Modeling Household and Interviewer Nonresponse Rates from Household and Regional Characteristics.

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Introduction

This paper is the first in a series that will examine the effects of a number of variables on refusal and noncontact rates in the Current Population Survey (CPS), the primary labor-force survey in the United States. The CPS, a monthly survey of 48,000 households, is used to measure the unemployment rate. A hierarchical logistic model will be developed in this project, which will consider the effects of variables measured at different levels. These levels include the national office, the regional office, the primary sampling unit, the field supervisor, the interviewer and the household. The model will take account of interactions and confounding within and across these levels.

This particular paper investigates a subset of the predictors of nonresponse rates in the CPS using logistic models. The types of predictors include interviewer work characteristics (e.g.: workload, # of attempted contacts), and household characteristics (e.g.: age, gender of respondent). Much previous research has examined simple effects to predict interviewer or household nonresponse rates. A recent review can be found in Groves and Couper (1998). In contrast, the present study examines confounding and interaction effects between the predictors. Confounding effects occur when two predictors share the same relationship with the nonresponse rate. Interaction effects occur when the relationship between a predictor and the nonresponse rate depends on another variable.

Confounding variables may be useful in choosing which variables would be effective in reducing nonresponse rates. Since some of the variables collected by surveys are thought to be proxies for unmeasured variables producing nonresponse, these confounding effects may help future studies select more meaningful variables to measure. The confounding effects may also suggest which types of measures would be useful to replace proxy variables. If "income" was confounded with "% white", then income might be substituted.

Interaction effects are important since they can change the nature of the relationship between variables and nonresponse. If there were an interaction between "income" and "% white" then both variables would be useful.

Multilevel models can be used to relate variables at different levels of aggregation. In this study they will be used to examine the effects at the household and interviewer level, and to examine the consistency of effects between the household and interviewer level, and between the interviewer and the regional office level.

Data

The data were selected from the Current Population Survey to cover a five-year period: 1994-1999. The households were matched longitudinally, and any households with no responses for all eight panels were deleted. The refusal and noncontact rates were from the first month in sample. The household characteristics for the nonresponse households were taken from their responses in subsequent panels. Over 400,000 households met these criteria. The term "refusal" is used throughout the paper, but a more appropriate term would be "reluctant response", since all households responded at least once during their time in the sample. Similarly, "non-contact" would be "difficult to contact", since those households which couldn't be contacted at all were deleted from this analysis.

Methods

Refusal and non-contact are modeled in a number of different analyses. At the household level logistic regressions relate the characteristics of respondents, interviewers' work characteristics, and area characteristics to build models of nonresponse. Similar models are developed aggregating data for each interviewer (Field Representative or FR). These two types of models give different perspectives on nonresponse. Multilevel logistic models are also developed to investigate the cross level relationships between the household, interviewer, and regional offices.

Variables

The predictors selected were:

AFE - Armed forces ever
AGE
BFR - % completed by Friday
BLK - Black respondent
CNT - # of attempted contacts MIS 1
HSP - Hispanic respondent
KID - Child under 6 at home
MAL - Male respondent
MAR - Married respondent
MFI - Mean family income
MRC - Received supplement on income
MUL - Multi-unit structure
NHH - FR workload
NUM - HH size
OWN - Own/Rent
REL - Relative
RUR - Rural/Urban
SCH - Respondent in school
SIZ - place size
SUN - Interviewer started Sunday
TEL - HH access to a telephone
USL - Usual hours worked
WHT - White respondent

The relationship between the variables used here and refusal and noncontact are thought to work through several mechanisms (Cialdini, 1990, Groves and Couper, 1998). Helping behavior and social isolation may work through many of the variables. MAR, REL, KID, and NUM all relate to multiperson households which are thought to have more helping behavior and less social isolation. OWN is thought to relate to less social isolation, as is TEL. SCH is thought to produce less social isolation. In contrast MUL and SIZ are thought to coincide with more social isolation.

The attitude toward the survey sponsor is supposed to relate to cooperation. In this case the sponsor is the government, so an appeal to authority as well as the legitimacy of the request should help cooperation. The AFE indicator is thought to work through this mechanism, and was found to relate to higher response rates in studies reviewed by Groves and Couper (1998).

The burden of the survey should affect the cooperation rate. The burden is highest in March, which has the income supplement. MRC is an indicator for this effect. Burden is relative to the respondent, so respondents who have less time may see even a short survey as too great a cost. USL, which is an indication of usual hours worked by the respondent is another indicator of level of burden (time pressure).

The ability to contact a household should relate to the noncontact portion of nonresponse. Multiperson households (MAR, REL, KID, NUM) should be easier to contact. More rural households (RUR) may be easier to contact. Respondents who have to spend much time away from home may be difficult to contact, so USL may be related to noncontact. A number of variables relate to the interrelationship between the interviewer and the household. BFR is the proportion of interviews to be completed that are completed by Friday. This should give an indication of how much time the interviewer has to track down difficult to contact households, as well as to persuade reluctant households to participate. It is also a measure of how difficult the set of households are to contact for a particular month in the FRs workload. Similarly, CNT measures the number of attempted contacts, which measures not only the persistence of the interviewer, but also the difficulty of contacting a household. The workload of the interviewer (NHH) may affect the amount of time available for contact and conversion attempts. It may also measure both the success of an interviewer (who may be given more cases because of their success), and the rural nature of the cases, since they need more travel time to reach each respondent. The confounding of the factors make interpreting the variables problematic, but they are worth including. Another measure of the time available is SUN, which measures if the interviewer began interviews on the first possible day. The impact of this on response rates could be an indication both of the additional amount of time available and of the interviewers' attitude.

Other demographic variables used here are AGE, which is thought to be curvilinear in its' relationship to nonresponse. Other studies have found conflicting results. BLK, WHT, and HSP measure the race and ethnicity of the respondent. Other studies have found mixed effects for race, and non-English households have lower nonresponse rates. The gender of the respondent (MAL) wasn't found to have an effect in many the studies reviewed by Groves and Couper (1998), but has the potential to interact with other variables.

Analysis Plan

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Household level

Three different types of logistic regression models were used to investigate the relationship between the predictors and refusal.

1. Using one predictor at a time, 24 logistic regressions were run producing 24 coefficients (Model 1 and 2).
2. Then all the predictors were entered into a model in pairs using 276 logistic regressions to produce 552 coefficients (Model 3).
3. Then the interaction terms between the pairs of predictors were added to the 276 logistic models to give 276 interaction coefficients (Model 4). This was repeated using noncontact as the dependent variable.

From these models the confounding and interaction effects can be determined (Hosmer & Lemeshow, 1989). For example, examining the relationship between home ownership (OWN) and refusal may be affected by whether the respondent is married (MAR).

Household level OWNership and MARital status				
Model	Constant	OWN	MAR	OWN*MAR
1a	-3.04	-2.342 (.012)		
1b	-3.87		-0.050 (.023)	
2	-3.28	-2.513 (.033)	0.578 (.023)	
3	-3.40	-1.522 (.043)	0.815 (.025)	-1.692 (.064)

Household level frequencies of refusal for MARital status and home OWNership				
		Refused	Not refused	Row %
Married	Owner	495	162606	0.30
	Not owner	3674	48506	7.04
Not Married	Owner	668	91285	0.73
	Not owner	3228	96300	3.24

In this example, the relationship between home ownership and refusal is slightly affected by whether the respondent is married, but there is an interaction. Model 1a shows that homeowners are less likely to refuse (-2.342). Adjusting for marital status in Model 2, married homeowners are even less likely to refuse (-2.513) (also Row% of 0.30 compared to 0.73). The interaction in Model 3 shows that the addition of marital status decreases the likelihood of refusal more than would be expected from their separate effects: (-1.692). The relationship between marital status and refusal is affected more strongly by home ownership. Model 1b shows married respondents are slightly less likely to refuse than non-married (-0.050). On the other hand when home ownership is included, the effect for marital status reverses. Thus, once ownership

is taken into account, what is left for marital status to explain is its effect for non-owners. This relationship for non-owners is in the opposite direction than that for owners (0.578). The interaction is clearest in the table of frequency counts and Row percents. Refusal rates are the Row %. Both ownership and marital status are needed to describe the relationship. Although owners have a lower refusal rate than non-owners, married owners have a lower rate than non-married owners. This effect is reversed for non-owners.
The estimates showing the 4 models can be seen in Table1a and Table1e.
The estimates can also be seen in odds ratio form (Table 1b), which is interpreted as the probability of refusal for owners relative to non-owners. For example, the effect of –2.342 for OWN, indicating lower refusal rate for owners, has an odds ratio of 0.091 of encountering a refusal for owners relative to non-owners.

Interviewer Level

The same analysis can be done for data aggregated at the interviewer level. The mean of the households values are used to predict the proportion of refusals. For example, examining the relationship between average home ownership and refusal may be affected by whether the average respondent is married.

Interviewer level OWNership and MARital status				
Model	Constant	OWN	MAR	OWN*MAR
1a	-2.89	-1.900 (.019)		
1b	-3.75		-0.279 (.042)	
2	-3.19	-2.235 (.037)	0.915 (.044)	
3	-3.48	-1.039 (.063)	1.611 (.053)	-1.88 (.093)

Mean refusal rates by MAR and OWN for different levels				
		Household	Interviewer	Regional Office
Married	Owner	0.003	0.005	0.005
	Not owner	0.107	0.077	0.078
Not Married	Owner	0.007	0.009	0.009
	Not owner	0.072	0.040	0.040

In this example, the relationship between home ownership and refusal is indeed affected by whether the average respondent is married, but there is an interaction. In Model 1a interviewers with more homeowners are less likely to have higher refusal rates (-1.900). This can also be seen in the table of mean refusals, where owners have refusal rates of 0.005-0.009 compared to non-owners 0.040-0.077. Model 2 shows the effect of home ownership increases when marital status enters (-2.235). But, again, the effect of marital status itself reverses in model 2 compared to model 1b because of the influence of ownership on the relationship between marital status and refusal. The interaction in model 3 shows that the addition of marital status decreases the refusal rate more than would be expected from their separate effects (-1.88). The table of means shows married owners have lower rates than non-married owners, but the reverse for non-owners. These results are similar to those seen from the respondent perspective.
These estimates at the interviewer level can be seen in Table2a and Table2e.

Multilevel Model

To further investigate the relationship between different levels of analysis a random intercepts multilevel logistic regression was done on each of the predictor variables separately (Snijders and Bosker, 1999). For example, for the OWN variable used above we looked at the effects from the household, interviewer, regional office levels, as well as the interaction between the household and interviewer levels, and the interviewer and regional office levels.

Multilevel model for home OWNership			Means: own	Means: non-own
Level	Estimate –MlwiN	Estimate – OLSE		
Household:	-1.059(0.074)	-0.029(0.002)	0.004	0.045
Interviewer:	-3.294(0.980)	0.096(0.002)	0.007	0.059
Regional Office:	3.488(0.254)	0.076(0.004)	0.009	0.059
HH*Interviewer:	5.517(0.141)	-0.015(0.003)		
Interviewer*RO:	6.914(1.603)	-0.160(0.007)		

Because of the presence of significant interactions, the single level effects must be interpreted with caution. The table above shows the multilevel coefficients (MlwiN) and the ordinary least square coefficients (OLSE). The OLSE estimates are what would have been obtained if the model used the means from the other levels (interviewer and regional office) without adjusting for the hierarchical nature of the data. The results from the multilevel model show that at the household level (adjusting for the effects at other levels) there is a lower probability of refusal for homeowners compared to non-homeowners (-1.059). This is consistent with the household analysis described above. This effect is more extreme at the interviewer level (-3.294). In contrast the unadjusted interviewer level model (model 1a above) found a slightly smaller effect (-1.90) than the unadjusted household level (-2.342, model 1a; household level). The difference in the effect isn't unusual in the presence of an interaction. The effect is reversed at the regional office level, so once you adjust for the other levels the regional office level shows home ownership is related to higher levels of refusal (3.488). The means show that owners have lower refusal rates at the regional office level, consistent with the other levels. Once the regional office levels are adjusted for the household level of refusal and the interviewer level of refusal what is left shows an increase in refusals for owners. Since there are interactions present, this shouldn't be interpreted without first considering the interactions.

The most useful parts of the multilevel model are the interactions between levels. Since they are adjusted for the level effects they show the inconsistencies between levels. For example higher average ownership at the interviewer level is related to higher household refusal (5.517), even though both levels show the reverse separately. This shows the reversal described above in the separate household and interviewer analyses. A similar effect is found between the interviewer and regional office levels, with higher average ownership at the regional level related to higher refusal rates at the interviewer level (6.914). Table3 shows the coefficients and standard errors for the separate analyses of each of the variables. Ordinary least squares estimates (OLSE) can give very different results. In the table above the contrast between the least squares analysis and the multilevel analysis is striking. This may be due to the "ecological fallacy" phenomenon (Steel, Tranmer, and Holt, 1997), where including means from other levels without adjusting for the level can produce incongruous results.

Logistic Regression Model

To examine the unique relationship of the predictor variables to refusal, a logistic regression model was built based on the presence of interactions with other variables.

To appreciate the relationship of a variable with the odds of refusal we took 4 steps:

1. Examine the single predictor relationship, e.g.: OWN OR: 0.096, Table 1B.
2. Examine the confounding variables, e.g.: refusal rates for OWN was most decreased by AGE (0.087), MAR (0.081), MUL (0.085), and REL(0.087). Refusal rates were increased most by CNT(0.100). See Table 1B.
3. Examine the interaction variables, e.g.: for OWN the refusal rates were decreased by AFE (armed forces), MAR (married), MNC (refused income question), NUM (size of household), REL (relative present), RUR (rural), TEL (telephone available), and WHT (white respondent). Refusal rates were increased most by BLK (black respondent), HSP (Hispanic respondent), KID (young child), MUL (multiunit structure) and SCH (respondent in school). Note that some variables can decrease the odds of refusal, (e.g.: MAR), but not as much as you would expect, which gives an interaction which appears to increase the odds of refusal. See Table 1F. The P-values, although adjusted for the number of coefficients within a level (1704 used as a Bonferroni adjustment) can only be used as a rough screener because the sample size is so large. The maximum adjusted R-squares were more useful.
4. Examine the logistic regression model (Table 4), e.g.: OWN has a lesser impact on the odds of refusal after adjusting for other variables, and several interactions have reversed direction.

The variables which will have the largest impact on the adjusted coefficient would be the confounding and interacting variables discussed earlier. The complete model is presented in Table 4. For example, OWN when adjusted for other variables (Table 4, estimate: -0.4765, or Odds Ratio of 0.621) had a similar pattern as it had by itself at the household (OR of 0.096) level. It also interacted with SCH (respondent attends school, OR: 7.501), BLK (Black respondent, OR: 3.065), TEL (household has access to a telephone, OR: 0.228), REL (relative present in household, OR: 0.848), and MAR (respondent is married, OR: 0.268). Adjusting for the other variables sometimes changed the relationship, for example, household ownership and attending school interacted in the two variable model described earlier (Table 1b, 1e), with ownership related to less refusal, and the interaction indicating lower refusal than might be expected by their combination (Table 1E-OR: 0.587). Adjusting for other variables reversed this interaction, with much higher levels of refusal than would have been expected from the combination of the two variables (Table 4, OR: 7.501).

A similar model was developed at the interviewer level, and the odds ratios are show in Table 4, column “Odds FR”. While most of the effects were consistent with the household level, there were some reversals. For example, households with young children present (KID) tend to refuse less often when examined using a single predictor model (OR: 0.953, see the Single HH column), but interviewers who have more such families have higher refusal rates (OR: 1.132, see the Single FR column). Once adjusted for other variables the aggregated level model shows interviewers with respondents who have young children produce higher refusal rates (OR: 1.374).

The same pattern of models were developed for noncontact (Tables 5A-5G, 6A-6G, 7, 8).

Results

The results are organized separately for models which use refusal as a dependent variable and models which use noncontact as the dependent variable. The model in Table 4 fit the data with a residual chi-square of 68.9565 with 54 degrees of freedom (p=0.09827). The models at the FR level and for noncontact didn’t fit as well.

Refusal

Household level:

From the one and two predictor models (Tables 1a-1h) the strongest relationships based on R-square were for OWN, CNT (number of attempted contacts), and MAL (male respondent). MNC (refusal of the income item anytime during the 8 months in sample) was also related. Because it is used more as an indicator of propensity to not respond it is more useful in combination with other variables. Predictors which have high odd ratios were SCH (respondent attends school), MAL, and BLK (respondent was Black). Predictors with low odds ratios were OWN, SUN (interviewer began on Sunday), RUR (rural), TEL (respondent has a telephone available), and WHT (respondent was White). In a model with many predictors (Table 4) the strongest relationships with refusal were for CNT, REL (relatives present), BFR (interviewer completed most interviews which would be completed by Friday), and NHH (number of households interviewed, a measure of workload). Most of the other variables had a less strong relationship with refusal, and AFE (armed forces respondent), KID (young child in household), and MAR (married respondent) had the least relationship when considered by themselves.

OWN-home ownership

Ownership had the strongest relationship with refusal. It was confounded with AGE, MAR, MUL, and REL by decreasing the odds of refusal. Own was confounded with CNT (number of attempted contacts) by increasing the odds of refusal. It also has interactions with AFE, MAR, MNC, NUM, REL, RUR, TEL, and WHT decreasing the odds of refusal, and with BLK, HSP, KID, MUL, and SCH increasing the odds of refusal (Tables 1e-1h). The lack of an interaction with AGE indicates that the respondents AGE confounds with ownership, but doesn’t interact with it. The strongest interactions were with MAL, MAR (respondent was married), MUL (multiunit structure), and REL.

The logistic regression with many predictors (Table 4) is consistent with the other analyses, but the unique relationship of ownership (adjusting for all other variables) is relatively less, as can be seen by the size of the Wald statistics. Part of this is due to the presence of a number of interactions with OWN. The interactions were different from the simple models for AFE, HSP, KID, MNC, MUL, NUM, RUR, and WHT, which became non-significant in the logistic regression. None of the interactions reversed the direction of their effect.

CNT-number of attempted contacts

CNT (number of attempted contacts) is confounded with BFR with increasing odds, and OWN and SIZ with decreasing odds. The strongest interaction was also with BFR, with increasing odds. The logistic model with many predictors (Table 4) showed slight interactions with KID increasing the odds, and MAL and SCH decreasing the odds. The interaction with BFR wasn't strong enough to be used in the model after adjusting for other terms.

MAL- respondent was male

MAL (respondent was male) is confounded with OWN with increasing odds, and AFE and REL with decreasing odds. The strongest interaction was with REL with increasing odds. The model with many predictors also found this strong interaction as well as slight interactions with TEL and WHT increasing odds and CNT and RUR decreasing odds.

Aggregate level:

The aggregate data at the interviewer level showed a similar pattern as the household level (Table 4; FR columns, Tables 2a-2h), but with less strong effects for most variables. This is also seen for the single predictor multilevel model (Table 3), where household interacts with the interviewer level (FR*HH) for many of the variables, suggesting the effects are more different than would be expected from the levels separately. OWN had the strongest relationship to refusal based on R-square, with a decrease in the odds of refusal. SUN also was related to lower odds, and SCH and MAL related to higher odds. They weren't as strong a relationship as OWN. The interactions were fewer as well.

OWN

For OWN, the household (OR: 0.096) and interviewer (OR: 0.150) levels in Tables 1B and 2B show lower likelihood of refusal, although the interviewer level is higher. It is confounded with MAR, MUL, and REL decreasing the odds of refusal, and RUR and SIZ increasing the odds. AGE and CNT, which were confounders at the household level weren't at the interviewer level. RUR and SIZ were added as counfounders at the interviewer level. The interactions were similar in direction to the household level, with only MNC and NUM dropping from the list, while CNT and SUN were added to the increased odds, and BFR added to the decreased odds. MAR and REL had the strongest interactions, with a decrease in odds.

Adjusting for the other variables in the logistic regression (Table 4), the difference is more pronounced. The household adjusted odds are 0.621, while the interviewer level odds are 1.089.

In the multilevel model (Table 3) the average ownership at the interviewer level interacts with the household level, so interviewers who work in areas with higher ownership would have more refusals than would be expected from the household and interviewer average data separately. The effect for ownership was higher refusal rates than would be expected at the regional office level, adjusting for the other levels (Table 3). There was also an interaction between the interviewer and regional office level, suggesting that adjusting for regional differences, interviewer refusal rates for homeowners would be higher than expected.

Home ownership showed a reversal between household and interviewer levels for both single predictor and multiple predictor models (Table 4). Rural households show a higher refusal rate, but when adjusted for other variables this effect disappears. Since one of the variables being adjusted for is population density, the single predictor makes more sense in this context.

Non-contact

Household level:

From the one and two predictor models (Tables 5a, 5d) the strongest relationships were for OWN, MAL, and CNT based on the R-squares. Predictors with low odds ratios were OWN and SUN. High odds ratios were found for BFR, SCH, MAL, and MNC. While AGE (age of respondent) didn't relate strongly to noncontact by itself with only a slight decrease in odds, it interacted with OWN to decrease the odds of noncontact and with SCH to increase the odds.

OWN

Ownership was related to lower levels on noncontact (OR: 0.098), and was confounded with AGE and MUL with decreased odds and CNT and NUM with increased odds. It had interactions with MUL (OR: 9.583), SIZ (OR:1.192), and AGE (OR:0.950) (Tables 5e-5h). In the larger logistic regression model (Table 8), which adjusts for the other variables the effect was reversed, with higher levels of noncontact associated with ownership (OR: 1.659). The interactions also changed, with higher noncontact associated with SCH (OR: 7.144), lower levels were with TEL (OR: 0.164), REL (OR: 0.324) and MAR (OR: 0.248).

MAL

Male respondents were associated with higher noncontact rates (OR: 2.160), and was confounded with AFE and MAR with increasing rates and REL, USL, NUM, and KID with decreased rates. Its strongest interaction was with REL with increasing rates. It also had positive interaction effects with MAR, RUR, and WHT. It had lower interaction effects with BLK and MUL. In the larger logistic model the effect reversed (OR:0.872) and interacted with BFR, MAR, NUM, REL, and WHT with increasing odds. It had decreasing odds with KID and RUR.

CNT

More attempted contacts were related to a higher noncontact rate (OR: 1.370). It was confounded with BFR with higher rates, and SIZ, OWN, and MUL with lower rates. The strongest interaction was with BFR with higher noncontact rates (OR:1.425). It had a slight interaction with MRC (OR: 0.918) and MUL (OR:0.952) decreasing odds. In the larger logistic model the interactions were increasing odds with RUR (OR:1.039 and decreasing with MRC (OR:0.922) and MUL (OR:0.936).

Aggregate level:

The aggregate data at the interviewer level showed a similar pattern to the household level with lower noncontact rates. The strongest effects were for OWN and MUL (OR:1.629) based on the R-squares (Tables 6d, 6h). Some of the highest nonresponse odds were for SCH and BLK. Some of the lowest odds were for OWN, MAR, SUN, and WHT.

OWN

OWN had lower noncontact odds (OR:0.156). It was confounded with NUM and SIZ having increased odds and MAR and AGE with decreased rates. It had interactions with most of the variables except SUN, USL, and MRC (March supplement) (Tables 6e-6h). The interactions which were in the larger logistic model (Table 8) were MAR (OR: 0.094), REL (OR: 0.823), SCH (OR: 7.588), and TEL (OR: 0.256). The multilevel model (Table 7) shows that adjusting for other levels produces lower nonresponse with ownership, but there is an interaction between the interviewer and household levels as well as the interviewer and regional office levels. Higher average ownership at the interviewer level would relate to higher than expected nonresponse at the household level. Similarly, higher ownership at the regional level would relate to higher than expected nonresponse rates at the interviewer level.

MUL

MUL had higher noncontact odds (OR:1.629). It was confounded with SUN having higher rates and OWN, SIZ, MAR, and WHT having lower rates. It interacted with OWN and REL with higher rates and MAL and SCH with lower rates. The effect for MUL showed attenuation in the multilevel analysis, from a significant lower odds at the household level to a similar coefficient but higher standard error at the FR level. There was a slight interaction suggesting that the household level was higher than would be expected after controlling for the other levels.

MAR

MAR had lower levels of nonresponse in the single predictor (OR: 0.432) and higher levels in the multiple predictor (OR: 1.792) models. The interaction effects tended to be smaller, but in the same direction as the household effects. The multilevel model was consistent with higher nonresponse rates, and no interactions between levels.

CNT

CNT (number of attempted contacts) had higher levels of nonresponse in the single predictor model (OR: 1.371). The rest of the patterns were also similar to the household level. The multilevel model showed an interaction between the interviewer and the household level. When the household rates were adjusted for regional and interviewers mean number of attempted contacts, then the noncontact rate was lower for more attempts. When the interviewer rates are adjusted for other levels, more attempted contacts were associated with more noncontact. This shows the different perspectives multilevel modeling affords. The interaction between the interviewer and household levels shows that the noncontact rate is higher than would be expected for the effects at each level separately. The interaction effect reversed for the interviewer and the regional level. When the interviewer rate was adjusted for regional differences, the interviewers had a lower number of noncontacts for the number of attempts than would be expected from the effects on each level separately.

Discussion

Refusal

Patterns of refusal and noncontact in this study will be discussed in the context of other studies, primarily from a recent review by Groves and Couper (1998). Five types of variables were used; respondent characteristics (AFE, AGE, BLK, HSP, MAL, MAR, REL, SCH, USL, and WHT), household characteristics (KID, MNC, NUM, OWN, and TEL), area characteristics (MFI, MUL, RUR, and SIZ), a design characteristic (MRC), and interviewer characteristics (BFR, CNT, NHH, SUN). The Groves and Couper review of studies provide effects from a mix of single predictor and multiple predictor models. The mix of model types and the differences between census match and reluctant households probably account for the differences in results.

The respondent characteristic which had the strongest relationship to refusal was MAL. SCH and BLK contributed to refusal to a lesser degree. WHT was the strongest respondent characteristic associated with a decrease in refusals. The findings about males is in contrast to the studies in Groves and Couper (1998,p.145), as is the findings about BLK and WHT (page 144). Kojetin (1994) found a similar effect for race as this study. The effect for MAL interacted with REL producing higher refusal rates. This was consistent with the literature, but not what was expected from theory. Part of this may be explained by the interaction between REL and OWN, producing a lower refusal rate. MAR had a slight relationship with reduced refusals, consistent with the mixed literature cited in Groves and Couper (1998, p.144&183). The interaction with OWN producing lower refusal rates is more consistent with theory. AGE had a slight relationship with fewer refusals, consistent with the literature. There was an interaction with SCH, suggesting that older students are more likely to refuse. The Groves and Couper study based on census data showed an effect for household age. This might be accounted for by the presence of other variables, such as usual hours, or it could be the household age measure is more predictive than the respondent age. Since the respondents characteristics for refusers comes from later panels of the survey, it could be that a different person refused in the first panel. Students in general were more likely to refuse, which doesn't support the theory if students are thought of as being more socially involved. The slight effect for higher refusal rates associated with longer work hours (USL) conflicts with some studies reviewed by Groves and Couper (1998, p.124). One of the theories they describe was that respondents who had less time available would be less likely to participate, which coincides with the data in the present analysis. The slight effect for AFE related to fewer refusals is in the direction of the theory, but only weakly. The slight effect for more refusals by Hispanics is contrary to theory and the literature (Groves and Couper (1998, p.144)). This might have to do with the different Hispanic populations in the US, as well as how Hispanic is defined by different surveys. The picture of a respondent least likely to refuse is a female homeowner, White, married, and not in school.

The household characteristic which was most associated with fewer refusals was home ownership (OWN). Groves and Couper (1998, page 147) report more refusals (non-significant). Kojetin (1994) reported Census blocks with more homeowners had fewer refusals. Since Groves and Couper included other measures of income in their model, this adjustment might be one of the reasons for the difference. Another possible reason is that this study used households which responded at least once in the survey period. Groves and Couper used census data matched to the survey. The households which never responded may be different in home ownership compared to the households which responded at least once. OWN interacted with respondent characteristics of MAR and REL, producing lower refusals. It also interacted with MUL, with owners of units in multiunit structures having higher refusal rates. Having a telephone available (TEL) was associated with lower refusals, consistent with theory. The number of household members (NUM) and small children present were slightly related to lower refusal rates, which was consistent with theory and the literature (Groves and Couper, (1998, p.138, p.139&144). Groves and Couper found that single person households were more likely to refuse. Similarly, this study found refusal decreased slightly with decreasing household size. The adjusted model showed a reversal, which may be related to the curvilinear effect described by Groves and Couper, with single member households having high refusal rates, the small households having low rates, but larger households having increasing rates. The picture of a household least likely to refuse is a married homeowner of a single family home, with a telephone, small children, and a larger household.

The characteristics of the area in which the household lives contributed less than the household characteristics, but MUL was one of the strongest. It was associated with higher refusal rates both in this study and those reported by Groves and Couper (1998) and Kojetin (1994). MUL also interacted with

OWN producing higher refusal rates. Rural areas (RUR) was associated with lower refusal rates in this study and in Kojetin (1994) and Groves and Couper (1998,p.176&181). Mean family income had a slight relationship with refusal, although family income was more strongly associated with refusal (unreported here), which is more consistent with the literature. Although measures of income were available the pattern of missing was related to the odds of refusal, so it was left to another study. Groves and Couper found higher rates for refusal associated with higher income. Population density (SIZ) was related to more refusals in this study as well as Kojetin (1994) and Groves and Couper (1998, p.147&181). The picture of an area with few refusals would be rural or single owner homes in a less populated area.

The design characteristics of the March supplement on income (MRC) is thought to increase refusal rates because of the increased burden. The effect was also found in this study, but it was a slight effect relative to the others. Part of the effect may be due to burden for households experiencing the supplement a second time, but part is probably due to interviewer expectations, since they know the burden they are asking of the respondents.

The interviewer characteristics of BFR (completion of interviews before Friday) and CNT (number of attempted contacts) were associated with higher refusal rates. The BFR effect may be an artifact, since the measure is based only on the percent of completed interviews which are completed before Friday. Those interviewers who had many refusals before Friday would have fewer households in the denominator of BFR. It could also be that households which initially refuse are reassigned to specialists, who are already finished with the interviews which they will manage to complete. The high rates for more attempted contacts is easier to explain. If a household is reluctant to participate it may avoid the interviewer, making more contact attempts necessary. NHH (number of households) and SUN (whether the interviewer started interviewing on the first possible day) were both associated with lower refusal rates. For NHH the lower refusal rates may be a result of more successful interviewers being given more work. For SUN the lower rates may be a measure of interviewer motivation.

The refusal rates from the aggregate data looked very similar to the household level. Most of the effects were less significant. The most consistent effects involved OWN and it's interactions with MAR and REL. Similarly the effects for MAL and SCH carried over. The effect for BFR reversed, with fewer refusals from the interviewers' perspective. The measure at the household level may relate to the difficulty of the interviewers cases that month, while the measure at the FR level may relate to their ability to complete interviews. This difference in perspectives is reflected in the multilevel model (Table 3). KID also reversed its' effect, with fewer refusals at the household level and more refusals at the interviewer level. Since KID was somewhat confounded with AGE and OWN as well as interacting with them to produce higher rates, after adjusting for other variables the difference between the levels disappears. From the household perspective, KID reduces refusal, but a caseload of households with small children is also likely reduce the propensity to respond of those households which usually would respond. Once adjusting for the effect the other levels there wasn't an interaction between the household and interviewer levels in the multilevel model. It was one of a few effects which didn't show an interaction. The other interactions appear to be interpretable as the attenuation of the effect mentioned earlier.

Noncontact

The pattern of noncontact was similar to refusal. The models produced different adjusted estimates for ownership. This may have to do with including CNT in the model. Once the household contact rate is adjusted for the number of attempted contacts, the difference between owners and non-owners reverses. Another reversal comes from young children present in a household. It is related to more non-contacts but fewer refusals. The lower refusal rate is consistent with Groves and Couper.

AGE was related to slightly fewer noncontacts. Groves and Couper (1998, p.113) found a higher rate of noncontact. Other effects were more consistent: BLK, MUL, and SIZ all producing higher noncontact, and KID, MAR, NUM, OWN, and RUR producing lower noncontact (see pages 86,92, and 113).

From the aggregate data the patterns were also similar. KID showed none of the reversal seen in the refusal data, but the BFR reversal was still there. Some effects seemed stronger. For example; NUM and MUL were better predictors of noncontact than they were of refusal.

Otherwise the patterns seen in the refusal data were very similar to the noncontact data. Since there are many potential reasons for noncontact this is somewhat surprising. There is a seasonal trend for noncontact, with more problems during the winter holidays and summer vacations. Since most of the noncontacts in the first interview are resolved by the end, the characteristics should be different if there are different mechanisms.

Limitations

This type of study relies on the pattern of converted refusers to be similar to those who consistently refuse. This is not a tenable assumption, but it may best describe reluctant households, rather than refusing households. While it doesn't address all of the non-response population, it models the borderline responders.

This study only considered a limited number of variables. Others would indubitably contribute to the model. In addition to different formulations of the variables already used, (such as age, number of household members), we would like to include more environmental variables and variables which address the interaction between interviewer and respondent. We would also like to include some characterization of the refusal (hostile break-off, no time, suspicion of government). There were other variables which tended to be missing (particularly income), which we would like to incorporate into the model. We would like to include administrative variables at the regional office level.

It is clear from the model presented that there are many interactions present. We would like to pursue higher order interactions where enough data is available.

The CPS is a short survey on a subject which is easy for the respondent to deal with, conceptually, in terms of memory, and emotionally. The slight burden of the CPS may relate to its high response rate. Other survey subjects and formats may yield different relationships. The difference between the CPS and a survey which takes more time and is on more difficult subjects would help address this effect.

Additional analyses are needed to examine the regional and interviewer effects. The current study used a multilevel model with random intercepts (which is easiest to relate to the single level models), but models with random slopes would add a useful perspective. Do the relationships between factors (such as home ownership) and nonresponse differ in a way between interviewers which relates to interviewer or household characteristics?

Additional outcome variables may also be useful. There has been an increase in other types of nonresponse (language problems, illness, missed appointments). These might give a more complete picture of survey outcomes.

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