age group $a$ by domain $d$ for the various block groups in the $i$-th area, $\hat{\pi}$ is the column matrix of estimated propensities to engage in the behavior

[^16]of interest, and $\pi$ is the column matrix of propensities given the manifestation of state and PSU effects.

Since $\tilde{N}$ is fixed, we may rewrite (G.3) as

$$
\begin{equation*}
\mathrm{MSE}_{\mathrm{i}}^{\mathrm{a}}=\tilde{N}^{t} \mathrm{E}\left[(\hat{\pi}-\pi)(\hat{\pi}-\pi)^{t}\right] \tilde{N} \tag{G.4}
\end{equation*}
$$

Since $\hat{\pi}$ and $\pi$ are nonlinear functions of $(\hat{\beta}, \hat{U})$ and $(\beta, U)$, respectively, the inner expectation of $\hat{\pi}$ (G.4) is difficult to compute exactly. Following McGibbon and Tomerlin (1989), we used a first-order Taylor linearization to simplify the calculation. Focusing on the predicted propensity for a specific domain and block group, and treating it as a function of ( $\hat{\beta}, \hat{U})$, we have that

$$
\hat{\pi}_{i b}^{d}(\hat{\beta}, \hat{U})=\hat{\pi}_{i b}^{d}(\beta, U)+\left[\begin{array}{l}
\frac{\partial \hat{\pi}_{i b}^{d}}{\partial \hat{\beta}}(\beta, U)  \tag{G.5}\\
\frac{\partial \hat{\pi}_{i b}^{d}}{\partial \hat{U}}(\beta, U)
\end{array}\right]^{t}\left[\begin{array}{l}
\hat{\beta}-\beta \\
\hat{U}-U
\end{array}\right]
$$

The first partial derivative of $\hat{\pi}_{i b}^{d}$ with respect to $\hat{\beta}$ is

$$
\begin{aligned}
\partial \frac{\hat{\pi}_{i b}^{d}}{\partial \hat{\beta}} & =\frac{\partial}{\partial \hat{\beta}}\left[\frac{1}{1+\exp \left[-\left(X_{i b}^{d} \hat{\beta}+Z_{i b} \hat{U}\right)\right]}\right] \\
& =\frac{-\frac{\partial}{\partial \hat{\beta}}\left[1+\exp \left[-\left(X_{i b}^{d} \hat{\beta}+Z_{i b} \hat{U}\right)\right]\right]}{\left\{1+\exp \left[-\left(X_{i b}^{d} \hat{\beta}+Z_{i b} \hat{U}\right)\right]\right\}^{2}} \\
& =\left(X_{i b}^{d}\right)^{t} \frac{\exp \left[-\left(X_{i b}^{d} \hat{\beta}+Z_{i b} \hat{U}\right)\right]}{\left\{1+\exp \left[-\left(X_{i b}^{d} \hat{\beta}+Z_{i b} \hat{U}\right)\right]\right\}^{2}},
\end{aligned}
$$

where $X_{i b}^{d}$ and $Z_{i b}$ are defined as in Sections 2.5 and 2.6. Evaluating at $(\beta, U)$, we have

$$
\frac{\partial \hat{\pi}_{i b}^{d}}{\partial \hat{\beta}}(\beta, U)=\left(X_{i b}^{d}\right)^{t} \frac{\exp \left[-\left(X_{i b}^{d} \beta+Z_{i b} U\right)\right]}{\left\{1+\exp \left[-\left(X_{i b}^{d} \beta+Z_{i b} U\right)\right]\right\}^{2}}=\left(X_{i b}^{d}\right)^{t} \pi_{i b}^{d}\left(1-\pi_{i b}^{d}\right)
$$

Similarly,

$$
\frac{\partial \hat{\pi}_{i b}^{d}}{\partial \hat{U}}(\beta, U)=Z_{i b}^{t} \pi_{i b}^{d}\left(1-\pi_{i b}^{d}\right)
$$

Substituting into (G.5) and noting that $\hat{\pi}_{i b}^{d}(\beta, U)=\pi_{i b}^{d}$, we have that

$$
\begin{aligned}
\hat{\pi}_{i b}^{d}(\hat{\beta}, \hat{U}) & =\pi_{i b}^{d}+\pi_{i b}^{d}\left(1-\pi_{i b}^{d}\right)\left[X_{i b}^{d} Z_{i b}\right]\left[\begin{array}{c}
\hat{\beta}-\beta \\
\hat{U}-U
\end{array}\right] \\
& =\pi_{i b}^{d}+\pi_{i b}^{d}\left(1-\pi_{i b}^{d}\right)\left[X_{i b}^{d}(\hat{\beta}-\beta)+Z_{i b}(\hat{U}-U)\right]
\end{aligned}
$$

Thus

$$
\begin{equation*}
\hat{\pi}_{i b}^{d}-\pi_{i b}^{d} \doteq \pi_{i b}^{d}\left(1-\pi_{i b}^{d}\right)\left[X_{i b}^{d}(\hat{\beta}-\beta)+Z_{i b}(\hat{U}-U)\right] \tag{G.6}
\end{equation*}
$$

Substituting into (G.4), we have

$$
\begin{equation*}
M S E_{i}^{a}=\tilde{N}^{t} \mathrm{E}\left\{[\stackrel{*}{C} \mathbb{X}(\hat{\beta}-\beta)+\stackrel{*}{C} \underline{Z}(\hat{U}-U)]\left[\stackrel{*}{C} \stackrel{*}{X}(\hat{\beta}-\beta)+\stackrel{*}{C} Z(\hat{Z}(\hat{U}-U)]^{t}\right\} \tilde{N}\right. \tag{G.7}
\end{equation*}
$$

where an asterisk over a $C, X$, or $Z$ indicates that the matrix has one row for every domain within every block group in the area as opposed to having one row per sample person as was the case for the model fitting.

We now make an additional simplifying assumption, treating $C$ as fixed even through it must be estimated. With that additional assumption, we have that

$$
\begin{align*}
& M S E_{i}^{a} \doteq \tilde{N}^{t}{ }^{*} E\left\{\left[{ }^{*}\left(\hat{X}(\hat{\beta}-\beta)+{ }^{*}(\hat{U}-U)\right]\left[\begin{array}{|c}
* \\
(
\end{array} \hat{\beta}-\beta\right)+{ }^{*}(\hat{U}-U)\right]^{t}\right\} \stackrel{*}{C} \tilde{N} \\
& =\tilde{N}^{t} \stackrel{*}{C} E\left[\stackrel{*}{X}(\hat{\beta}-\beta)(\hat{\beta}-\beta)^{t}\right] \stackrel{*}{C} \tilde{N}+  \tag{G.8}\\
& +2 \tilde{N}^{t} \stackrel{*}{C} E\left[\stackrel{*}{X}(\hat{\beta}-\beta)(\hat{U}-U)^{t} Z^{t}\right] \stackrel{*}{C} \tilde{N}+ \\
& +\tilde{N}^{t} \stackrel{*}{C} E\left[\stackrel{*}{Z}(\hat{U}-U)(\hat{U}-U)^{t^{Z}}{ }^{*}\right] \stackrel{*}{C} \tilde{N} \text {. }
\end{align*}
$$

Since $\stackrel{*}{X}$ and ${ }^{*}$ are fixed, we may further simplify to

$$
\begin{align*}
M S E_{i}^{a} & \doteq \tilde{N}^{t} \stackrel{*}{C} X \mathrm{E}\left[(\hat{\beta}-\beta)(\hat{\beta}-\beta)^{t}\right] \stackrel{*}{X}^{t} \stackrel{*}{C} \tilde{N}  \tag{G.9}\\
& +2 \tilde{N}^{t}{ }^{*} \stackrel{*}{X} \mathrm{E}\left[(\hat{\beta}-\beta)(\hat{U}-U)^{t}\right] Z^{t}{ }^{t} \stackrel{*}{C} \tilde{N}+\tilde{N}^{t} \stackrel{*}{C} \stackrel{*}{Z} \mathrm{E}\left[(\hat{U}-U)(\hat{U}-U)^{t}\right] Z^{t}{ }^{t} \tilde{C}^{*} \tilde{N}
\end{align*}
$$

At this point, it is important to note that we estimated $\hat{U}_{i j}=0$ for every PSU $j$ which was not in sample. We could have made random draws for these variables from the normal distribution with mean zero and variance $\hat{\sigma}_{2}^{2}$, but we saw no reason to introduce extra noise into the system. Random draws might have been an appropriate step if we had been interested in the distribution of propensities across all PSUs, but this was not a primary goal of our work. Rather, our primary goal was to minimize the mean square error of the predictions for the states and large MSAs. For this goal, we think that estimating a zero random effect for all nonsample counties was the best course of action. Our initial MSE estimates ignored the fact that these zero predictions have a nonzero error associated with them. We show both the original formula for estimating mean square error and the revised formula.

Let $U_{S}$ denote the vector of random effects for the states and the sample PSUs. Let $U_{\$}$ denote the corresponding vector for the nonsample PSUs in states of interest. Let $Z_{\$}$ be a matrix with as many rows as ${ }_{Z}^{*}$ and as many columns as there are nonsample PSUs in the states of interest, where each row of $Z_{\mathbb{S}}$ is mostly zeroes. A one in the $j$-th column of the $i$-th row of $Z_{\mathbb{\$}}$ indicates that the $i$-th domain and block group combination is in the $j$-th nonsample PSU. Let $Z_{S}$ denote the columns of ${ }_{Z}^{*}$ corresponding to the random effects for states and sample PSUs. Then we may write

$$
\lambda=X \beta+\left[\begin{array}{ll}
Z_{S} & Z_{\$}
\end{array}\right]\left[\begin{array}{l}
U_{S}  \tag{G.10}\\
U_{\mathrm{S}}
\end{array}\right]
$$

and

$$
\begin{equation*}
\hat{\pi}-\pi \doteq C\left[X(\hat{\beta}-\beta)+Z_{S}\left(\hat{U}_{S}-U_{S}\right)-Z_{\$} U_{\$}\right] \tag{G.11}
\end{equation*}
$$

Since all the true random effects (those for states, sample PSUs and nonsample PSUs) are assumed to be mutually independent and since the estimates of the model parameters are independent of the true random effects for areas not in sample, the mean square error can be rewritten as

$$
\begin{align*}
& M S E_{i}^{a} \doteq \tilde{N}^{t} \stackrel{*}{C} \stackrel{*}{X} \mathrm{E}\left[(\hat{\beta}-\beta)(\hat{\beta}-\beta)^{t}\right] X^{t} \stackrel{*}{C} \tilde{N} \\
&+2 \tilde{N}^{t} \stackrel{*}{C} \stackrel{*}{X} \mathrm{E}\left[(\hat{\beta}-\beta)\left(\hat{U}_{S}-U_{S}\right)^{t}\right]{ }^{*}{ }_{S}^{t} \stackrel{*}{C} \tilde{N}+  \tag{G.12}\\
&+\tilde{N}^{t} \stackrel{*}{C}^{*} Z_{S} \mathrm{E}\left[\left(\hat{U}_{S}-U_{S}\right)\left(\hat{U}_{S}-U_{S}\right)^{t}\right] Z_{S}^{t} \stackrel{*}{C} \tilde{N}+ \\
&+\tilde{N}^{t} \stackrel{*}{C} Z_{\$} \mathrm{E}\left(U_{S} U_{S}^{t}\right) Z_{\$}^{t} \stackrel{*}{C} \tilde{N}
\end{align*}
$$

The fourth term is the term that was omitted from the original MSE calculations.

We now examine each of the terms in (G.12) in turn. Starting with the $\beta$-term, we have that

$$
\beta=\left(X^{t} V^{-1} X\right)^{-1}\left(X^{t} V^{-1} X\right) \beta
$$

and

$$
\hat{\beta}=\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} \zeta
$$

So

$$
\begin{equation*}
\hat{\beta}-\beta=\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}(\zeta-X \beta) \tag{G.13}
\end{equation*}
$$

We demonstrated in Section C.1, that the covariance matrix for $\zeta$ is $V$. Thus, if we treated $V$ as fixed rather than as a parameter to be estimated, we have that

$$
\begin{align*}
\mathrm{E}\left[(\hat{\beta}-\beta)(\hat{\beta}-\beta)^{t}\right] & =\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} \mathrm{E}\left[(\zeta-X \beta)(\zeta-X \beta)^{t}\right] V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} \\
& =\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} V V^{-1} X\left(X^{t} V^{-1} X\right)^{-1}  \tag{G.14}\\
& =\left(X^{t} V^{-1} X\right)^{-1}\left(X^{t} V^{-1} X\right)\left(X^{t} V^{-1} X\right)^{-1} \\
& =\left(X^{t} V^{-1} X\right)^{-1}
\end{align*}
$$

Temporarily skipping the second term of (G.12) and looking instead at the third term of (G.12), we have from Section C. 1 that

$$
\hat{U}=G Z^{t} P \zeta
$$

where we have dropped the $S$ subscript since it is clear that we are only talking about the random effects for states and sample PSUs in this equation. Using Lemma C. 1 that $P X=0$, we can rewrite this as

$$
\hat{U}=G Z^{t} P(\zeta-X \beta)
$$

By the definition of $\zeta$ and $\varepsilon$ from Section C.1, we have then that

$$
\hat{U}=G Z^{t} P\left(Z U+W^{-1} \varepsilon\right)
$$

Thus,

$$
\begin{gather*}
\mathrm{E}(\hat{U}-U)(\hat{U}-U)^{t}=\mathrm{E}\left\{\left[G Z^{t} P\left(Z U+W^{-1} \varepsilon\right)-U\right]\left[U^{t} Z^{t}+\varepsilon^{t} W^{-1} P Z G-U^{t}\right]\right\} \\
=\mathrm{E}\left(G Z^{t} P Z U U^{t} Z^{t} P Z G\right)+\mathrm{E}\left(G Z^{t} P W^{-1} \varepsilon U^{t} Z^{t} P Z G\right)+ \\
+\mathrm{E}\left(G Z^{t} P Z U \varepsilon^{t} W^{-1} P Z G\right)+\mathrm{E}\left(G Z^{t} P W^{-1} \varepsilon \varepsilon^{t} W^{-1} P Z G\right)+  \tag{G.15}\\
-\mathrm{E}\left(G Z^{t} P Z U U^{t}\right)-\mathrm{E}\left(U U^{t} Z^{t} Z^{t} P Z G\right) \\
-\mathrm{E}\left(U \varepsilon^{t} W^{-1} P Z G\right)+\mathrm{E}\left(U U^{t}\right)
\end{gather*}
$$

We now ignore the fact that $G$ and $P$ are both estimated from the data and instead treat them as fixed. We can then bring the expected value operator inside each term to focus just on the variability in $U$ and in $\varepsilon$. Here we note that in Section C.1, we showed that $U$ and $\varepsilon$ are uncorrelated, the $\operatorname{Cov}(\varepsilon)=\mathrm{C}^{-1}$, and that $P V P=P$.

Using this simplifying assumption and the results from Section C.1, we have that

$$
\begin{align*}
\mathrm{E}(\hat{U}-U)(\hat{U}-U)^{t} & =G Z^{t} P Z G Z^{t} P Z G+0+0+G Z^{t} P W^{-1} C^{-1} W^{-1} P Z G+ \\
& -G Z^{t} P Z G-G Z^{t} P Z G-0+G \\
& =G Z^{t} P(V-R) P Z G+G Z^{t} P R P Z G-2 G Z^{T} P Z G+G  \tag{G.16}\\
& =G Z^{t} P V P Z G-2 G Z^{t} P Z G+G \\
& =G Z^{t} P Z G-2 G Z^{t} P Z G+G \\
& =G-G Z^{t} P Z G
\end{align*}
$$

The fourth term is quite simple. By definition, $\mathrm{E}\left(U_{\$} U_{\$}^{t}\right)=\sigma_{2}^{2} I$, where $I$ is the identity matrix of order equal to the number of nonsample PSUs in the states of interest.

Returning now to the second term of (G.12) and using the representations developed for the first and third terms, we have that

$$
\begin{align*}
& \left.\mathrm{E}(\hat{\beta}-\beta)(\hat{U}-U)^{t}=\mathrm{E}\left\{\left[\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}\left(Z U+W^{-1} \varepsilon\right)\right]\left[U^{t} Z^{t}+\varepsilon^{t} W^{-1}\right) P Z G-U^{t}\right]\right\} \\
& =\mathrm{E}\left[\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} Z U U^{t} Z^{t} P Z G\right]+\mathrm{E}\left[\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} Z U \varepsilon^{t} W^{-1} P Z G\right]+  \tag{G.17}\\
& +\mathrm{E}\left[\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} W^{-1} \varepsilon U^{t} Z^{t} P Z G\right]+\mathrm{E}\left[\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} W^{-1} \varepsilon \varepsilon^{t} W^{-1} P Z G\right]+ \\
& \quad-\mathrm{E}\left[\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} Z U U^{t}\right]-\mathrm{E}\left[\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} W^{-1} \varepsilon U^{t}\right]
\end{align*}
$$

Again, we ignore the stochastic nature of $V, P$ and $G$, and write

$$
\begin{align*}
& E(\hat{\beta}-\beta)(\hat{U}-U)^{t}=\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} Z G Z Z^{t} P Z G+0+0\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} W^{-1} C^{-1} W^{-1} P Z G+ \\
&-\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} Z G-0 \\
&=\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1}(V-R) P Z G+\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} R P Z G-\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} Z G \\
&=\left(X^{t} V^{-1} X\right)^{-1} X^{t} P Z G-\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} Z G  \tag{G.18}\\
&=\left(X^{t} V^{-1} X\right)^{-1} X^{t}\left(P-V^{-1}\right) Z G \\
&=-\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} X\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} Z G \\
&=-\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} Z G
\end{align*}
$$

Substituting the results from (G.14), (G.15), and (G.16) back into (G.12), we have that

$$
\begin{align*}
& M S E_{i}^{a} \doteq \tilde{N}^{t} \stackrel{*}{C} *^{*}\left(X^{t} V^{-1} X\right)^{-1} \stackrel{*}{X}^{t} \stackrel{*}{C} \tilde{N}-2 \tilde{N}^{t} \stackrel{*}{C} X^{*}\left(X^{t} V^{-1} X\right)^{-1} X^{t} V^{-1} Z G Z^{t} \stackrel{*}{C} \tilde{N}  \tag{G.19}\\
& +\tilde{N}^{t} \stackrel{*}{C} Z^{*}\left(G-G Z^{t} P Z G\right) Z^{t} \stackrel{*}{C} \tilde{N}+\sigma_{2}^{2} \tilde{N}^{t} \stackrel{*}{C} Z_{\mathrm{S}} Z_{\$}^{t} \stackrel{*}{C} \tilde{N}
\end{align*}
$$

We now make a final approximation which is to substitute estimated parameters for unknown parameters. This substitution should be accurate asymptotically.

$$
\begin{align*}
& +\tilde{N}^{t} \stackrel{\hat{*}}{C} Z\left(\hat{G}-\hat{G} Z^{t} \hat{P} Z \hat{G}\right) Z^{t} \stackrel{*}{C} \tilde{N}+\hat{\sigma}_{2}^{2} \tilde{N}^{t} \stackrel{\hat{*}}{C} Z_{\Phi} Z_{\mathrm{S}}{ }^{t} \stackrel{\hat{*}}{C} \tilde{N} \tag{G.20}
\end{align*}
$$

The original report on this project also gave a computationally fast form of this mean square error estimator. The problems with calculating the forms given here are that V is too large to practically invert and that Z is mostly full of zeroes. By using lemma C. 13 and by writing out the summations implicit in the matrix equations given here, the calculations become much more practical. The derivation of that form is, however, extremely tedious and doesn't add very much to the intuitive understanding of the mean square error estimation and was thus dropped from this report. If someone, however, is trying to replicate the results, it would be useful to have that original version of the report, keeping in mind that the fourth term was inadvertently omitted in that derivation.

## G. 2 Asymptotic Theory

As $n \rightarrow \infty$, we expect that most of the approximations employed to estimate $\mathrm{E}\left(\hat{\pi}_{i}^{W}-\pi_{i}\right)^{2}$ will tend to become more and more accurate. Recall that there were five major approximations:
(1) Assume that $\mathrm{E}\left[\left(\hat{\pi}_{i b}^{a d}-\pi_{i b}^{a d}\right)\left(\hat{\pi}_{i b}^{a^{\prime} d}-\pi_{i b}^{a^{\prime} d}\right)\right]=$ for $a \neq a^{\prime}$
(2) Assume that $\mathrm{E}\left[(\hat{\pi}-\pi)(\hat{\pi}-\pi)^{7}\right] \doteq \mathrm{E}\left\{[C X(\hat{\beta}-\hat{\beta})+C Z(\hat{U}-U)]\left[C Z(\hat{\beta}-\beta)+[C X(\hat{\beta}-\beta)+C Z(\hat{U}-U)]^{\prime}\right\}\right.$
(3) Assume that $\operatorname{Cov}(\hat{C})=0$
(4) Assume that $\operatorname{Cov}(\hat{G})=0$
(5) Assume that $C, G, P$ and $V$ may be replaced by $\hat{C}, \hat{G}, \hat{P}$ and $\hat{V}$ in the final expression.

All of these assumptions should be asymptotically correct with the exception of the first. The third assumption is perhaps the least troubling since there is a fairly large set of block groups represented in the sample. The fourth assumption, on the other hand, is the most troubling since the numbers of states and PSUs represented in the sample are such smaller.

## G. 3 Unrepresented Sources of Error

As mentioned in Sections 2.6 and G.2, the unrepresented component of most concern is the component due to estimation of $G$, the matrix of the between-state and between-PSU residual variances. This is a limitation of the empirical Bayes method that had been of concern since the earliest work using the method (e.g., Harville, 1977). Prasad and Rao (1990) developed an approximate method for taking the uncertainty about $G$ into effect when estimating $\mathrm{E}\left[(\hat{U}-U)(\hat{U}-U)^{t}\right]$, but their method has only been demonstrated to work well for linear mixed models where $G$ does not depend on $\pi$ and where a strictly unbiased estimator for $G$ is available. We worked out a rough application of their correction to MSE estimates when there was only one level of random effects. This rough correction had almost no impact on the MSEs for the oversampled city estimates, but did inflate the square root of the MSEs on the smaller states and on the balances of the states with oversampled cites by 2 to 20 percent. Since these inflations appeared to be unstable, we decided not to incorporate them into the official MSE estimates.

Leaving out the correlations between age groups does not have any effect on the MSEs for age group specific estimates, but does have an effect on area totals and on estimates for domains that cut across ages such as estimates by sex or race, not crossed by age. We could have incorporated these correlations with larger and faster computers.

The final source of error that was neglected was that due to the clustering of the sample by segment and by household. Other aspects of the sample design such as clustering at the county/MSA level and differential weighting were fully reflected in the estimated MSEs. We had originally intended on fitting models with additional random effects for segments and households, but the data became too thin. With a rare characteristic, the segment and household level residuals tend to be small and negative but are occasionally large and positive. This causes the empirical Bayesian procedure to become biased and unstable. This problem might be partially rectified by going to a full Bayesian approach, but even with such an approach, estimates of variance components at the segment and household levels are likely to remain unstable for rare characteristics. Another possible solution might be to use a leaner X matrix.

In the course of evaluating the effect of initially omitting the fourth term of the MSE, we noticed another possible source of underestimation of the MSE. We noted that on theoretical grounds, one would expect $\sigma_{2}^{2}$ to be larger (perhaps considerably larger) than $\sigma_{1}^{2}$. This is because one expects the heterogeneity in the logit propensity to be greater among PSUs than among states. We, in fact, often observed the opposite pattern in our estimated components of variance. Furthermore, we often estimated $\sigma_{2}^{2}$ to be zero. We theorize that our estimated values of $\sigma_{2}^{2}$ are too small due to overfitting of the fixed part of the model. If we had not allowed so many fixed predictors into the model, our estimates of $\sigma_{2}^{2}$ would certainly have been larger and that would have increased the importance of the fourth component of the MSE.

## G. 4 Derivation of Goodness of Fit Statistic

As discussed in Section 3.1.3, our approach was to form a Wald statistic along the lines of

$$
T=\left(\hat{\pi}_{\sim}^{W}-{\underset{\sim}{\hat{\pi}}}^{D}\right)^{t} \hat{\Psi}^{-1}\left({\underset{\sim}{\hat{\pi}^{W}}}^{W}-\hat{\pi}^{D}\right)
$$

where the squiggly line under a symbol indicates the vector of estimated propensities for the $L$ homogenous groups described in that section and

$$
\hat{\Psi}^{s}=\operatorname{Cov}\left({\underset{\sim}{\hat{\pi}}}^{W}-{\underset{\sim}{\hat{\pi}}}^{D}\right)=\mathrm{E}\left({\underset{\sim}{\hat{\pi}}}^{W}-{\underset{\sim}{\hat{\pi}}}^{D}\right)^{t}\left({\underset{\sim}{\hat{\pi}}}^{W}-\hat{\pi}^{D}\right) .
$$

Under the null hypothesis that $\mathrm{E}\left({\underset{\sim}{\pi}}^{W}-{\underset{\sim}{\pi}}^{D}\right)=0$ and certain regularity assumptions, $T$ is approximately asymptotically distributed as a chi-square variable with $L$ degrees of freedom. The model is rejected if $T$ is too large relative to what is expected from a chi-square variable. The problem that we faced was how to define the meaning of the expected value in null hypothesis and in the definition of the variance-covariance matrix $\hat{\Psi}$. We would have found it most satisfying to have defined the expectation as over all possible samples, over the distribution of the state and PSU random effects, and over the distribution of person level random outcomes. However, we were not able to derive a method of doing this within the time and budget available. Accordingly, we did something simpler. We conditioned on the state and PSU random effects, on the estimated $\beta$ vector, on the estimated set of random effects, and on the partition induced by the fitted model. This means that the expectation we used was just over all possible samples and over the conditional distribution of the person level random events given that state and PSU random effects are fixed and equal to our estimated state and PSU random effects and that the true $\beta$ vector is equal to the estimated $\beta$ vector. A less conditional definition of the expectation in the
equation for $\hat{\Psi}$ would have almost certainly resulted in larger variances which would, in turn, have led to less significant test results since $T$ would have tended to be smaller. Although it would probably have been possible with more work to derive the variance not conditioning on the random effects or on the estimated parameters, it is doubtful that we could have found the variance without conditioning on the partition induced by the model. Since the partition is random, the distribution of $\hat{\pi}^{W}-{\underset{\sim}{\hat{\pi}}}^{D}$ depends on the order statistics of the entire set of personlevel predicted propensities.

Conditioning on fixed and random effects, $\mathrm{E}\left(\hat{\pi}^{D} \mid S, \hat{\beta}, \hat{U}\right)=\hat{\pi}^{W}$ is a constant, so the conditional variance of $\hat{\pi}^{W}-\hat{\pi}^{D}$ given the NHSDA sample (denoted by $S$ ) and the estimated model parameters is

$$
\begin{aligned}
& \left.\Psi_{1}=\operatorname{Cov}\left(\hat{\pi}^{W}-\hat{\pi}^{D} \mid S, \hat{\beta}, \hat{U}\right)=\left[\begin{array}{cc}
\operatorname{Var}\left(\left.\frac{\sum_{i, j, k \in G_{1}} w_{i j k} y_{i j k}}{\sum_{i, k, k \in G_{1}} w_{i j k}} \right\rvert\, S, \hat{\beta}, \hat{U}\right) & 0 \\
\ddots & \\
0 & \operatorname{Var}\left(\left.\frac{\sum_{i, j, k \in G_{L}} w_{i j k} y_{i j k}}{\sum_{i, j, k \in G_{L}} w_{i j k}} \right\rvert\, S, \hat{\beta}, \hat{U}\right)
\end{array}\right)\right] \\
& =\left[\begin{array}{ccc}
\frac{\hat{\pi}_{1}^{W}\left(1-\hat{\pi}_{1}^{W}\right) D e f f_{1}}{n_{1}} & 0 \\
& \ddots & \\
0 & \frac{\hat{\pi}_{L}^{W}\left(1-\hat{\pi}_{L}^{W}\right) D e f f_{L}}{n_{L}}
\end{array}\right] \text {, }
\end{aligned}
$$

$G_{g}$ is the set of sample cases in the g -th homogenous group, $n_{g}$ is the sample size for the group, and Deff $_{g}$ is the design effect for the group due to unequal weighting. Standard sampling theory informs us that this design effect is equal to one plus the relative variation in the sampling weights within the group. That is

$$
\operatorname{Deff}_{g}=1+\frac{\left(\sum_{i j, k \in G_{g}} w_{i j k}-\bar{w}_{g}\right)^{2}}{\bar{w}_{g}^{2}}
$$

We could have used $\Psi_{1}$ to form a Wald statistic $T_{1}=\left({\underset{\sim}{\pi}}^{W}-{\underset{\sim}{\hat{\pi}}}^{D}\right)^{t} \Psi_{1}^{-1}\left({\underset{\sim}{\hat{\pi}}}^{W}-{\underset{\sim}{\hat{\pi}}}^{D}\right)$, but we were concerned that the variance was too small due to the strongly conditional nature of the definition of $\Psi_{1}$. To remove the conditioning on the particular sample that was selected for the 1991-1993 NHSDA, we used SUDAAN. We instructed SUDAAN to get the variance covariance matrix for the $L$ group means, where the dependent variable was defined as $W^{-1} \varepsilon$, as defined in Section 1 of Appendix C and the weight vector was defined as $W C W \underset{\sim}{1}{ }_{n}$, where $\underset{\sim}{1}{ }_{n}$ is just a column vector of $n$ ones. Since $\varepsilon=C^{-1}(y-\pi)$, the weighted dependent variable as defined here is equal to $W C W W^{-1} C^{-1}(y-\pi)=W(y-\pi)$, as desired. If the NHSDA were a simple random sample and we instructed SUDAAN accordingly, SUDAAN would then estimate the variance covariance matrix of the $L$ group means to be $\Psi_{1}$. However, we instructed SUDAAN to treat the sample as the stratified two stage design that the NHSDA really is. For first stage strata, we used pairs of noncertainty PSUs and collections of 25 area segments from each certainty PSU, including the six oversampled MSAs. For the first stage clusters, we used noncertainty PSUs and half samples of 12 to 13 area segments from each of the strata defined in the certainty PSUs. We also instructed SUDAAN to treat the PSUs as drawn with unequal probability and with replacement. As a result, the variance covariance matrix estimated by SUDAAN is $\Psi_{2}$, the variance of $\underset{\sim}{\hat{\pi}^{W}}{ }_{\sim}^{W} \hat{\sim}^{D}$
conditioned on the estimated parameters but not conditioned on the sample or on the person level outcomes.

We could then have calculated the Wald statistic as $T_{2}=\left({\underset{\sim}{\pi}}^{W}-\hat{\sim}_{\sim}^{D}\right)^{t} \Psi_{2}^{-1}\left({\underset{\sim}{\tilde{\pi}^{W}}}^{W}-\hat{\pi}^{D}\right)$, as indeed, SUDAAN has an option to support. However, it is fairly well known that when the dimension of the ${\underset{\sim}{\pi}}^{W}-{\underset{\sim}{\pi}}^{D}$ vector is large, then the stability of the variance-covariance matrix becomes more critical for the chi-square approximation to the distribution of $T$ to be reasonably good. Since we knew that in this case the vector did have high dimension (40) and that the stability of our estimated variance covariance matrix was limited by perhaps fewer than 40
degrees of freedom, we did not feel comfortable using this test. Instead, we used the Satterwaithe adjustment to $T_{1}$ suggested by Rao and $\operatorname{Scott}$ (1981).

Let $\Lambda=\Psi_{1}^{-1} \Psi_{2}$. This is often referred to as a design effect matrix. If both $\Psi_{1}$ and $\Psi_{2}$ were diagonal, then the matrix $\Lambda$ would have the design effects for the $L$ group means on its main diagonal. From linear algebra, we know that the eigenvalues of a diagonal matrix are equal to the elements on the main diagonal. Rao and Scott used these facts to suggest using the eigenvalues of $\Lambda$ to adjust $T_{1}$. Let $\bar{\mu}$ be the average eigenvalue of $\Lambda$ and let $V_{\mu}^{2}$ be the relative variance of the eigenvalues. Then Rao and Scott's Satterwaithe-adjusted Wald statistic is

$$
T_{3}=\frac{T_{1}}{\bar{\mu}\left(1+V_{\mu}^{2}\right)}
$$

with adjusted degrees of freedom $L^{\prime}=\frac{L}{1+V_{\mu}^{2}}$.

Appendix H: Inadequacy of Traditional Measure of Design-Based Mean Square Error

## Appendix H. Inadequacy of Traditional Measure of Design-Based Mean Square Error

The first formal approach to evaluation of small area estimates that was proposed in the literature on the subject was to examine the mean-squared difference between the model-based estimates and the design-consistent estimates across the small areas (Gonzalez, 1973). This approach has some appeal for estimators based on fixed-effect models that do not have area-specific effects, but it does not apply to composite estimators or estimators based on mixed effect models. The approach is based on the following error decomposition, where $E_{D}$ indicates expectation with respect to the sample design:

$$
\begin{aligned}
\mathrm{E}_{\mathrm{D}}\left[\frac{1}{L} \sum_{i}\left(\pi_{i}^{F}-\pi_{i}^{D}\right)^{2}\right]= & \mathrm{E}_{\mathrm{D}}\left[\frac{1}{L} \sum_{i}\left(\pi_{i}^{F}-\mathrm{E}_{\mathrm{D}} \pi_{i}^{F}+\mathrm{E}_{\mathrm{D}} \pi_{i}^{F}-\mathrm{E}_{\mathrm{D}} \pi_{i}^{D}+\mathrm{E}_{\mathrm{D}} \pi_{i}^{D}-\pi_{i}^{D}\right)^{2}\right] \\
= & \mathrm{E}_{\mathrm{D}}\left[\frac{1}{L} \sum_{i}\left(\pi_{i}^{F}-\mathrm{E}_{\mathrm{D}} \pi_{i}^{F}\right)^{2}\right]+\mathrm{E}_{\mathrm{D}}\left[\frac{1}{L} \sum_{i}\left(\mathrm{E}_{\mathrm{D}} \pi_{i}^{F}-\mathrm{E}_{\mathrm{D}} \pi_{i}^{D}\right)^{2}\right]+ \\
& +\mathrm{E}_{\mathrm{D}}\left[\frac{1}{L} \sum_{i}\left(\pi_{i}^{D}-\mathrm{E}_{\mathrm{D}} \pi_{i}^{D}\right)^{2}\right]-\mathrm{E}_{\mathrm{D}}\left[\frac{1}{L} \sum_{i}\left(\pi_{i}^{F}-\mathrm{E}_{\mathrm{D}} \pi_{i}^{F}\right)\left(\pi_{i}^{D}-\mathrm{E}_{\mathrm{D}} \pi_{i}^{D}\right)\right] \\
= & \frac{1}{L} \sum_{i} \mathrm{E}_{\mathrm{D}}\left(\pi_{i}^{F}-\mathrm{E}_{\mathrm{D}} \pi_{i}^{F}\right)^{2}+\frac{1}{L} \sum_{i} \mathrm{E}_{\mathrm{D}}\left(\mathrm{E}_{\mathrm{D}} \pi_{i}^{F}-\mathrm{E}_{\mathrm{D}} \pi_{i}^{D}\right)^{2}+ \\
& \quad+\frac{1}{L} \sum_{i} \mathrm{E}_{\mathrm{D}}\left(\pi_{i}^{D}-\mathrm{E}_{\mathrm{D}} \pi_{i}^{D}\right)^{2}-\frac{1}{L} \sum_{i} \mathrm{E}_{\mathrm{D}}\left(\pi_{i}^{F}-\mathrm{E}_{\mathrm{D}} \pi_{i}^{F}\right)\left(\pi_{i}^{D}-\mathrm{E}_{\mathrm{D}} \pi_{i}^{D}\right) \\
= & \frac{1}{L} \sum_{i} \mathrm{Var}_{\mathrm{D}}\left(\pi_{i}^{F}\right)+\frac{1}{L} \sum_{i} \operatorname{Bias}_{\mathrm{D}}\left(\pi_{i}^{F}\right)+\frac{1}{L} \sum_{i} \mathrm{Var}_{\mathrm{D}}\left(\pi_{i}^{D}\right)-\frac{1}{L} \sum_{i} \operatorname{Cov}_{\mathrm{D}}\left(\pi_{i}^{F} \pi_{i}^{D}\right)
\end{aligned}
$$

By definition, the design-based mean square error of $\pi_{i}^{F}$ is
$\operatorname{MSE}_{\mathrm{D}}\left(\pi_{i}^{F}\right)=\operatorname{Var}_{\mathrm{D}}\left(\pi_{i}^{F}\right)+\operatorname{Bias}_{\mathrm{D}}\left(\pi_{i}^{F}\right)$.

Often when unbiased estimators are impractical, one tries to obtain an estimator with minimum mean square error (MSE). To estimate the MSE separately for each small area is too unstable. By averaging across the small areas, the stability of this evaluation measure is improved. The sum of the first two terms on the right is the average of the design-based mean square error of $\pi_{i}^{F}$ across all the small areas. It is straightforward to estimate the two variance terms using survey methods. If the covariance term can be assumed to be zero, then the design-based variance of $\pi_{i}^{D}$ can be subtracted off the observed mean squared deviation between the two estimators across the areas so as to leave an unbiased estimate of the average mean square
error of $\pi_{i}^{F}$. As mentioned above, when a fixed effect model is used that does not contain any area-specific effects, it is reasonable to assume that $\pi_{i}^{F}$ and $\pi_{i}^{D}$ are independent and thus that their covariance is zero. However, when random effect models are used and the estimator is $\pi_{i}^{M}$, the covariance between $\pi_{i}^{M}$ and $\pi_{i}^{D}$ can become quite strong, thereby invalidating this approach. This is most easily seen by recalling that small area estimators based upon mixed effect models are closely related to composite estimators. Since $\pi_{i}^{C}=\Gamma_{i} \pi_{i}^{F}+\left(1-\Gamma_{i}\right) \pi_{i}^{D}$, it is obvious that by choosing $\Gamma_{i}=0$, we would achieve $\mathrm{E}_{\mathrm{p}}\left[\frac{1}{L} \sum_{i}\left(\pi_{i}^{C}-\pi_{i}^{D}\right)^{2}\right]=0$.

If one were to naively assume that the covariance between $\pi_{i}^{C}$ and $\pi_{i}^{D}$ were zero and then used this approach to estimate the mean square error of $\pi_{i}^{C}$, one would estimate negative mean square error. This approach is thus not appropriate for evaluating small area estimates based on compositing or upon mixed effect models. Accordingly, the approach was not used. The various estimates were compared across the small domains of interest only to see whether the expected shrinkage patterns were realized.

## Appendix I: Estimates and Confidence Intervals for Estimates

## Appendix I. Estimated Percentage of Population with Substance Abuse Behaviors for 26 States. Estimates Based on Data From the 1991-1993 NHSDA. 95\% Confidence Intervals

| State | Licit Substance Use In Past Month |  |  |  | Illicit Substance Use In Past Month |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Cigarette Use |  | Alcohol Use |  | Any Illicit Drug Use |  | Any Illicit But Mrj Use |  | Cocaine Use |  |
| Total United States | 25.46 | (25.29-25.64) | 49.92 | (49.32-50.51) | 5.83 | (5.69-5.98) | 2.44 | (2.37-2.52) | 0.80 | (0.75-0.85) |
| North East Region |  |  |  |  |  |  |  |  |  |  |
| New Jersey | 24.54 | (23.72-25.37) | 56.36 | (54.43-58.26) | 5.40 | (4.85-6.02) | 1.89 | (1.64-2.19) | 1.01 | (0.80-1.26) |
| New York | 23.73 | (23.27-24.19) | 53.37 | (51.71-55.02) | 6.44 | (6.01-6.89) | 2.37 | (2.19-2.56) | 0.82 | (0.74-0.91) |
| Pennsylvania | 26.87 | (26.26-27.49) | 52.32 | (50.11-54.53) | 5.07 | (4.60-5.59) | 2.04 | (1.81-2.30) | 0.59 | (0.48-0.72) |
| South Region |  |  |  |  |  |  |  |  |  |  |
| Florida | 24.36 | (23.82-24.90) | 45.84 | (43.89-47.81) | 4.95 | (4.52-5.41) | 1.99 | (1.78-2.23) | 0.69 | (0.58-0.83) |
| Georgia | 26.34 | (25.43-27.27) | 45.10 | (42.39-47.83) | 5.82 | (5.02-6.73) | 2.04 | (1.72-2.41) | 0.59 | (0.42-0.83) |
| Kentucky | 31.44 | (30.48-32.41) | 38.45 | (35.44-41.55) | 4.53 | (3.93-5.21) | 1.66 | (1.38-2.00) | 0.44 | (0.32-0.61) |
| Louisiana | 25.73 | (24.67-26.83) | 45.79 | (43.19-48.42) | 4.38 | (3.78-5.08) | 2.01 | (1.68-2.40) | 0.81 | (0.59-1.12) |
| North Carolina | 26.60 | (25.91-27.31) | 43.76 | (41.14-46.42) | 5.85 | (5.27-6.50) | 1.79 | (1.55-2.07) | 0.59 | (0.46-0.75) |
| Oklahoma | 26.93 | (25.92-27.96) | 37.52 | (34.32-40.84) | 6.96 | (5.99-8.06) | 4.15 | (3.69-4.66) | 0.56 | (0.42-0.76) |
| South Carolina | 28.95 | (27.70-30.24) | 43.56 | (40.04-47.15) | 4.99 | (4.15-5.99) | 1.66 | (1.35-2.05) | 0.66 | (0.44-0.98) |
| Tennessee | 29.51 | (28.35-30.70) | 38.20 | (34.90-41.62) | 4.53 | (3.80-5.39) | 1.91 | (1.60-2.28) | 0.96 | (0.71-1.30) |
| Texas | 26.19 | (25.47-26.92) | 48.90 | (47.06-50.74) | 5.57 | (5.05-6.15) | 2.24 | (1.97-2.54) | 0.79 | (0.63-0.98) |
| Virginia | 25.01 | (24.29-25.73) | 48.09 | (45.74-50.45) | 5.55 | (4.95-6.23) | 2.71 | (2.46-2.98) | 1.25 | (1.00-1.57) |
| West Virginia | 30.63 | (29.48-31.79) | 36.40 | (32.84-40.12) | 4.23 | (3.61-4.95) | 1.41 | (1.15-1.73) | 0.56 | (0.41-0.75) |
| North Central Region |  |  |  |  |  |  |  |  |  |  |
| Illinois | 25.96 | (25.40-26.52) | 50.64 | (48.99-52.28) | 4.64 | (4.36-4.94) | 1.94 | (1.78-2.10) | 0.69 | (0.61-0.78) |
| Indiana | 24.52 | (23.71-25.34) | 44.50 | (41.37-47.68) | 4.49 | (3.95-5.11) | 1.85 | (1.56-2.19) | 0.50 | (0.38-0.67) |
| Kansas | 24.15 | (23.07-25.26) | 52.56 | (49.35-55.76) | 5.01 | (4.26-5.89) | 3.19 | (2.79-3.63) | 0.77 | (0.58-1.02) |
| Michigan | 26.95 | (26.12-27.79) | 52.23 | (49.38-55.07) | 5.52 | (4.89-6.23) | 1.55 | (1.29-1.85) | 0.61 | (0.48-0.79) |
| Minnesota | 22.57 | (21.70-23.47) | 58.68 | (55.77-61.54) | 4.62 | (4.02-5.31) | 1.38 | (1.14-1.68) | 0.32 | (0.23-0.45) |
| Missouri | 25.22 | (24.44-26.01) | 50.52 | (47.85-53.19) | 4.98 | (4.37-5.67) | 2.82 | (2.50-3.19) | 0.89 | (0.71-1.11) |
| Ohio | 29.19 | (28.53-29.86) | 48.87 | (46.49-51.25) | 5.37 | (4.87-5.92) | 2.52 | (2.27-2.80) | 0.78 | (0.64-0.94) |
| Wisconsin | 23.51 | (22.50-24.54) | 55.07 | (51.48-58.61) | 4.07 | (3.49-4.73) | 1.93 | (1.64-2.27) | 0.84 | (0.64-1.11) |
| West Region |  |  |  |  |  |  |  |  |  |  |
| California | 22.84 | (22.46-23.22) | 52.90 | (52.15-53.66) | 8.23 | (7.86-8.62) | 3.91 | (3.69-4.14) | 0.97 | (0.86-1.10) |
| New Mexico | 28.42 | (26.73-30.16) | 49.82 | (46.71-52.92) | 7.76 | (6.44-9.33) | 3.54 | (2.90-4.32) | 0.85 | (0.57-1.27) |
| Oregon | 25.53 | (24.61-26.47) | 52.29 | (48.87-55.69) | 7.08 | (6.28-7.99) | 3.31 | (2.89-3.78) | 0.38 | (0.28-0.51) |
| Washington | 23.73 | (22.80-24.67) | 54.48 | (51.64-57.29) | 6.07 | (5.32-6.91) | 3.20 | (2.74-3.74) | 0.46 | (0.34-0.63) |

Appendix I. Estimated Percentage of Population with Substance Abuse Behaviors for 26 States. Estimates Based on Data From the 1991-1993 NHSDA. 95\% Confidence Intervals (Continued)

| State | Past Year Dependency |  |  |  | Past Year Treatment |  |  |  |  |  | Past Year Arrest |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Dependent On Illicit Drugs |  | Dependent On Alcohol |  | Received Treatment For Illicit Drug Use |  | Received Treatment For Alcohol Use |  | Needed Treatment <br> For Illicit Drug Use |  |  |  |
| Total United States | 1.24 | (1.19-1.29) | 3.08 | (2.97-3.20) | 0.70 | (0.66-0.74) | 0.69 | (0.65-0.74) | 2.85 | (2.76-2.95) | 1.79 | (1.72-1.86) |
| North East Region |  |  |  |  |  |  |  |  |  |  |  |  |
| New Jersey | 1.26 | (1.11-1.43) | 2.48 | (2.14-2.88) | 0.68 | (0.56-0.83) | 0.64 | (0.49-0.83) | 2.03 | (1.77-2.34) | 1.35 | (1.16-1.56) |
| New York | 1.09 | (1.00-1.18) | 2.02 | (1.82-2.24) | 0.64 | (0.55-0.75) | 0.41 | (0.33-0.51) | 2.46 | (2.28-2.66) | 1.32 | (1.21-1.43) |
| Pennsylvania | 0.88 | (0.78-0.99) | 2.76 | (2.41-3.16) | 0.56 | (0.48-0.65) | 0.69 | (0.56-0.85) | 2.19 | (1.95-2.45) | 1.28 | (1.16-1.42) |
| South Region |  |  |  |  |  |  |  |  |  |  |  |  |
| Florida | 0.93 | (0.84-1.04) | 2.36 | (2.07-2.69) | 0.69 | (0.60-0.80) | 0.58 | (0.47-0.70) | 2.46 | (2.21-2.74) | 1.61 | (1.47-1.75) |
| Georgia | 1.21 | (1.06-1.38) | 3.61 | (3.01-4.32) | 0.71 | (0.58-0.87) | 0.45 | (0.33-0.62) | 3.78 | (3.23-4.42) | 2.49 | (2.25-2.76) |
| Kentucky | 0.90 | (0.79-1.02) | 2.06 | (1.72-2.45) | 0.57 | (0.47-0.67) | 0.48 | (0.35-0.65) | 2.27 | (1.93-2.66) | 1.67 | (1.48-1.88) |
| Louisiana | 0.99 | (0.86-1.14) | 3.93 | (3.31-4.67) | 0.64 | (0.53-0.77) | 0.59 | (0.42-0.82) | 2.77 | (2.29-3.36) | 2.32 | (2.06-2.62) |
| North Carolina | 1.14 | (1.02-1.27) | 2.55 | (2.21-2.95) | 0.64 | (0.53-0.76) | 0.50 | (0.39-0.64) | 2.40 | (2.11-2.74) | 1.68 | (1.53-1.85) |
| Oklahoma | 1.50 | (1.34-1.69) | 4.05 | (3.32-4.93) | 0.86 | (0.71-1.04) | 1.49 | (0.97-2.26) | 3.77 | (3.07-4.63) | 1.37 | (1.19-1.58) |
| South Carolina | 1.18 | (1.02-1.36) | 3.01 | (2.41-3.77) | 0.53 | (0.42-0.66) | 0.55 | (0.38-0.81) | 2.14 | (1.72-2.66) | 1.80 | (1.55-2.08) |
| Tennessee | 0.91 | (0.80-1.04) | 2.06 | (1.69-2.51) | 0.60 | (0.50-0.70) | 0.53 | (0.38-0.76) | 2.08 | (1.72-2.52) | 2.10 | (1.83-2.41) |
| Texas | 1.47 | (1.33-1.63) | 3.37 | (2.95-3.84) | 0.61 | (0.51-0.73) | 0.69 | (0.55-0.87) | 3.06 | (2.73-3.43) | 1.84 | (1.66-2.05) |
| Virginia | 1.11 | (1.01-1.23) | 3.03 | (2.63-3.48) | 0.65 | (0.55-0.76) | 0.61 | (0.50-0.75) | 2.91 | (2.54-3.33) | 1.54 | (1.39-1.69) |
| West Virginia | 0.84 | (0.73-0.97) | 2.12 | (1.73-2.59) | 0.49 | (0.39-0.61) | 0.73 | (0.52-1.02) | 2.15 | (1.77-2.62) | 1.29 | (1.10-1.50) |
| North Central Region |  |  |  |  |  |  |  |  |  |  |  |  |
| Illinois | 0.88 | (0.81-0.94) | 3.08 | (2.83-3.36) | 0.54 | (0.48-0.59) | 0.66 | (0.56-0.78) | 2.32 | (2.15-2.51) | 1.72 | (1.57-1.90) |
| Indiana | 0.97 | (0.87-1.09) | 2.15 | (1.80-2.55) | 0.52 | (0.43-0.62) | 0.66 | (0.49-0.89) | 1.98 | (1.70-2.30) | 2.30 | (2.08-2.55) |
| Kansas | 1.13 | (1.00-1.27) | 3.51 | (2.88-4.26) | 0.66 | (0.55-0.79) | 0.86 | (0.59-1.24) | 2.73 | (2.25-3.31) | 2.40 | (2.10-2.74) |
| Michigan | 1.08 | (0.96-1.22) | 3.36 | (2.82-3.99) | 0.76 | (0.65-0.89) | 0.70 | (0.52-0.93) | 3.05 | (2.63-3.53) | 1.99 | (1.79-2.21) |
| Minnesota | 1.00 | (0.87-1.14) | 3.12 | (2.58-3.77) | 0.84 | (0.70-1.02) | 0.80 | (0.59-1.10) | 2.19 | (1.84-2.60) | 1.67 | (1.45-1.91) |
| Missouri | 1.03 | (0.92-1.15) | 2.16 | (1.83-2.55) | 0.70 | (0.59-0.84) | 0.68 | (0.50-0.91) | 3.26 | (2.82-3.76) | 2.10 | (1.85-2.38) |
| Ohio | 0.96 | (0.87-1.07) | 2.73 | (2.36-3.15) | 0.70 | (0.59-0.83) | 0.81 | (0.64-1.01) | 2.56 | (2.28-2.87) | 2.25 | (2.06-2.47) |
| Wisconsin | 0.98 | (0.88-1.11) | 2.95 | (2.41-3.60) | 0.61 | (0.51-0.73) | 0.59 | (0.44-0.79) | 2.41 | (1.99-2.92) | 1.53 | (1.30-1.80) |
| West Region |  |  |  |  |  |  |  |  |  |  |  |  |
| California | 1.91 | (1.78-2.04) | 4.87 | (4.62-5.14) | 0.97 | (0.87-1.08) | 0.81 | (0.71-0.94) | 4.23 | (3.99-4.48) | 2.15 | (1.99-2.33) |
| New Mexico | 1.62 | (1.41-1.87) | 3.66 | (2.93-4.57) | 0.77 | (0.61-0.96) | 0.92 | (0.55-1.56) | 3.30 | (2.61-4.17) | 2.63 | (2.07-3.32) |
| Oregon | 1.99 | (1.79-2.22) | 2.75 | (2.32-3.25) | 0.90 | (0.75-1.08) | 0.61 | (0.43-0.85) | 2.22 | (1.90-2.58) | 1.88 | (1.64-2.15) |
| Washington | 1.96 | (1.74-2.19) | 3.51 | (2.94-4.19) | 0.85 | (0.72-1.00) | 0.51 | (0.36-0.71) | 3.55 | (3.01-4.18) | 1.91 | (1.61-2.26) |

## Appendix I. Estimated Percentage of Population with Substance Abuse Behaviors for 25 MSAs. Estimates Based on Data From the 1991-1993 NHSDA. 95\% Confidence Intervals

| MSA | Licit Substance Use In Past Month |  |  |  | Illicit Substance Use In Past Month |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Cigarette Use |  | Alcohol Use |  | Any Illicit Drug Use |  | Any Illicit But Mrj Use |  | Cocaine Use |  |
| Anaheim-Santa Ana, CA | 21.01 | (20.19-21.84) | 52.25 | (50.58-53.91) | 8.82 | (7.78-9.98) | 4.85 | (4.25-5.53) | 1.23 | (0.93-1.61) |
| Atlanta, GA | 23.70 | (22.80-24.63) | 50.98 | (49.52-52.45) | 5.86 | (5.15-6.66) | 1.95 | (1.62-2.36) | 0.56 | (0.40-0.79) |
| Baltimore, MD | 24.96 | (24.00-25.95) | 44.84 | (43.48-46.20) | 5.03 | (4.37-5.80) | 1.80 | (1.48-2.19) | 0.70 | (0.53-0.93) |
| Boston, MA | 27.51 | (26.70-28.33) | 61.51 | (60.37-62.63) | 6.73 | (5.98-7.55) | 2.57 | (2.17-3.03) | 0.94 | (0.74-1.20) |
| Chicago, IL | 24.73 | (24.42-25.04) | 53.82 | (53.49-54.16) | 5.53 | (5.34-5.72) | 2.34 | (2.23-2.45) | 0.94 | (0.87-1.02) |
| Dallas, TX | 25.95 | (25.06-26.85) | 50.23 | (48.39-52.08) | 5.69 | (4.95-6.53) | 2.38 | (2.04-2.78) | 1.05 | (0.80-1.37) |
| Denver, CO | 27.13 | (26.83-27.44) | 58.42 | (58.09-58.75) | 8.30 | (8.07-8.54) | 2.94 | (2.80-3.07) | 1.01 | (0.93-1.08) |
| Detroit, MI | 26.52 | (25.61-27.46) | 54.17 | (52.79-55.54) | 5.50 | (4.83-6.25) | 1.38 | (1.12-1.71) | 0.60 | (0.45-0.81) |
| El Paso, TX | 20.41 | (18.86-22.05) | 45.85 | (42.18-49.56) | 3.58 | (2.62-4.89) | 1.85 | (1.35-2.51) | 0.53 | (0.33-0.85) |
| Houston, TX | 25.07 | (24.03-26.13) | 50.94 | (49.37-52.50) | 4.05 | (3.47-4.71) | 2.43 | (2.07-2.86) | 0.60 | (0.44-0.82) |
| Los Angeles, CA | 21.82 | (21.54-22.11) | 49.34 | (49.01-49.68) | 6.68 | (6.48-6.89) | 2.72 | (2.60-2.84) | 0.90 | (0.84-0.97) |
| Miami-Hialeah, FL | 20.88 | (20.60-21.17) | 44.40 | (44.05-44.75) | 3.75 | (3.59-3.92) | 2.26 | (2.15-2.37) | 0.89 | (0.82-0.96) |
| Minneapolis-St. Paul, MN | 22.64 | (21.73-23.57) | 65.87 | (64.62-67.10) | 5.19 | (4.54-5.92) | 1.51 | (1.22-1.87) | 0.36 | (0.26-0.50) |
| Nassau-Suffolk, NY | 20.22 | (19.38-21.08) | 59.60 | (58.36-60.84) | 6.57 | (5.84-7.38) | 1.99 | (1.65-2.41) | 0.37 | (0.28-0.49) |
| New York, NY | 23.15 | (22.85-23.45) | 48.84 | (48.50-49.19) | 5.99 | (5.80-6.19) | 2.40 | (2.29-2.51) | 1.06 | (0.99-1.15) |
| Newark, NJ | 24.10 | (23.10-25.13) | 62.17 | (60.45-63.85) | 6.20 | (5.39-7.11) | 1.91 | (1.60-2.28) | 1.37 | (0.98-1.92) |
| Oakland, CA | 23.33 | (22.61-24.07) | 65.02 | (63.55-66.46) | 11.39 | (10.31-12.57) | 5.11 | (4.59-5.69) | 1.47 | (1.17-1.85) |
| Philadelphia, PA-NJ | 25.89 | (25.20-26.59) | 59.13 | (58.06-60.19) | 5.72 | (5.11-6.40) | 2.22 | (1.94-2.55) | 0.64 | (0.51-0.81) |
| Phoenix, AZ | 24.83 | (23.85-25.84) | 53.69 | (52.12-55.25) | 6.82 | (5.95-7.81) | 3.99 | (3.45-4.62) | 1.01 | (0.77-1.31) |
| San Antonio, TX | 26.09 | (24.71-27.52) | 54.43 | (51.55-57.27) | 4.35 | (3.39-5.55) | 2.17 | (1.67-2.81) | 0.78 | (0.51-1.17) |
| San Bernardino, CA | 23.32 | (22.39-24.27) | 49.12 | (47.64-50.60) | 7.42 | (6.62-8.32) | 4.60 | (4.07-5.20) | 0.64 | (0.49-0.84) |
| San Diego, CA | 22.25 | (21.36-23.16) | 49.08 | (47.60-50.55) | 7.07 | (6.22-8.03) | 3.59 | (3.09-4.17) | 0.93 | (0.70-1.23) |
| St. Louis, MO-IL | 25.27 | (24.52-26.03) | 55.02 | (53.73-56.30) | 5.19 | (4.56-5.90) | 2.53 | (2.21-2.88) | 0.95 | (0.75-1.21) |
| Tampa-St. Petersburg, FL | 25.55 | (24.76-26.36) | 41.22 | (39.75-42.70) | 5.27 | (4.56-6.08) | 2.03 | (1.66-2.47) | 0.57 | (0.43-0.74) |
| Washington, DC | 22.61 | (22.40-22.81) | 53.82 | (53.59-54.05) | 5.38 | (5.26-5.51) | 2.58 | (2.50-2.67) | 1.03 | (0.98-1.08) |

Appendix I. Estimated Percentage of Population with Substance Abuse Behaviors for 25 MSAs. Estimates Based on Data From the 1991-1993 NHSDA. 95\% Confidence Intervals (Continued)

| MSA | Past Year Dependency |  |  |  | Past Year Treatment |  |  |  |  |  | Past Year Arrest |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Depe | ent On Illicit Drugs | Dependent On Alcohol |  | Received Treatment For Illicit Drug Use |  | $\begin{gathered} \text { Received } \\ \text { Treatment For } \\ \text { Alcohol Use } \end{gathered}$ |  | Needed Treatment For Illicit Drug Use |  |  |  |
| Anaheim-Santa Ana, CA | 2.17 | (1.88-2.51) | 6.01 | (5.37-6.72) | 1.01 | (0.77-1.31) | 0.55 | (0.39-0.78) | 4.45 | (3.91-5.06) | 1.53 | (1.20-1.94) |
| Atlanta, GA | 1.24 | (1.06-1.45) | 4.47 | (3.84-5.20) | 0.74 | (0.60-0.91) | 0.38 | (0.27-0.55) | 4.83 | (4.21-5.53) | 1.74 | (1.52-1.98) |
| Baltimore, MD | 0.89 | (0.75-1.05) | 2.15 | (1.74-2.65) | 0.58 | (0.45-0.75) | 0.45 | (0.32-0.65) | 2.28 | (1.90-2.73) | 1.30 | (1.11-1.52) |
| Boston, MA | 1.68 | (1.46-1.92) | 4.38 | (3.83-5.01) | 0.97 | (0.77-1.22) | 2.18 | (1.69-2.81) | 3.88 | (3.41-4.41) | 1.66 | (1.39-1.98) |
| Chicago, IL | 0.89 | (0.82-0.97) | 3.46 | (3.33-3.60) | 0.53 | (0.49-0.59) | 0.71 | (0.66-0.77) | 2.75 | (2.63-2.88) | 1.51 | (1.41-1.62) |
| Dallas, TX | 1.63 | (1.45-1.84) | 3.31 | (2.80-3.91) | 0.65 | (0.53-0.80) | 0.45 | (0.31-0.66) | 2.47 | (2.10-2.90) | 1.55 | (1.31-1.82) |
| Denver, CO | 1.26 | (1.16-1.37) | 4.57 | (4.41-4.73) | 0.63 | (0.57-0.70) | 0.96 | (0.89-1.04) | 3.83 | (3.68-3.99) | 2.26 | (2.12-2.40) |
| Detroit, MI | 1.18 | (1.02-1.37) | 3.59 | (3.11-4.14) | 0.78 | (0.66-0.92) | 0.51 | (0.38-0.69) | 3.58 | (3.15-4.06) | 1.77 | (1.53-2.04) |
| El Paso, TX | 0.79 | (0.57-1.08) | 3.66 | (2.59-5.13) | 0.55 | (0.36-0.85) | 0.53 | (0.28-1.03) | 2.50 | (1.92-3.25) | 1.62 | (1.20-2.19) |
| Houston, TX | 2.10 | (1.87-2.37) | 1.96 | (1.53-2.50) | 0.81 | (0.68-0.98) | 0.71 | (0.53-0.94) | 3.86 | (3.40-4.37) | 1.56 | (1.32-1.84) |
| Los Angeles, CA | 1.50 | (1.39-1.61) | 7.13 | (6.96-7.31) | 0.75 | (0.65-0.88) | 0.50 | (0.46-0.55) | 4.04 | (3.89-4.20) | 1.85 | (1.74-1.97) |
| Miami-Hialeah, FL | 0.74 | (0.67-0.82) | 2.04 | (1.94-2.14) | 0.56 | (0.44-0.72) | 0.48 | (0.44-0.52) | 2.16 | (2.04-2.29) | 1.22 | (1.13-1.32) |
| Minneapolis-St. Paul, MN | 1.15 | (0.99-1.34) | 3.45 | (2.93-4.06) | 0.93 | (0.75-1.16) | 0.93 | (0.65-1.34) | 2.38 | (2.04-2.78) | 1.77 | (1.50-2.08) |
| Nassau-Suffolk, NY | 1.00 | (0.85-1.17) | 1.10 | (0.83-1.44) | 0.64 | (0.49-0.83) | 0.50 | (0.36-0.68) | 1.87 | (1.56-2.24) | 1.14 | (0.93-1.40) |
| New York, NY | 0.94 | (0.85-1.02) | 1.77 | (1.68-1.87) | 0.66 | (0.52-0.84) | 0.26 | (0.23-0.29) | 2.50 | (2.38-2.63) | 0.79 | (0.72-0.87) |
| Newark, NJ | 1.43 | (1.24-1.65) | 2.50 | (2.00-3.12) | 0.89 | (0.74-1.07) | 0.77 | (0.59-1.01) | 1.90 | (1.56-2.31) | 1.40 | (1.10-1.77) |
| Oakland, CA | 2.98 | (2.68-3.31) | 3.88 | (3.24-4.65) | 1.37 | (1.19-1.57) | 2.07 | (1.69-2.53) | 5.22 | (4.63-5.87) | 1.94 | (1.64-2.28) |
| Philadelphia, PA-NJ | 0.98 | (0.85-1.13) | 2.82 | (2.45-3.25) | 0.82 | (0.71-0.95) | 0.61 | (0.47-0.78) | 2.99 | (2.67-3.33) | 1.37 | (1.20-1.57) |
| Phoenix, AZ | 1.55 | (1.37-1.75) | 3.61 | (3.04-4.28) | 0.65 | (0.53-0.80) | 0.67 | (0.46-0.98) | 3.14 | (2.68-3.68) | 1.48 | (1.12-1.96) |
| San Antonio, TX | 1.38 | (1.19-1.61) | 2.53 | (1.69-3.76) | 0.53 | (0.37-0.74) | 0.42 | (0.22-0.79) | 2.90 | (2.20-3.81) | 1.60 | (1.30-1.96) |
| San Bernardino, CA | 2.09 | (1.82-2.39) | 3.92 | (3.42-4.50) | 1.15 | (0.96-1.37) | 1.19 | (0.89-1.59) | 3.84 | (3.35-4.39) | 2.41 | (2.01-2.89) |
| San Diego, CA | 1.38 | (1.15-1.65) | 2.99 | (2.51-3.56) | 0.74 | (0.56-0.98) | 0.52 | (0.34-0.79) | 3.19 | (2.75-3.71) | 2.18 | (1.82-2.60) |
| St. Louis, MO-IL | 0.96 | (0.85-1.09) | 2.46 | (2.09-2.90) | 0.74 | (0.62-0.87) | 0.62 | (0.45-0.85) | 2.75 | (2.37-3.19) | 2.09 | (1.77-2.45) |
| Tampa-St. Petersburg, FL | 0.98 | (0.84-1.13) | 2.10 | (1.67-2.63) | 0.66 | (0.55-0.80) | 0.41 | (0.29-0.60) | 2.08 | (1.76-2.45) | 1.44 | (1.22-1.70) |
| Washington, DC | 1.07 | (1.02-1.13) | 3.59 | (3.49-3.69) | 0.56 | (0.51-0.60) | 0.87 | (0.83-0.92) | 2.66 | (2.58-2.75) | 1.33 | (1.27-1.40) |

## Appendix I. Estimated Number of Persons with Substance Abuse Behaviors for 25 MSAs. Estimates Based on Data From the 1991-1993 NHSDA. $\mathbf{9 5 \%}$ Confidence Intervals



| State | Licit Substance Use In Past Month |  |  |  | Illicit Substance Use In Past Month |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Cigarette Use |  | Alcohol Use |  | Any Illicit Drug Use |  | Any Illicit But Mrj Use |  | Cocaine Use |  |
| Total United States | 52,444 | (52,084-52,805) | 102,802 | (101,582-104,022) | 12,015 | (11,712-12,326) | 5,031 | $(4,878-5,189)$ | 1,647 | (1,552-1,747) |
| North East Region |  |  |  |  |  |  |  |  |  |  |
| New Jersey | 1,581 | (1,529-1,635) | 3,631 | (3,507-3,754) | 348 | (312-388) | 122 | (106-141) | 65 | (51-81) |
| New York | 3,534 | (3,466-3,602) | 7,948 | (7,701-8,193) | 959 | (896-1,026) | 352 | (326-381) | 122 | (110-136) |
| Pennsylvania | 2,672 | (2,612-2,733) | 5,203 | $(4,983-5,423)$ | 505 | (458-556) | 203 | (180-229) | 59 | (48-72) |
| South Region |  |  |  |  |  |  |  |  |  |  |
| Florida | 2,744 | (2,683-2,805) | 5,164 | (4,944-5,386) | 557 | (509-610) | 225 | (201-252) | 78 | (65-93) |
| Georgia | 1,433 | (1,384-1,484) | 2,454 | (2,307-2,603) | 317 | (273-366) | 111 | (94-131) | 32 | (23-45) |
| Kentucky | 960 | (930-989) | 1,174 | $(1,082-1,268)$ | 138 | (120-159) | 51 | (42-61) | 14 | (10-19) |
| Louisiana | 872 | (835-909) | 1,551 | (1,463-1,640) | 148 | (128-172) | 68 | (57-81) | 27 | (20-38) |
| North Carolina | 1,501 | (1,461-1,541) | 2,468 | (2,321-2,618) | 330 | (297-366) | 101 | (87-117) | 33 | (26-42) |
| Oklahoma | 690 | (664-717) | 962 | (880-1,047) | 178 | (154-207) | 106 | (95-119) | 14 | (11-19) |
| South Carolina | 851 | (814-889) | 1,280 | $(1,177-1,386)$ | 147 | (122-176) | 49 | (40-60) | 19 | (13-29) |
| Tennessee | 1,215 | (1,167-1,264) | 1,573 | (1,437-1,713) | 187 | (157-222) | 79 | (66-94) | 39 | (29-53) |
| Texas | 3,601 | (3,502-3,702) | 6,724 | (6,472-6,977) | 767 | (695-845) | 308 | (271-349) | 108 | (87-135) |
| Virginia | 1,307 | (1,270-1,345) | 2,514 | (2,391-2,637) | 290 | (259-326) | 141 | (128-156) | 65 | (52-82) |
| West Virginia | 458 | (441-476) | 545 | (492-601) | 63 | (54-74) | 21 | (17-26) | 8 | (6-11) |
| North Central |  |  |  |  |  |  |  |  |  |  |
| Region |  |  |  |  |  |  |  |  |  |  |
| Illinois | 2,434 | (2,382-2,488) | 4,749 | (4,594-4,903) | 435 | (409-463) | 182 | (167-197) | 65 | (57-73) |
| Indiana | 1,123 | (1,086-1,161) | 2,039 | $(1,895-2,184)$ | 206 | (181-234) | 85 | (72-100) | 23 | (17-31) |
| Kansas | 485 | (464-508) | 1,057 | (992-1,121) | 101 | (86-118) | 64 | (56-73) | 15 | (12-20) |
| Michigan | 2,052 | (1,989-2,116) | 3,978 | (3,760-4,194) | 420 | (372-474) | 118 | (98-141) | 47 | (36-61) |
| Minnesota | 807 | (776-839) | 2,098 | (1,994-2,200) | 165 | (144-190) | 49 | (41-60) | 12 | (8-16) |
| Missouri | 1,065 | (1,032-1,098) | 2,134 | (2,021-2,246) | 210 | (185-239) | 119 | (106-135) | 38 | (30-47) |
| Ohio | 2,612 | (2,552-2,672) | 4,372 | $(4,159-4,585)$ | 481 | (436-530) | 226 | (203-251) | 70 | (58-84) |
| Wisconsin | 945 | (905-987) | 2,215 | (2,070-2,357) | 164 | (141-190) | 78 | (66-91) | 34 | (26-45) |
| West Region |  |  |  |  |  |  |  |  |  |  |
| California | 5,559 | (5,466-5,652) | 12,877 | (12,693-13,061) | 2,004 | (1,913-2,099) | 951 | (897-1,007) | 237 | (210-268) |
| New Mexico | 341 | (321-362) | 597 | (560-635) | 93 | (77-112) | 43 | (35-52) | 10 | (7-15) |
| Oregon | 612 | (590-634) | 1,253 | (1,171-1,335) | 170 | (150-191) | 79 | (69-91) | 9 | (7-12) |
| Washington | 971 | (934-1,010) | 2,230 | (2,114-2,345) | 248 | (218-283) | 131 | (112-153) | 19 | (14-26) |

## Appendix I. Estimated Number of Persons with Substance Abuse Behaviors for 25 MSAs. Estimates Based on Data From the 1991-1993 NHSDA. 95\% Confidence Intervals

| MSA | Licit Substance Use In Past Month |  |  |  | Illicit Substance Use In Past Month |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Cigarette Use |  | Alcohol Use |  | Any Illicit Drug Use |  | Any Illicit But Mrj Use |  | Cocaine Use |  |
| CA | 419 | (403-436) | 1,043 | (1,010-1,076) | 176 | (155-199) | 97 | (85-110) | 25 | (19-32) |
| Atlanta, GA | 575 | (553-597) | 1,236 | (1,201-1,272) | 142 | (125-161) | 47 | (39-57) | 14 | (10-19) |
| Baltimore, MD | 498 | (479-518) | 895 | (868-922) | 100 | (87-116) | 36 | (29-44) | 14 | (11-18) |
| Boston, MA | 865 | (840-891) | 1,934 | (1,899-1,970) | 212 | (188-238) | 81 | (68-95) | 30 | (23-38) |
| Chicago, IL | 1,232 | (1,217-1,247) | 2,681 | (2,664-2,698) | 275 | (266-285) | 117 | (111-122) | 47 | (44-51) |
| Dallas, TX | 550 | (531-569) | 1,065 | (1,026-1,104) | 121 | (105-139) | 51 | (43-59) | 22 | (17-29) |
| Denver, CO | 365 | (361-369) | 786 | (782-791) | 112 | (109-115) | 40 | (38-41) | 14 | (13-15) |
| Detroit, MI | 953 | (920-987) | 1,946 | (1,897-1,995) | 197 | (173-225) | 50 | (40-61) | 22 | (16-29) |
| El Paso, TX | 93 | (86-101) | 209 | (192-226) | 16 | (12-22) | 8 | (6-11) | 2 | (2-4) |
| Houston, TX | 667 | (640-695) | 1,355 | (1,314-1,397) | 108 | (92-125) | 65 | (55-76) | 16 | (12-22) |
| Los Angeles, CA | 1,555 | (1,535-1,576) | 3,517 | (3,493-3,541) | 476 | (462-491) | 194 | (185-203) | 65 | (60-69) |
| Miami-Hialeah, FL | 334 | (330-339) | 710 | (705-716) | 60 | (57-63) | 36 | (34-38) | 14 | (13-15) |
| MN | 461 | (442-480) | 1,341 | (1,315-1,366) | 106 | (92-120) | 31 | (25-38) | 7 | (5-10) |
| Nassau-Suffolk, NY | 440 | (422-459) | 1,298 | $(1,271-1,325)$ | 143 | (127-161) | 43 | (36-52) | 8 | (6-11) |
| New York, NY | 1,640 | (1,619-1,662) | 3,461 | (3,437-3,485) | 425 | (411-439) | 170 | (163-178) | 75 | (70-81) |
| Newark, NJ | 361 | (346-377) | 932 | (907-958) | 93 | (81-107) | 29 | (24-34) | 21 | (15-29) |
| Oakland, CA | 403 | (391-416) | 1,123 | (1,098-1,148) | 197 | (178-217) | 88 | (79-98) | 25 | (20-32) |
| Philadelphia, PA-NJ | 1,045 | (1,017-1,073) | 2,387 | (2,344-2,430) | 231 | (206-258) | 90 | (78-103) | 26 | (21-33) |
| Phoenix, AZ | 440 | (422-457) | 951 | (923-978) | 121 | (105-138) | 71 | (61-82) | 18 | (14-23) |
| San Antonio, TX | 271 | (257-286) | 566 | (536-596) | 45 | (35-58) | 23 | (17-29) | 8 | (5-12) |
| San Bernardino, CA | 495 | (475-515) | 1,042 | (1,011-1,074) | 158 | (140-177) | 98 | (86-110) | 14 | (10-18) |
| San Diego, CA | 465 | (446-484) | 1,025 | (995-1,056) | 148 | (130-168) | 75 | (65-87) | 19 | (15-26) |
| St. Louis, MO-IL | 507 | (492-522) | 1,104 | (1,078-1,130) | 104 | (91-118) | 51 | (44-58) | 19 | (15-24) |
| Tampa-St. Petersburg, FL | 466 | (451-480) | 751 | (724-778) | 96 | (83-111) | 37 | (30-45) | 10 | (8-13) |
| Washington, DC | 756 | (749-763) | 1,800 | (1,793-1,808) | 180 | (176-184) | 86 | (84-89) | 34 | (33-36) |

## Appendix I. Estimated Number of Persons with Substance Abuse Behaviors for 25 MSAs. Estimates Based on Data

 From the 1991-1993 NHSDA. 95\% Confidence IntervalsAppendix I. Estimated Number of Persons with Substance Abuse Behaviors for 26 States. Estimates Based on Data From the 1991-1993 NHSDA. $\mathbf{9 5 \%}$ Confidence Intervals

| State | Past Year Dependency |  |  | Past Year Treatment |  |  |  |  |  | Past Year Arrest |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Dependent On Illicit Drugs | Dependent On Alcohol |  | Received Treatment For Illicit Drug Use |  | Received Treatment For Alcohol Use |  | Needed Treatment For Illicit Drug Use |  |  |  |
| Total United States | 2,549 (2,444-2,658) | 6,350 | (6,126-6,582) | 1,447 | (1,365-1,533) | 1,429 | (1,336-1,529 | 5,877 | (5,690-6,071) | 3,689 | (3,549-3,835) |
| North East Region |  |  |  |  |  |  |  |  |  |  |  |
| New Jersey | 81 (72-92) | 160 | (138-185) | 44 | (36-53) | 41 | (32-53) | 131 | (114-151) | 87 | (75-100) |
| New York | 162 (149-175) | 301 | (270-334) | 95 | (82-111) | 62 | (50-76) | 367 | (340-395) | 196 | (180-213) |
| Pennsylvania | 87 (78-98) | 275 | (240-315) | 55 | (47-65) | 68 | (55-85) | 217 | (194-243) | 128 | (115-142) |
| South Region |  |  |  |  |  |  |  |  |  |  |  |
| Florida | 105 (94-117) | 266 | (233-303) | 78 | (67-90) | 65 | (53-79) | 277 | (248-309) | 181 | (166-197) |
| Georgia | 66 (58-75) | 197 | (164-235) | 39 | (32-47) | 25 | (18-34) | 206 | (176-240) | 136 | (123-150) |
| Kentucky | 28 (24-31) | 63 | (53-75) | 17 | (14-21) | 15 | (11-20) | 69 | (59-81) | 51 | (45-57) |
| Louisiana | 34 (29-39) | 133 | (112-158) | 22 | (18-26) | 20 | (14-28) | 94 | (77-114) | 79 | (70-89) |
| North Carolina | 64 (58-72) | 144 | (125-166) | 36 | (30-43) | 28 | (22-36) | 136 | (119-154) | 95 | (86-105) |
| Oklahoma | 39 (34-43) | 104 | (85-126) | 22 | (18-27) | 38 | (25-58) | 97 | (79-119) | 35 | (30-41) |
| South Carolina | 35 (30-40) | 89 | (71-111) | 15 | (12-19) | 16 | (11-24) | 63 | (50-78) | 53 | (46-61) |
| Tennessee | 38 (33-43) | 85 | (70-103) | 25 | (21-29) | 22 | (15-31) | 86 | (71-104) | 87 | (75-99) |
| Texas | 202 (182-225) | 463 | (405-528) | 84 | (71-100) | 95 | (75-119) | 421 | (376-472) | 254 | (228-282) |
| Virginia | 58 (53-64) | 158 | (138-182) | 34 | (29-40) | 32 | (26-39) | 152 | (133-174) | 80 | (73-89) |
| West Virginia | 13 (11-15) | 32 | (26-39) | 7 | (6-9) | 11 | (8-15) | 32 | (27-39) | 19 | (17-22) |
| North Central Region |  |  |  |  |  |  |  |  |  |  |  |
| Illinois | 82 (76-89) | 289 | (265-315) | 50 | (45-55) | 62 | (52-73) | 218 | (201-235) | 162 | (147-178) |
| Indiana | 45 (40-50) | 98 | (83-117) | 24 | (20-28) | 30 | (23-41) | 91 | (78-105) | 105 | (95-117) |
| Kansas | 23 (20-25) | 70 | (58-86) | 13 | (11-16) | 17 | (12-25) | 55 | (45-67) | 48 | (42-55) |
| Michigan | 82 (73-93) | 256 | (215-304) | 58 | (50-68) | 53 | (40-71) | 232 | (200-269) | 151 | (136-168) |
| Minnesota | 36 (31-41) | 112 | (92-135) | 30 | (25-37) | 29 | (21-39) | 78 | (66-93) | 60 | (52-68) |
| Missouri | 43 (39-48) | 91 | (77-108) | 30 | (25-35) | 29 | (21-39) | 138 | (119-159) | 89 | (78-100) |
| Ohio | 86 (78-95) | 244 | (211-281) | 63 | (53-74) | 72 | (57-91) | 229 | (204-256) | 202 | (184-221) |
| Wisconsin | 40 (35-44) | 118 | (97-145) | 25 | (21-29) | 24 | (18-32) | 97 | (80-117) | 62 | (52-72) |
| West Region |  |  |  |  |  |  |  |  |  |  |  |
| California | 464 (433-498) | 1,186 | (1,124-1,251) | 236 | (213-262) | 198 | (172-228) | 1,029 | (971-1,090) | 524 | (483-568) |
| New Mexico | 19 (17-22) | 44 | (35-55) | 9 | (7-12) | 11 | (7-19) | 40 | (31-50) | 32 | (25-40) |
| Oregon | 48 (43-53) | 66 | (56-78) | 22 | (18-26) | 15 | (10-20) | 53 | (46-62) | 45 | (39-52) |

## Appendix I. Estimated Number of Persons with Substance Abuse Behaviors for 25 MSAs. Estimates Based on Data From the 1991-1993 NHSDA. 95\% Confidence Intervals

| Washington | 80 | (71-90) | 144 | (120-172) | 35 | (29-41) | 21 | (15-29) | 145 | (123-171) | 78 | (66-93) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Past Year Dependency |  |  |  | Past Year Treatment |  |  |  |  |  | Past Year Arrest |  |
| MSAs | Dependent On Illicit Drugs |  | Dependent On Alcohol |  | Received Treatment For Illicit Drug Use |  | Received Treatment For Alcohol Use |  | Needed Treatment For Illicit Drug Use |  |  |  |
| Anaheim-Santa Ana, CA | 43 | (38-50) | 120 | (107-134) | 20 | (15-26) | 11 | (8-16) | 89 | (78-101) | 31 | (24-39) |
| Atlanta, GA | 30 | (26-35) | 108 | (93-126) | 18 | (14-22) | 9 | (7-13) | 117 | (102-134) | 42 | (37-48) |
| Baltimore, MD | 18 | (15-21) | 43 | (35-53) | 12 | (9-15) | 9 | (6-13) | 45 | (38-54) | 26 | (22-30) |
| Boston, MA | 53 | (46-60) | 138 | (120-157) | 30 | (24-38) | 69 | (53-88) | 122 | (107-139) | 52 | (44-62) |
| Chicago, IL | 45 | (41-49) | 172 | (166-179) | 27 | (24-29) | 36 | (33-38) | 137 | (131-144) | 75 | (70-81) |
| Dallas, TX | 35 | (31-39) | 70 | (59-83) | 14 | (11-17) | 10 | (7-14) | 52 | (44-61) | 33 | (28-39) |
| Denver, CO | 17 | (16-18) | 61 | (59-64) | 9 | (8-9) | 13 | (12-14) | 52 | (50-54) | 30 | (29-32) |
| Detroit, MI | 42 | (37-49) | 129 | (112-149) | 28 | (24-33) | 18 | (14-25) | 129 | (113-146) | 63 | (55-73) |
| El Paso, TX | 4 | (3-5) | 17 | (12-23) | 3 | (2-4) | 2 | (1-5) | 11 | (9-15) | 7 | (5-10) |
| Houston, TX | 56 | (50-63) | 52 | (41-66) | 22 | (18-26) | 19 | (14-25) | 103 | (90-116) | 41 | (35-49) |
| Los Angeles, CA | 107 | (99-115) | 508 | (496-521) | 54 | (46-63) | 36 | (33-39) | 288 | (277-300) | 132 | (124-141) |
| Miami-Hialeah, FL | 12 | (11-13) | 33 | (31-34) | 9 | (7-11) | 8 | (7-8) | 35 | (33-37) | 20 | (18-21) |
| Minneapolis-St. Paul, MN | 23 | (20-27) | 70 | (60-83) | 19 | (15-24) | 19 | (13-27) | 49 | (42-57) | 36 | (31-42) |
| Nassau-Suffolk, NY | 22 | (19-25) | 24 | (18-31) | 14 | (11-18) | 11 | (8-15) | 41 | (34-49) | 25 | (20-30) |
| New York, NY | 66 | (61-73) | 125 | (119-132) | 47 | (37-59) | 18 | (16-21) | 177 | (168-186) | 56 | (51-62) |
| Newark, NJ | 21 | (19-25) | 38 | (30-47) | 13 | (11-16) | 12 | (9-15) | 28 | (23-35) | 21 | (17-27) |
| Oakland, CA | 51 | (46-57) | 67 | (56-80) | 24 | (21-27) | 36 | (29-44) | 90 | (80-101) | 33 | (28-39) |
| Philadelphia, PA-NJ | 40 | (34-46) | 114 | (99-131) | 33 | (29-38) | 25 | (19-32) | 121 | (108-135) | 55 | (48-63) |
| Phoenix, AZ | 27 | (24-31) | 64 | (54-76) | 12 | (9-14) | 12 | (8-17) | 56 | (48-65) | 26 | (20-35) |
| San Antonio, TX | 14 | (12-17) | 26 | (18-39) | 5 | (4-8) | 4 | (2-8) | 30 | (23-40) | 17 | (14-20) |
| San Bernardino, CA | 44 | (39-51) | 83 | (72-95) | 24 | (20-29) | 25 | (19-34) | 81 | (71-93) | 51 | (43-61) |
| San Diego, CA | 29 | (24-35) | 62 | (52-74) | 15 | (12-20) | 11 | (7-16) | 67 | (57-78) | 45 | (38-54) |
| St. Louis, MO-IL | 19 | (17-22) | 49 | (42-58) | 15 | (12-18) | 12 | (9-17) | 55 | (47-64) | 42 | (36-49) |
| Tampa-St. Petersburg, FL | 18 | (15-21) | 38 | (30-48) | 12 | (10-15) | 8 | (5-11) | 38 | (32-45) | 26 | (22-31) |
| Washington, DC | 36 | (34-38) | 120 | (117-124) | 19 | (17-20) | 29 | (28-31) | 89 | (86-92) | 45 | (42-47) |


[^0]:    ${ }^{1}$ SAMHSA, 1996

[^1]:    ${ }^{2}$ Detailed definitions of these dependence measures can be found in Appendix A.

[^2]:    ${ }^{3}$ Adjustments of NHSDA substance abuse statistics based on ratios of administrative record arrest counts divided by NHSDA survey estimated arrest reports have been proposed by D. Wright and J. Gfroerer (1994). "The use of external data sources and ratio estimation to improve estimates to hard-core drug use from the NHSDA," in Harrison, L. and Hughes, A., eds. The Validity of Self-Reported Drug Use: Improving the Accuracy of Survey Estimates. NIDA Research Monograph 167, NIH Pub. No. 96-4147, Washington, DC, Supt. Of Docs., U.S. Government Printing Office. However, these adjustments were not done for this report.

[^3]:    ${ }^{4}$ Whether or not a person is using a certain drug at a certain time $T$ can be thought of as a random variable until time $T$, at which point it becomes a fixed characteristic of the person. The choice of a distribution for that random variable depends upon prior information. Examining one extreme, if the person's drug using habits are known for all $\mathrm{t}<\mathrm{T}$ as well as the habits of all close friends, associates and family, and if it is known whether the person was involved in some sort of treatment plan in the time leading up to time T, then the propensity is close to either one or zero. Examining the other extreme, if nothing is known about the person other than that they live in the U. S. and are at least 12 years old, then the propensity will be some sort of national average. The more we know about a person's prior history and present situation, the more we tend to view current drug use as a fixed state of existence rather than as a random event.

[^4]:    ${ }^{6}$ Recall that this is interpreted not as the actual rate at any particular point in time but as the mean of the underlying process. Also note that the word "true" must be interpreted in light of the inherent limitations of the NHSDA measurement protocol, meaning that only substance abuse that is voluntarily reported to interviewers is of interest.

[^5]:    ${ }^{7}$ The approach follows the approach of Breslow and Clayton (1993) quite closely. The phrase penalized quasi-likelihood appears due to Green (1987).
    ${ }^{8}$ Within each of the four census regions, those states for which small area estimates were not produced were grouped together in a regional residual. These four regional residuals were treated the same as states in all the procedures.

[^6]:    ${ }^{9}$ Further information on these long form Census data can be found in the technical documentation for Summary Tape File \#3 of the 1990 Census of Population and Housing as well as in the booklet "1990 Census of Population and Housing Tabulation and Publication Program" prepared by the U.S. Bureau of Census.
    ${ }^{10}$ A well known example of this concerns annual doctor visits. Since the poor have access to Medicaid and the upper end of the income distribution has excellent access to health care, the graph of doctor visits against income is U-shaped.

[^7]:    ${ }^{12}$ Two variables are collinear if the correlation between them is equal to one. The model fitting procedures would fail if any pair of variables was collinear or even approximately collinear.

[^8]:    ${ }^{13}$ Elimination procedures are procedures that involve fitting a series of models, where the ( $n+1$ )-th model is obtained either adding the most important previously omitted variable from the $n$-th model or deleting the least important currently included variable in the $n$-th model.
    ${ }^{14}$ Collinear predictor variables also cause linear models to fail because the matrix X ' X becomes ill-conditioned, making it difficult or impossible to invert it.

[^9]:    ${ }^{15}$ See for example, Hansen, Hurwitz, and Madow, Volume 2, Section 6, Theorem 15.

[^10]:    ${ }^{16}$ The included predictor variables were not, however, identical to the outcome variables of interest here. Otherwise, it would have been possible to get a perfect fit and have a rank correlation of 1 .

[^11]:    ${ }^{17}$ It is likely that the Census Bureau would insist on performing the match itself and on adding noise to the prediction variables to protect confidentiality.

[^12]:    ${ }^{1}$ Sometimes the determinate of this matrix is called "the Jacobian," sometimes the matrix itself is labeled "the Jacobian."

[^13]:    ${ }^{2}$ See Cramer (1946) for a set of conditions and a proof.

[^14]:    NOTE:
    T : Indicates a tract-level variable, C : Indicates a county-level variable, B : Indicates a block-level variable, O : Other

[^15]:    NOTE: $\mathrm{T}:$ Indicates a tract-level variable, C : Indicates a county-level variable, B : Indicates a block-level variable, O : Other

[^16]:    1 "Mean square error" is used to mean the same thing that is labeled "variance" in sections 1.6 and 2.6. Neither term is wholely satisfactory. "Mean square prediction error" would probably be more appropriate but is rather long.

