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Time to Readmission Among Chronically Ill Community-Resident Beneficiaries: Variations by Geographic Area and Provider Type

FINAL Report

CMS Contract No. HHSM-500-2005-000201/T.O. 0001

Submitted To

Centers for Medicare and Medicaid Services

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September 17, 2010

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1. Abstract

This report is focused on the potential role of care continuity in avoiding readmission for chronically ill beneficiaries dwelling in the community. Although the concept of care continuity has been of interest for decades, there is little consensus on the best ways to identify or measure it, particularly in claims data. This report focuses on the single largest provider of evaluation and management (E&M) services for each beneficiary to identify high, medium or low continuity. The sample consists of beneficiaries with a hospitalization in 2004 who were also enrolled in Medicare in 2003. For those readmitted, the average time to readmission was 64 days, and about 48 percent had a readmission within 30 days of discharge, which is consistent with previous research. In Cox proportional hazard modeling, high continuity was associated with reduced readmissions. More specifically, those with high continuity had a 6 percent lower risk of all-cause readmission, controlling for demographic, chronic illness and geographic factors. Results are similar if you consider same-cause readmission or shift from state to Dartmouth Hospital Referral Region as the geographic unit of interest. Interactions between chronic illness or illness severity and care continuity were tested as a final step. Here, there was a significant, but extremely small interaction for medium continuity and the ACG risk adjuster.

Ultimately, these results point to the potential value of care continuity when it comes to reducing readmissions. However, further work is required to understand the best way to identify care continuity, particularly in claims data. The majority provider approach used here does not account for the number of providers seen by any one

beneficiary, a limitation that could be addressed in future research. That said, the findings from this study are consistent with previous research on continuity and re-admissions.

2. Introduction

Repeat hospitalizations are not uncommon in the Medicare population. Over the past decade, there has been growing interest in examining rates and frequencies of readmission. Identification of factors associated with variation in readmission may point to opportunities to improve quality of care and reduce unnecessary Medicare expenditures. This report follows this vein of research to examine the potential role of care continuity in avoiding readmission for chronically ill beneficiaries dwelling in the community. Care for chronic illness is expensive and much of the increase in national health expenditures in the last decade involves chronic care. Reducing readmissions, especially for beneficiaries with chronic illness, may be part of a strategy to reduce expenditures in the Medicare population. Specifically, this report aims to answer the following questions:

- What are the rates of readmission for community-dwelling beneficiaries?
- What factors affect risk of readmission for this population?
- Is there an association between care continuity for those with chronic illness and risk of readmission?

This study is unique in several ways. First, it uses the Chronic Conditions Warehouse (CCW) to identify chronically ill beneficiaries residing in the community, excluding long-stay nursing home residents. Second, it estimates the impact of factors

affecting time to readmission using survival analysis. Third, it considers the impact that continuity of care has on risk of readmission for this population.

3. Background

3.1 Extent of the Problem: Prevalence and Cost to Medicare

Some of the earliest studies of Medicare beneficiaries estimated that approximately half of all inpatient hospital patient discharges were readmitted within one year and 23 percent were readmitted within 60 days (Anderson and Steinberg 1984). A more recent study suggests that readmission rates may have increased over these earlier estimates. Using 2003-2004 Medicare claims, Jencks and colleagues found that 28 percent of all discharged beneficiaries were readmitted within 60 days (Jencks, Williams and Coleman 2009). Mor and colleagues recently examined readmission of nursing home residents, who make up a small but very vulnerable portion of all aged Medicare beneficiaries, and found that the rate for this subpopulation may be rising as well (Mor, Intrator, Feng et al. 2010). In 2006, approximately 24 percent of residents discharged alive from a hospital stay were readmitted, a rate that is up from 18 percent in 2000. (The current study focuses on community-dwelling beneficiaries and does not include long-stay nursing home residents.) Studies have found significant geographic variation in readmission rates. Jencks and colleagues found that state average readmission rates varied between 13 and 23 percent (Jencks, Williams and Coleman 2009). Similarly, Mor and colleagues found the rates of readmission of nursing home residents varied from 15 to 28 percent across states, which may be related to service use and physician practice patterns that vary from region to region (Mor, Intrator, Feng et al. 2010).

The costs of readmissions are substantial. Jencks and colleagues estimate that Medicare spends over $17 billion for unplanned readmissions (Jencks, Williams and Coleman 2009). Mor and colleagues estimate that in 2006 alone there was $4.3 billion in Medicare payments for readmissions of beneficiaries who were residing in a nursing home (Mor, Intrator, Feng et al. 2010).

It may be possible to prevent some readmissions. One study using data from the AHRQ Health Care Utilization Project (HCUP) found that 19 percent of those admitted with a preventable condition were readmitted for a preventable condition within 6 months (Friedman and Basu 2004).[1] A two-month retrospective study based in London found that of the 4.3 percent of all discharges that resulted in a readmission, 71 percent were determined to have been avoidable if proper care had been delivered (Shalchi, Saso, Li et al. 2009). The top reasons for a readmission identified by this study were inadequate or incomplete treatment and incorrect or incomplete diagnosis.

3.2 The Role of Care Continuity in Preventing Readmissions

Given that some readmissions appear to be avoidable and many occur for conditions that are related to the initial admission, approaches such as a medical home may be part of a strategy to reduce readmissions among chronically ill Medicare beneficiaries and reduce associated costs. Although specific definitions and models vary, the underlying concept of the medical home is that responsibility for care is assumed by a

[1] Note that the HCUP data spans all ages.

single provider, who works with the patient (and his or her family, if appropriate) and a team of providers involved in the patient's care; care is based on his or her individual needs, in order to manage the health and coordinate the care of that patient across the continuum of care providers and services (Rosenthal 2008; Berenson and Rich 2010). Although the concept has been discussed since the 1960s, the idea of the medical home has become reenergized in recent years and is frequently promoted by primary care organizations, researchers, policy makers, and the current administration (Rosenthal 2008; Fields, Leshen and Patel 2010). Given the focus on "whole person" care and coordination across different providers, the medical home would seem to have particular value for those with chronic illness. In fact, some of the most well known and successful medical home models were initiated with this population in mind, and medical home models overlap substantially with the chronic care model (Fields, Leshen and Patel 2010; Holmboe, Arnold, Weng et al. 2010).

Approaching patient care in this way is purported to result in better quality, lower costs and greater patient satisfaction (Berenson and Rich 2010). There is some evidence to support these claims. A review of seven well known medical home models found increases in quality and cost savings (reduced hospitalizations and emergency room use) (Fields, Leshen and Patel 2010). A recent evaluation of the Group Health medical home pilot revealed greater patient satisfaction, fewer visits but more total communication (for example by email and telephone), approximately one-quarter fewer emergency room visits and 6 percent fewer hospitalizations as compared to Group Health members not included in the pilot (Reid, Coleman, Johnson et al. 2010b). The evaluation also found

that the medical home model resulted in approximately $10 decrease in per member per month costs (Reid, Coleman, Johnson et al. 2010b).

Some evidence corroborates the idea that medical homes may indeed have special value in care for the chronically ill. The Group Health pilot evaluation showed that patients in the medical home sites were more likely to participate in chronic illness self-management courses as compared to patients in other sites, and pilot patients were also more likely to rate their care for chronic illness higher than non-pilot patients (Reid, Coleman, Johnson et al. 2010a). Another study found that chronically ill pediatric patients in primary care practices that scored higher on an index assessing the degree to which the practice operated as a medical home had fewer hospitalizations and lower utilization of emergency departments (Cooley, McAllister, Sherrieb et al. 2009). Further, systematic reviews of integrated or coordinated care (which include elements of the medical home model) for patients with chronic illness indicate that improved coordination leads to better results in the management of such illnesses (Ouwens, Wollersheim, Hermens et al. 2005; Tsai, Morton, Mangione et al. 2005).

At the core of the medical home is a strong foundation of primary care and an ongoing relationship with a primary care provider (PCP) (Rosenthal 2008; Landon, Gill, Antonelli et al. 2010). A continuous relationship between patient and provider allows for the necessary accumulation of knowledge and development of comfort in the relationship (Rosenthal 2008). Care continuity has been discussed and promoted for decades outside of the medical home concept, and there have been a number of efforts to create care continuity measures and estimate the effects on outcomes of interest (Saultz and Lochner 2005; Wolinsky, Miller, Geweke et al. 2007; Wolinsky, Bentler, Liu et al. 2010).

In the context of elder care and chronic illness, several studies suggest that a long-term relationship with a PCP results in better outcomes. Using a sample of over 5,400 elders, Wolinsky and colleagues found that better care continuity, as assessed using two separate measures, was associated with significantly lower mortality over a 12 year period (Wolinsky, Bentler, Liu et al. 2010). A recent study conducted in Canada by Knight and colleagues found that greater care continuity was associated with decreased risk for hospitalization (Knight, Dowden, Worrall et al. 2009b). Another study conducted by Lin and colleagues examined the association between care continuity for a sample of randomly selected diabetic patients in Taiwan and found that lower care continuity was associated with increased rates of hospitalization and greater risk for admissions for ambulatory care sensitive conditions (Lin, Huang, Wang et al. 2010b).[2] However, other studies have found no effect of care continuity on outcomes. A recent study examining the effect of having a regular provider on outcomes for diabetes patients found only small differences (Hueston 2010). Specifically, patients with a regular physician were found to have lower glycated hemoglobin and were more likely to receive an influenza vaccination, but there were no differences in blood pressure, cholesterol levels or percent achieving goals for their diabetes management. A review of the Medicare Care Coordination Demonstration projects similarly found only minimal improvements in health outcomes (Brown, Peikes, Chen et al. 2008). Thus, more studies are needed in

[2] Although findings from Lin and Knight are not directly interpretable for the US because of differences in healthcare systems, they do suggest that care continuity may be an important feature in maintaining and promoting higher quality care.

order to determine whether continuous care from a PCP should be part of a chronic illness management strategy.

4. Data and Methods

4.1 Data

This analysis uses data from the Chronic Conditions Warehouse (CCW) claims files from 2003-2004. As part of the 2003 Medicare Prescription Drug, Modernization, and Improvement Act, CMS created the CCW which contains Medicare beneficiary data from enrollment, eligibility, inpatient, institutional, and other provider claims, and assessments from the Minimum Data Set (MDS) and the Outcome Assessment and Information Set (OASIS) (Schneider, O'Donnell and Dean 2009). In addition, the data include chronic condition flags developed by CMS, ResDAC and Buccaneer. One of the goals of the CCW is to facilitate research across data sources through the use of a consistent beneficiary link key. The objective is to facilitate following individual beneficiaries over time or across data sources. The current study was focused on provider and inpatient claims for two years, but also used MDS data to identify long stay nursing home residents, who should not be included in a study of community residing beneficiaries. Demographic information comes from the 2003 Medicare denominator file and chronic condition flags from Chronic Condition Summary file. Preadmission characteristics were derived from 2003 data, while hospital admissions, readmissions and date of death were observed in 2004. At the time of this study, the CCW for 1999-2004 included only the 5-percent sample.

4.2 Sample

The population of interest for this study is community-resident aged Medicare beneficiaries who were hospitalized in 2004 and therefore at risk for readmission in that year. The study does not include those who were eligible for Medicare due to a permanent disability and those receiving benefits for end stage renal disease. Although these two groups also need chronic care and experience readmissions, they are likely to have different service use patterns than Medicare beneficiaries who are eligible by virtue of age. Beneficiaries who were long-stay nursing home residents (defined as 90 days or more of nursing home care) at the end of 2003 were excluded, leaving beneficiaries who were primarily community based. These two groups are likely to have different access to primary care and may use hospitalization differently. A small group of beneficiaries in the sample are likely in the process of becoming long stay nursing home residents over the course of the study window. An illustration of this would be the community dwelling resident who is hospitalized at some point in the study period, discharged to a nursing home, and has been a resident for 10, 20, or even 60 days at the close of the study window (January 1, 2004) but goes on to stay in the facility for longer than 90 days after the window has ended. This group is likely small and has been left in the sample.

The study group also did not include beneficiaries whose only hospital discharge in 2004 was for a hospitalization that began in 2003; this condition removed 8,903 discharged beneficiaries from the potential sample. As with the Jencks study, readmissions that occurred on the same day as a discharge were not counted as readmissions for the purpose of the analysis, because the majority of these are known to be transfers (Jencks, Williams and Coleman 2009). In this case, neither the initial

admission nor the readmission was used in the study; however, beneficiaries experiencing same-day readmission could enter the study based on a subsequent hospitalization.

The study relied on fee-for-service claims and thus was restricted to beneficiaries enrolled in fee-for-service Medicare, i.e. beneficiaries enrolled in Medicare Advantage plans were excluded. The primary sample for this analysis, drawn from the 5% sample of Medicare beneficiaries, thus includes aged, community-resident, fee-for-service Medicare beneficiaries who experienced a hospital admission in 2004 and were enrolled in Medicare A and B in 2003 and 2004.[3]

4.3 Measures

4.3.1 Time to Readmission

Time to readmission, the dependent variable for the study, was defined as the number of days between the first hospital discharge in 2004 and the next admission in 2004, regardless of cause (all-cause readmission). Time to first 'same-diagnosis' readmission was also calculated by counting the days between a discharge and the first readmission for the same diagnosis. 'Same-diagnosis' was defined as an admission having the same 3 digit primary diagnosis code as the index admission, the first admission in 2004. This definition does not identify beneficiaries who are readmitted for

[3] These years were selected because they are the most recent two years in a five years series of CCW that the study was permitted to use as part of an MRAD sample project. Ideally this analysis could be repeated in more recent data.

post surgical infection or other complications that may be related to the original admission diagnosis but bear a different ICD-9.

4.3.2 Care Continuity

The degree of continuity of care was assessed using the percentage of evaluation and management (E&M) services provided in any setting[4] to a beneficiary by the provider with the highest proportion of these services. The definition rests on the idea that a beneficiary receiving all or almost all of his or her E&M services from one provider is experiencing continuity of care while a beneficiary who receives no E&M services is not experiencing continuity of care. Similarly, a beneficiary receiving E&M services from many providers, for example 10 percent from each of 10 providers, is receiving more fragmented care than one who receives most care from one provider.

The challenge for the definition is to assign a degree of continuity to situations between these two extremes. Because there is no clear clinical definition for the degree of care concentration that represents continuity, any categorization is somewhat arbitrary. Providers were identified by the tax identification number (Tax ID) on physician bills. In theory this should capture solo practitioners and group practices where primary care may be shared across multiple physicians or physician/physician assistant/nurse practitioner teams. However, in practice, there are situations where a single UPIN (provider identifier) is associated with multiple tax ID numbers. At the same time, individual

[4] Note, for this sample, about 60 percent of E&M visits were provided in a primary care setting and 40 percent in other types of settings.

providers can also have multiple UPINs, making neither provider indicator ideal. For this analysis, the proportion of E&M claims made by each provider was ranked from highest to lowest to identify the dominant provider.

A beneficiary is defined as experiencing high continuity of care when at least 90 percent of his or her E&M services are provided by one provider. Medium continuity is defined as occurring when 40 to 90 percent of E&M services are provided by the highest-ranked provider. If anything less than 40 percent of E&M care is provided by the highest-ranked provider, this is coded as "low or no continuity"; for the analyses, this was the reference condition.[5]

The development of the care continuity variable was thus a multi-step process that involved identifying evaluation and management (E&M) services and then aggregating them up to the provider level and the beneficiary level for each beneficiary. The base for the continuity measure is the total E&M expenditures per beneficiary. Table 1 shows

[5] As a sensitivity test, we used a lower threshold for 'high' continuity (65 percent as the indicator of high continuity, 35-65 as medium continuity and 0-35 as low or no continuity.) We also calculated a care continuity measure from Christakis et al., (2001) that combined information on the number of E&M visits and number of E&M providers to create an overall score between 0 and 1. For more detail see Christakis DA, Mell L, Koepsell TD et al., (2001). Association of lower continuity of care with greater risk of emergency department use and hospitalization in children. Pediatrics, 103(3): 524-529.

that on average beneficiaries use about $1,000 in E&M service per year. The distribution is quite skewed with a few high outliers.[6]

Table 1: Medicare Costs (E&M and Other), Dollars per Beneficiary, 2003

	Mean	Minimum	First Quartile	Median	Third Quartile	Maximum
Total costs	2,617	7	1249	2749	5,537	1,306,636
E&M costs	975	1	265	557	1120	124,051
Non-E&M costs	1,722	0	208	706	1930	1,300,318

Beneficiaries: N=320,820

E&M services make up a relatively small proportion of total Medicare services: Table 2 demonstrates that for 75 percent of beneficiaries, E&M services are less than 15 percent of their total expenditures.

[6] Outlier expenditures were not trimmed, because it was not possible to differentiate erroneously reported expenditures from true expenditures.

Table 2: Provider E&M as Proportion of Beneficiary Total Medicare Expenditures

Statistic	Proportion
Minimum	0
First Quartile	0.025
Median	0.062
Third Quartile	0.153
Maximum	1

Beneficiaries: N=320,820

As shown in Table 3 below, the average provider accounted for about $246 in E&M services per beneficiary in 2003. As indicated by the median, the distribution of per-provider expenditures is skewed, with a small number of beneficiaries using a large volume of E&M care. The same is true for non-E&M services.

Table 3: E&M Paid Amount (in Dollars) per Beneficiary per Provider, 2003

	Mean	Minimum	First Quartile	Median	Third Quartile	Maximum
E&M costs	246.65	0	81.0	141.6	267.38	96,001
Non-E&M costs	322.32	0	29.81	91.2	262.33	1,284,055

Claims: N= 1,524,419

For those who do use E&M services, most beneficiaries do not have single providers accounting for the vast majority of this care. As shown in Table 4, about 75 percent of beneficiaries do not have a single provider who accounts for more than 35 percent of all E&M services.

Table 4: First Provider E&M as Proportion of Individual Beneficiary Total E&M Medicare Expenditures

Statistic	Proportion
Minimum	0
First Quartile	0.068
Median	0.157
Third Quartile	0.348
Maximum	1

For 75 percent of beneficiaries in this sample, no one provider accounts for much more than one-third of all E&M services.[7] Using the definition above, 19.3 percent of beneficiaries (58,896) had low to no continuity; 52.7 percent (160,963) had medium continuity; and 27.9 percent (85,265) had high continuity.

4.3.3 Chronic Illness

The Johns Hopkins Advanced Clinical Groups (ACG) Risk Adjustment software was also used to identify chronic conditions using inpatient and ambulatory claims from 2003. These variables were included in the statistical models as flags for disease group

[7] Because there is no clear basis for identifying inaccurate data, outliers were not trimmed before expenditures were rolled up to the provider level. This could have increased the number of beneficiaries assigned to the 'high' care continuity group. A sensitivity analysis revealed that if the top 1 percent of carrier claim expenditures were removed, the distribution of high, medium and low care continuity changed only slightly, with a few percentage points of beneficiaries shifting from high to medium continuity.

membership. In addition, a definition of chronic illness for adults recently developed by Hwang and colleagues (Hwang, Weller, Ireys et al. 2001) was used to identify a general group of 'chronically ill' beneficiaries. These methods of identifying chronic illness are described below.

Adjusted Clinical Groups (ACG)

The John Hopkins Adjusted Clinical Groups (ACG) is a risk adjustment method that measures morbidity burden based on disease patterns, age and gender. The strategy is based on a disease burden approach, which focuses on commonly occurring patterns of disease across all types of medical conditions rather than focusing on a specific condition or hierarchy of conditions. The software produces flags for specific chronic conditions, along with counts of conditions, a frailty flag and different relative risk scores for high future costs (Johns Hopkins University 2010).

The ACG software was applied to all 2003 ambulatory and inpatient claims to produce variables for this study. The analysis used flags for nine chronic conditions, a count of all chronic conditions and a relative risk score indicating the probability that a beneficiary would be a high-cost patient in the next years; for this last variable, 2003 claims data reflecting service use was used to predict costliness for the target year, 2004. The relative risk score is between zero and one with higher scores indicating a great chance of high costs in the following year. This was used as a risk adjuster in the models for time to readmission for all beneficiaries. For the models for time to readmission for beneficiaries with specific conditions, a count of comorbid conditions was used instead of the risk score. These two variables are correlated and thus it is not advisable to use them together in the same model.

Hwang/ AHRQ Clinical Classification System (CCS)

An overarching definition of chronic illness based on the functional limitations imposed by the condition and likely duration has been developed, refined and disseminated by the Agency for Healthcare Research and Quality, beginning with work by Hwang and colleagues (Hwang, Weller, Ireys et al. 2001). To operationalize this definition of chronic illness, they asked a panel of physicians to categorize 578 ICD-9 diagnoses as chronic or not. The group used a Delphi method for achieving consensus and identified 177 diagnoses as chronic for adults. For the current study, the 177 diagnoses were used to create a dichotomous variable indicating the presence of one or more chronic conditions. Diagnoses were derived from all ambulatory and inpatient claims for 2003.[8],[9]

4.3.4 Geographic Variation

Utilization of healthcare services is known to vary across states and regions, whether due to state policies, provider practice patterns, or other factors (Fisher,

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[8] This method can generate false positive identifications of chronic illness because it includes 'rule out' diagnoses, i.e., a situation where a beneficiary is undergoing a test or procedure to rule out a specific condition and does not have this condition. Although the results may be negative, the claim will still indicate the chronic condition diagnosis, thus incorrectly identifying the beneficiary as having this chronic illness.

[9] This classification method can also be applied using the AHRQ Clinical Classification Software (CCS) to develop a count of the number of chronic conditions for each beneficiary. The CCS creates categories of similar diagnoses so that a single illness is not counted multiple times.

Wennberg, Stukel et al. 2003a, 2003b). To control for differences in readmission rates that are due to these factors, this study used two different types of geographic indicators – states and Hospital Referral Regions (HRRs). State indicators were included in analyses because they have policy relevance due to state programs (e.g. Medicaid, licensing of facilities, credentialing rules for providers) and beneficiaries can readily be identified by state. The HRRs, which are based on hospital use and referral patterns, were also used (Dartmouth Institute of Health Policy and Clinical Practice 2010). HRRs are identified by examining where patients are referred to for major cardiovascular procedures and neurosurgery (the HRR assignments are updated annually). The basic goal is to identify market areas where providers face similar financial, regulatory and market area forces. The HRR classification thus may be superior to classification by state, because states often include all or portions of several distinct health market areas and some health market areas include portions of several states. There are 306 HRRs in the United States, so analysis using the HRR classification generates 306 comparative statistics, more difficult to compare than statistics for fifty states. However, this more specific level of geography may control for regional variation with more precision.

4.3.5 Other Covariates

Indicators for beneficiary age and sex were derived from the Denominator file. The Denominator file includes age at the end of each reference year; age at the end of 2003 was used in this study. Beneficiary race was also taken from the Medicare Denominator file, which reports five categories: White, Black, Asian, Hispanic, American Indian/Alaskan Native and "other/unknown." For this study, we collapsed these categories into White/Non-White. Date of death, if present, was obtained from the

2004 Denominator file; by definition, no one in the study group died in 2003. A variable indicating the number of hospitalizations in the 12 months prior to the index admission in 2004 was created from the 2003 and 2004 inpatient claims. Indicators were created for zero, one, two, three and four or more hospitalizations.[10]

4.4 Analytic Strategy

Descriptive statistics were calculated to provide a profile of the sample population and are presented here for beneficiaries with and without a readmission in 2004. Mean rates of readmission and care continuity are also presented. Cox proportional hazard modeling was used to estimate the effect of care continuity on time to first readmission, controlling for variation in demographics, health status and area characteristics. Cox proportional hazard models assume that each included independent variable proportionally affects the probability of experiencing the event of interest (in this case, readmission) before a given point in time. A beneficiary is considered 'censored' if the event of interest (readmission) does not occur during the observation period. The survival time without the event occurring is either the time to death after the initial discharge in 2004 or the time from the initial admission to the end of the observation period (December 31, 2004), whichever comes first. In this study, estimates are for the

[10] It would be valuable to include information concerning beneficiary eligibility for Medicaid and QMB/SLMB status. This would require information from Medicaid enrollment files, not available to this project. The indicator for Medicaid and Buy-In status in the CCW is known to be so inaccurate that it should not be used (ResDAC 2008).

risk of readmission for the sample population, beneficiaries at risk for readmission, specifically those with a hospital discharge in 2004.

The models include age, race/ethnicity, care continuity and a measure of health status: either the chronic conditions count or the probability of being a high cost beneficiary (relative risk score) in 2004 (depending on model). Geographic identifiers, either states or HRRs, were used to stratify the models. This approach creates a different baseline hazard function for each strata and controls for geographic variation. Although this approach is efficient, it does entail dropping some observations due to missing strata values. The more strata, the larger the problem, so the HRR models eliminate many more cases than the state models.

5. Results

5.1 Descriptive Statistics:

5.1.1 Readmission

The study sample consists of 305,124 beneficiaries who were at risk of a rehospitalization in 2004 because they had a hospital discharge in that year. For those who were readmitted, the average time to first readmission was 64.6 days (Table 5). Censoring indicates that an individual either died or reached the end of the study window before being readmitted. There are a small number of individuals (N=454) where the date of death is the same as the date of their readmission. These individuals are not shown as censored observations in the table or the analyses. However, a sensitivity test counting these individuals as censored did not change estimation results. The days to the

end of the study for the same-diagnosis readmission group are longer (on average) than for all-cause readmission because same-diagnosis readmission is less common. This means more beneficiaries reach the end of the study without a readmission, increasing the average days to end of the study.

Table 5: Time to Readmission or the End of the Study Period

	Number of Beneficiaries	Days to Readmission	Days to End of Study Period After Index Hospitalization (includes censored cases)	Censored (%)
All-cause readmission	119,153	64.57	125.00	61.1%
Same-diagnosis readmission	27,502	64.17	147.50	60.00%

The majority (48%) of those with a readmission had their first readmission within 30 days of discharge (Table 6). This is true both for all-cause and same-diagnosis readmissions. A relatively modest number of additional admissions occur between 30 and 60 days post-discharge, and a larger portion (about one-third) do not have a readmission until 90 days post discharge or later.

Table 6: Duration and Time to First Readmission by Type in 2004

Days to Readmission	All-cause		Same-diagnosis	
	Number	Percent	Number	Percent
30 Days	56,696	47.90%	13,414	48.77%
60 Days	19,025	16.07%	4,182	15.21%
90+ Days	42,637	36.02%	9,906	36.02%
Total	118,358	100.0%	27,502	100.0%

5.1.2 Prevalence of Chronic Conditions

Table 7 shows the prevalence of the ACG conditions for 2003 for the study sample (N=305,124). The most common conditions are hypertension, hyperlipidemia, and ischemic heart disease, with approximately 43 percent, 24 percent, and 23 percent, respectively, of beneficiaries falling into these condition groups in the time period studied. As many have pointed out, individuals with chronic illness often have other comorbid health conditions (Cunningham 2009; Schneider, O'Donnell et al. 2009). Thus, the same patients may be counted in multiple disease group categories. To understand the extent of comorbid illness, the third column in Table 7 shows that a relatively small number of beneficiaries with each diagnosis have just that diagnosis and no other identified chronic condition. Between 80 and 100 percent of the beneficiaries identified as having each chronic condition also have at least one other chronic condition, indicating that comorbidity is a defining feature of chronic illness.

Table 7: Prevalence of Chronic Conditions for those with Co-morbid Chronic Health Problems and those with a Single Chronic Illness (N=305,124)

	Number	Percent	Number with Condition Alone	Percent with Condition Alone
Asthma	12,155	3.98	1,029	8.47%
Congestive heart failure	42,905	14.06	2,358	5.50%
Chronic obstructive pulmonary disease	41,233	13.51	5,312	12.88%
Chronic kidney disease	7,285	2.39	0	---
Depression	164,880	5.4	1,543	0.94%
Diabetes	56,728	18.59	0	---
Hyperlipidemia	72,930	23.9	7,334	10.06%
Hypertension	132,524	43.43	25,732	19.42%
Ischemic heart disease	69,780	22.87	4,413	6.32%

5.1.3 Beneficiaries With and Without Readmission

Table 8 compares beneficiary characteristics between those who are readmitted (all-cause readmission) and those who are not. Although there are statistically significant differences in age and race, the size of the differences is very small. Greater proportions of the group of beneficiaries who were readmitted during the study period are identified with chronic illnesses. For example, 11 percent of those without a readmission are identified with CHF but 19 percent of those with a readmission are identified with this illness. Beneficiaries with a readmission have a higher mean number of chronic conditions (3.3) compared to those who were not readmitted (2.4).

Table 8: Demographic Profile by All-cause Readmission

	No Readmission	Readmission	p-value*
Number of beneficiaries	185,971	119,153	
Mean number of readmissions, 2004	0	1.8	---
Male	41.39	40.72	<.0001
Age (years)	77	77.8	<.0001
Race/ethnicity			
White	88.36	87.35	<.0001
Black	7.59	8.81	<.0001
Latino	1.86	1.99	.09
Other race/ethnicity	2.19	1.90	<.0001
2003 ACG Conditions			
Asthma	3.38	4.93	<.0001
Chronic obstructive pulmonary disease	10.94	17.53	<.0001
Chronic renal failure	1.84	3.24	<.0001
Congestive heart failure	10.77	19.19	<.0001
Depression	4.44	6.9	<.0001
Diabetes	16.12	22.45	<.0001
Hyperlipidemia	22.98	25.34	<.0001
Hypertension	39.92	48.91	<.0001
Ischemic heart disease	19.63	27.92	<.0001
Frailty	6.8	9.72	<.0001
Mean chronic conditions	2.42	3.3	<.0001
Risk score (ACG, risk of high future costs)	2.42	3.31	<.0001
Care Continuity			

	No Readmission	Readmission	p-value*
High	13.62	10.72	<.0001
Medium	57.80	56.34	
Low to no continuity	28.58	32.94	
Number of Hospitalizations, 2003			
One	17.66	20.70	<.0001
Two	6.60	10.47	<.0001
Three	2.50	4.90	<.0001
Four or more	1.88	5.378	<.0001

N=305,124; p-values based on chi-squares for discrete variables and t-test for continuous variables

Percent with characteristic unless otherwise indicated

Beneficiaries with a same-diagnosis readmission look quite similar to those with any readmission in age, race and sex (Table 9). On average, the readmitted group has almost one full chronic condition more than the comparison group and a higher risk score (the higher the score the greater the chances of being a high cost beneficiary in 2004). Turning to care continuity, those with no same-cause readmission appear to have a slightly higher rate of high continuity (12.6 for no readmission versus 10.7 for those with a readmission.)

Table 9: Demographic Profile by Same-diagnosis Readmission

	No Same-diagnosis Readmission	Same-diagnosis Readmission	p-value
Number of beneficiaries	277,622	27,502	
Mean number of readmissions, 2004	0.56	2.20	<.0001
Mean age (years)	77	76	<.0001
Male	40.9	43.4	<.0001
Race/ethnicity			
White	88.09	86.66	<.0001
Black	7.95	9.26	<.0001
Latino	1.89	1.99	0.25
Other race/ethnicity	2.07	2.09	0.83
ACG Chronic conditions			
Asthma	3.85	5.33	<.0001
Congestive heart failure	13.34	21.35	<.0001
Chronic obstructive pulmonary disease	12.92	19.54	<.0001
Chronic renal failure	2.28	3.51	<.0001
Depression	5.2	7.4	<.0001
Diabetes	18.11	23.42	<.0001
Hyperlipidemia	23.64	25.57	<.0001
Hypertension	42.83	49.54	<.0001
Ischemic heart	22.16	30.02	<.0001
Frailty	7.8	9.38	<.0001
Mean chronic conditions	2.7	3.44	<.0001
Risk score (ACG, risk of high future	0.039	0.054	<.0001

	No Same-diagnosis Readmission	Same-diagnosis Readmission	p-value
costs)			
Continuity of Care			
High	12.59	10.71	<.0001
Medium	57.26	56.59	
Low to no continuity	30.14	32.69	
Number of Hospitalizations, 2003			
One	18.69	20.19	<.0001
Two	7.83	10.82	<.0001
Three	3.25	5.58	<.0001
Four or more	2.85	7.17	<.0001

N=305,124

Percent with characteristic unless otherwise indicated

5.2 Models: Risk of Readmission

Cox proportional hazard models were fitted to estimate the impact of care continuity and other factors on risk of first readmission controlling for location effects for beneficiaries who experienced a hospital admission in 2004. To review, the hazard models assume that each included independent variable proportionally affects the probability of experiencing the event of interest (in this case, readmission) before a given point in time. The coefficient estimated for each risk factor thus represents its impact on the probability of readmission at each time in the observation period. The coefficients are directly translated into risk ratios, which show the ratio of the risk of experiencing readmission for those with the risk factor relative to the risk of those without the risk

factor. A positive estimated coefficient for a risk factor indicates that it is associated with increased risk of readmission; an estimated risk ratio greater than one indicates that the factor is associated with increased risk. In like manner, a negative estimated coefficient and its calculated risk ratio, which is by definition less than one, indicate that the factor is associated with lower risk, i.e. is protective against readmission. The models were highly significant overall, indicting a very low probability that the independent variables were not related to risk of readmission.

The estimated coefficients for the Cox proportional hazard model for all-cause readmissions including state fixed effects (Table 10) show that high care continuity in the 12 months before the index admission has a positive, protective effect (lowering the risk of readmission after a 2004 hospitalization after accounting for other risk factors). Those with high care continuity have a 6.0 percent smaller risk of rehospitalization than those with little to no care continuity, the reference group. Medium care continuity is not significantly different from the reference group.

The effects of other risk factors are also of interest. Greater age is slightly or minimally associated with greater risk of readmission, controlling for everything else in the model and state-level fixed effects. Race/ethnicity was not shown to have a significant effect on readmissions. The variables indicating recent health services use and overall health status were highly associated with risk. First, the ACG risk adjuster, which combines information on multiple chronic conditions to predict future costs, was strongly associated, increasing the risk of readmission by 32.6 percent. Beneficiaries who experienced one, two, three or four or more hospitalizations in the year prior to the index admissions had increasingly greater risks of readmission after their first hospitalization in

2004. Those with four or more hospitalizations in the 12 months prior to the index admission in 2004 were estimated to have a 30.6 percent greater risk of readmission than those without a hospitalization in the 12 months prior to the index admission.

Similar impacts were estimated for these risk factors for models restricted to beneficiaries with a specific chronic illness flag for chronic obstructive pulmonary disease, congestive heart failure and depression, and for those with any flagged chronic illness (Appendix C).

Even after accounting for these risk factors, which are themselves associated with chronic conditions, the presence of most of the nine chronic conditions was estimated to increase the risk of readmission by an amount ranging from 2.2 to 7.9 percent. Those with ischemic heart disease, for example, have 7.9 percent higher risk than those without ischemic heart disease, controlling for everything else in the model. Chronic obstructive pulmonary disease, chronic renal failure and diabetes were not significant after controlling for everything else in the model, including continuity. An alternative model included a count of chronic conditions rather than the individual chronic conditions; this variable was not significant either with or without the predicted future cost risk adjuster (results not shown).

Table 10: Cox Proportional Hazard Regression for Risk of Readmission (all-cause), All Beneficiaries with a Hospitalization in 2004

Variable	Parameter Estimate	Standard Error	P-value	Hazard Ratio	HR Lower CL	HR Upper CL
Care Continuity						
High	-0.062	0.008	0.00	0.940	0.925	0.954
Medium	-0.007	0.005	0.17	0.993	0.983	1.003
Demographics						
Age	0.006	0.000	0.00	1.006	1.005	1.006
Non-white	0.001	0.008	0.89	1.001	0.986	1.016
Male	0.006	0.005	0.24	1.006	0.996	1.015
Chronic Conditions						
Asthma	0.051	0.013	0.00	1.052	1.025	1.080
Congestive heart failure	0.021	0.009	0.02	1.021	1.004	1.039
Chronic obstructive pulmonary disease	0.016	0.008	0.06	1.016	0.999	1.032
Chronic renal failure	0.002	0.008	0.76	1.002	0.986	1.019
Major depression	0.022	0.007	0.00	1.022	1.008	1.036
Diabetes	0.012	0.006	0.06	1.012	0.999	1.024
Hyperlipidemia	0.031	0.006	0.00	1.031	1.019	1.043
Hypertension	0.036	0.007	0.00	1.037	1.023	1.051
Ischemic heart disease	0.076	0.007	0.00	1.079	1.064	1.094
Previous Hospitalizations						
Two	0.119	0.011	0.00	1.127	1.103	1.151
Three	0.122	0.017	0.00	1.129	1.093	1.167
Four or more	0.267	0.020	0.00	1.306	1.255	1.359
ACG, risk of high future costs	0.282	0.061	0.00	1.326	1.177	1.494
Test	Chi Square	p value				
Likelihood Ratio	1383.1744	0.0000				
Score	1355.7935	0.0000				
Wald	1352.1068	0.0000				
Number	295,729					

State stratification

The same model was estimated for risk of same-diagnosis as opposed to all-cause readmission (again with state fixed effects) (Table 11). The pattern of the impact of the risk factors is quite similar, although by definition the risk of same-diagnosis rehospitalization is lower than for all-cause rehospitalization. High care continuity is associated with a risk that is 5.9 percent lower than for those with limited continuity. Medium care continuity has a modest impact with a 1 percent decrease in the risk for same-diagnosis readmissions. The ACG risk adjuster for high expected costs and the indicator variable for 1, 2 or 4 or more hospitalizations in the 12 months prior to the index admission are all significantly associated with greater risk of same-diagnosis readmission. Most of the chronic conditions are significant and predictive of a shorter time to readmission. However, there are a few exceptions. Major depression and diabetes that are not significant, while congestive heart failure and chronic obstructive pulmonary disease are predictive of a lower probability of readmission. Age and male sex are both predictive of higher hazard.

Table 11: Cox Proportional Hazard Regression for Risk of First Same-diagnosis Readmission, All Beneficiaries with Hospitalization in 2004

Variable	Parameter Estimate	Standard Error	P-value	Hazard Ratio	HR Lower CL	HR Upper CL
Care Continuity						
High	-0.060	0.008	0.00	0.941	0.927	0.956
Medium	-0.010	0.005	0.05	0.990	0.981	1.000
Demographics						
Age	0.005	0.000	0.00	1.005	1.004	1.005
Non-white	0.011	0.007	0.13	1.011	0.997	1.025
Male	0.014	0.005	0.00	1.015	1.005	1.024
Chronic Conditions						
Asthma	0.035	0.012	0.01	1.035	1.010	1.061
Congestive heart failure	-0.030	0.008	0.00	0.971	0.955	0.986
Chronic obstructive pulmonary disease	-0.026	0.008	0.00	0.974	0.960	0.989
Major depression	-0.003	0.008	0.65	0.997	0.982	1.012
Diabetes	0.003	0.007	0.63	1.003	0.990	1.016
Hyperlipidemia	0.022	0.006	0.00	1.022	1.010	1.034
Hypertension	0.028	0.006	0.00	1.028	1.017	1.039
Ischemic heart disease	0.019	0.007	0.00	1.019	1.006	1.033
Previous Hospitalizations						
One	0.058	0.007	0.00	1.060	1.046	1.074
Two	0.069	0.010	0.00	1.071	1.050	1.093
Three	0.027	0.015	0.08	1.027	0.997	1.058
Four +	0.041	0.018	0.02	1.042	1.007	1.078
Risk score (ACG, risk of high future costs)	0.327	0.054	0.00	1.387	1.248	1.540
Test	Chi-square	DF	P-value			
Likelihood Ratio	644.8212	18	0.0000			
Score	645.3039	18	0.0000			
Wald	645.1733	18	0.0000			
Number	221,194					

Stratified by State

The next overview model repeats the model for risk of same-diagnosis readmission but adjusts for beneficiary residence location using Hospital Referral Regions (HRRs) rather than state (Table 12). Only 102,056 beneficiaries could be included in this model, a substantial decrease from the number (227,557) included in the model grouping observations by state. This occurs because in some strata there are variables with zero cells. This occurs when, for example, there is an HRR with no beneficiaries with depression in the sample. The variable indicating the presence of depression will be 0 for every sample member in that HRR. It is not possible to estimate the model within that stratum so the beneficiaries in that stratum are dropped. Despite this limitation, the analysis yields similar results, with greater risk of readmission for older beneficiaries. In contrast to the model using state indicators to account for location factors (which showed slight effects for most chronic conditions), several chronic conditions (congestive heart failure, major depression, and hyperlipidemia) are not significantly associated with risk of same-diagnosis readmission. Results for the key risk factors of interest, care continuity (both and the high and medium levels) are significantly negatively related to risk of rehospitalization, supporting the hypothesis that care continuity is important to rehospitalization.

Table 12: Cox Proportional Hazard Regression for Risk of First Same-diagnosis Readmission, All Beneficiaries, HRR Stratification, 2004

Variable	Parameter Estimate	Standard Error	P-value	Hazard Ratio	HR Lower CL	HR Upper CL
Care Continuity						
High	-0.063	0.013	0.00	0.939	0.916	0.963
Medium	-0.021	0.008	0.01	0.980	0.965	0.995
Demographics						
Age	0.006	0.000	0.00	1.006	1.005	1.006
Non-white	-0.004	0.011	0.75	0.996	0.974	1.019
Male	-0.001	0.007	0.86	0.999	0.984	1.013
Chronic Conditions						
Asthma	0.052	0.020	0.01	1.053	1.012	1.096
Congestive heart failure	0.008	0.013	0.55	1.008	0.982	1.035
Chronic obstructive pulmonary disease	0.029	0.012	0.02	1.029	1.004	1.054
Major depression	0.011	0.012	0.39	1.011	0.987	1.036
Diabetes	0.023	0.010	0.03	1.024	1.003	1.045
Hyperlipidemia	0.005	0.009	0.57	1.005	0.987	1.024
Hypertension	0.027	0.009	0.00	1.027	1.009	1.045
Ischemic heart disease	0.034	0.011	0.00	1.035	1.013	1.056
Previous Hospitalizations						
One	0.071	0.011	0.00	1.073	1.051	1.096
Two	0.136	0.016	0.00	1.146	1.110	1.182
Three	0.162	0.025	0.00	1.176	1.120	1.236
Four +	0.283	0.030	0.00	1.327	1.251	1.407
Risk score (ACG, risk of high future costs)	0.375	0.089	0.00	1.455	1.222	1.732
Test	ChiSq	DF	ProbChiSq			
Likelihood Ratio	605.3132	18	0.00			
Score	590.9637	18	0.00			
Wald	589.2096	18	0.00			
Number	102,056					

Stratified by HRR

As a final step in the analysis, the basic, all-cause re-admissions model was run with interaction terms for care continuity with each chronic condition and the risk score

for high future costs (separate models were run for each condition.) Table 13 below presents the results for the care continuity/risk score model (all other models not shown.) There is a small, but significant interaction between the risk score and medium continuity. In practical terms, the effects is small - as the relative risk for high future costs increases by one standard deviation for the medium continuity group, the rate of readmission decreases an additional 0.5%.

None of the interaction terms for the chronic conditions and care continuity are significant (results not shown). There was some evidence of a significant interaction between depression and medium continuity, but only when UPIN was used as the physician identifier (model not shown). It is difficult to know what this means without further vetting of the UPIN versus TIN as the physician identifier.

Table 13: Cox Proportional Hazard Regression for Risk of First Same-diagnosis Readmission, All Beneficiaries, State Stratification, Care Continuity Interactions, 2004

Variable	Parameter Estimate	Standard Error	P-value	Hazard Ratio	HR Lower CL	HR Upper CL
Care Continuity						
High	-0.062	0.009	0.00			
Medium	0.000	0.006	0.96			
Demographics						
Age	0.006	0.000	0.00	1.006	1.005	1.006
Non-white	0.001	0.008	0.89	1.001	0.986	1.016
Male	0.006	0.005	0.25	1.006	0.996	1.015
Chronic Conditions						
Asthma	0.051	0.013	0.00	1.052	1.025	1.080
Congestive heart failure	0.021	0.009	0.02	1.022	1.004	1.040
Chronic obstructive pulmonary disease	0.015	0.008	0.06	1.016	0.999	1.032
Major depression	0.002	0.008	0.78	1.002	0.986	1.019
Diabetes	0.022	0.007	0.00	1.022	1.008	1.036
Hyperlipidemia	0.011	0.006	0.07	1.012	0.999	1.024
Hypertension	0.030	0.006	0.00	1.031	1.019	1.043
Ischemic heart disease	0.036	0.007	0.00	1.037	1.023	1.051
Previous Hospitalizations						
One	0.076	0.007	0.00	1.079	1.064	1.094
Two	0.120	0.011	0.00	1.127	1.104	1.152
Three	0.122	0.017	0.00	1.130	1.093	1.167
Four +	0.267	0.020	0.00	1.306	1.255	1.359
Risk for high future costs						
Risk score (ACG, risk of high future costs)	0.293	0.257	0.25			
High continuity * Risk score	0.102	0.244	0.68			
Medium continuity * Risk score	-0.208	0.098	0.03			
Test	ChiSq	DF	ProbChiSq			
Likelihood Ratio	1388.4684	20	0.0000			
Score	1360.8762	20	0.0000			
Wald	1357.1306	20	0.0000			
Number	227,557					

6. Discussion and Implications

This study is focused on the relationship between care continuity and hospital readmissions, controlling for the presence of chronic illness and other factors. Overall, the findings concerning readmission rates are in line with previous findings (Jencks, Williams and Coleman 2009) both at the overall and state level, which provides corroboration of the definition of readmission used here. Although the specification of the care continuity variable is somewhat experimental, an association was found between high levels of care continuity and decreased probability of readmission in 2004. The findings are supported by the studies from Wolinksy, Knight, and Lin, who all found care continuity to be associated with better outcomes (Wolinsky, Miller, Geweke et al. 2007; Knight, Dowden, Worrall et al. 2009b; Lin, Huang, Wang et al. 2010a; Wolinsky, Bentler, Liu et al. 2010). It would be worthwhile to replicate these findings in more recent data to see if this relationship holds over time.

The definition of care continuity used here is somewhat conservative because it captures only situations where a single provider accounts for the vast majority of E&M care. It is possible that some beneficiaries have a high degree of care continuity with multiple care givers providing E&M services and future work on this topic should work towards identifying this group. For example, Pham and colleagues used a measure of multiple provider continuity, where patients are identified as having care continuity with any provider that bills for at least 25 percent of that patient's E&M visits (Pham, Schrag, O'Malley et al. 2007). For this study, however, providers meeting their 25 percent

threshold would fall in the medium continuity group. Other measures of care continuity incorporate time, in that, for continuity, visits should be conducted without significant lapses in between (Wolinsky, Miller, Geweke et al. 2007; Wolinsky, Bentler, Liu et al. 2010). It would be valuable for future works to also consider this factor. The Brandeis team has already begun to work up some of these more nuanced definitions of continuity. The results appear to be similar to the results shown here, but require further vetting.

In addition to care continuity, patient characteristics including age and sex appear to explain a portion of the variation in risk of readmission, after controlling for geographic variation using state or HRR stratification. Both are associated with increased probability of readmission. The study by Knight and colleagues also found sex to be a factor, with females having a decreased risk of hospitalization (Knight, Dowden, Worrall et al. 2009a). Similarly, most of the chronic conditions included in this study are associated with increased risk of readmissions, as are hospitalizations in the previous year. No one chronic condition has a disproportionately stronger association with readmissions, suggesting a comprehensive view of chronic illness makes sense in this population (i.e., elders with a hospitalization). Chronic conditions were found to predict hospitalizations in the study by Knight and colleagues, where the number of chronic conditions was significantly associated with increased risk for hospitalization (Knight, Dowden, Worrall et al. 2009a). These findings underline the importance of controlling for chronic conditions when examining time to readmission.

Because of the differences in their patterns of readmission, long-stay nursing home residents were not included in this study. Previous studies of readmission rates for all Medicare beneficiaries have mixed these two populations. It is likely that various

factors affect the readmission risk for nursing home residents and community residents in different ways; in particular, the continuity of care measure is likely to have a different effect. To get a full picture of factors affecting readmission risk, it would be worthwhile to estimate the same models of risk of readmission for nursing home residents for comparison.

6.1 Limitations

Two fundamental tasks of this study of the impact of continuity of care on outcomes for chronically ill Medicare beneficiaries were limited by the limitations of claims data.

First, the method developed here to identify the continuity of a beneficiary's care, while it breaks new ground, has substantial limitations. The method relies on identification of unique providers, which is difficult using UPIN and TIN information available on claims. Although identification is improving with the implementation of NPIs, the present study uses data from 2003 and 2004 when there were still issues (e.g., super UPINs with thousands of providers). The current study opted for the TIN to capture consistency within a multi-group practice and retain cases with missing UPINs, but there are limitations to this approach. The same TIN may cover providers who do not actually work collaboratively. Even when a patient consistently sees the same provider, it cannot be ascertained with certainty whether that provider is actually coordinating care. This underscores the value of having a consistent definition of a medical home and practical methods for measuring the degree of "homeness." While the present study adds

to the literature on the impact of care continuity, it did not target other important features of a medical home, including coordination and integration across providers, quality of patient-provider relationship, or shared decision making.

Second, chronic illness is difficult to identify definitively from claims. Claims data are designed for billing and thus lack the clinical detail needed to truly identify an individual's chronic illness status. Although researchers have developed systems for inferring illness status from claims, these have limitations. First, beneficiaries who use more services (either because of illness or preference) have a greater chance of being identified as 'chronically ill.' Second, providers are not consistent in recording diagnoses on claims. The same condition may be coded differently based on location, provider type or sophistication of the billing system. In addition to these operational problems, diagnostic uncertainty and the dynamic nature of chronic illness can lead to a potentially imprecise measure of a beneficiary's chronic status. In the process of identifying an illness, for example, an individual may have testing or other procedures to rule out a specific diagnosis. In these instances, a diagnosis code does not signal the presence of a specific disease. To overcome this, many categorization schemes exclude diagnoses associated with certain procedures.

6.2 Acknowledgment

As a final note, the Brandeis team would like to thank numerous reviewers at CMS for their thoughtful comments. Their contributions have improved this manuscript and provided food for thought as we move forward with this work.

7. Appendix A: 21 CCW Chronic Conditions

Acute Myocardial Infarction

Alzheimer's Disease

Alzheimer's Disease, Related Disorders, or Senile Dementia

Atrial Fibrillation

Cataract

Chronic Kidney Disease

Chronic Obstructive Pulmonary Disease

Depression

Diabetes

Glaucoma

Heart Failure

Hip/Pelvic Fracture

Ischemic Heart Disease

Osteoporosis

Rheumatoid arthritis/ Osteoarthritis (RA/OA)

Stroke / Transient Ischemic Attack

Female Breast Cancer

Colorectal Cancer

Prostate Cancer

Lung Cancer

Endometrial Cancer

8. Appendix B: Alternative Specifications of Chronic illness

The CCW diagnostic groups require a great deal of data, and thus it is useful to look at other methods for identifying chronic illness. Table 14 shows the prevalence of 11 ACG chronic conditions with CCW prevalence rates for overlapping conditions. Five ACG conditions do not have CCW equivalents. In part, this may reflect the fact that ACG is not focused specifically on elders. However, conditions like arthritis and asthma would seem to be chronic conditions. There are also definitional issues – ACG pulls out hypertension as its own category, while the CCW includes this under ischemic heart disease. Second, the prevalence rates vary for similar conditions. This reflects both definitional issues (the inclusion of different ICD-9 and procedure codes) and the use of different data to identify disease group members. In the case of congestive heart failure (CHF) the difference is large (almost double the number of beneficiaries in CCW). The difference is also large for ischemic heart disease, but as mentioned above, some hypertension ICD-9 codes are included in the CCW definition of ischemic heart disease.

Table 14: Comparison of ACG and CCW Flags by Condition

	ACG		CCW			
Condition	Number	Percent	Number	Percent		
Arthritis	55,414	14.23	---	---		
Asthma	18,795	4.83	---	---		
Chronic obstructive pulmonary disease	54,797	14.08	64,455	16.56		
Chronic renal failure	18,068	4.64	43,785	11.25		
Congestive heart failure	57,968	14.89	104,006	26.72		
Depression	32,305	8.3	56,365	14.48		
Diabetes	80,329	20.6	100,959	25.93		
Hyperlipidemia	88,245	22.67	---	---		
Hypertension	170,760	43.86	---	---		
Ischemic heart disease	87,648	22.51	155,174	39.86		
Lower back pain	47,843	12.29	---	---		

Based on these two methods alone, it is clear that there is variation in how researchers define a given chronic condition. Any two studies on CHF, for example, may actually be looking at slightly different populations.

9. Appendix C: Disease Subgroup Models

The models estimated for all beneficiaries included indicators for the presence of specific chronic conditions, which were found to increase risk for readmission after other factors were accounted for. By restricting the analysis sample to beneficiaries with a specific chronic condition, findings for the risk factors can be corroborated. The analysis reported here estimates models for readmission for beneficiaries with chronic obstructive pulmonary disease (COPD), congestive heart failure (CHF) and depression. A further model is estimated for all beneficiaries who have any chronic illness flag using the Hopkins overall measure of chronic illness. Both COPD and CHF are prevalent, high cost conditions with high rates of hospitalization. Depression, on the other hand, is a psychiatric illness that can be debilitating as a primary diagnosis or as a comorbid condition with other medical problems (such as depression associated with acute myocardial infarction). The Hopkins definition captures the broader or cross-condition view of chronic illness. Table 15 below shows the readmission rates for each of these categories of beneficiaries. Beneficiaries flagged with CHF and COPD have very similar hospitalization rates and have the highest rates for each time point. The rates for depression and the Hopkins Chronic Illness are not very different, however, with the overall chronic category having the lowest rates at each time point. Each category of chronic illness has higher hospitalization rates compared to the overall rate for the sample at each time point. About one-quarter of the sample had a readmission within 30 days of discharge. About one-third had a readmission by 60 days and only a small proportion were added by 90 days.

Table 15: Readmission rates by Condition Category

	Beneficiaries with hospitalization 2004	Beneficiaries with readmission 2004	Readmission 0-30		Readmission 0-60		Readmission 0-90	
	Number	Number	Number	Percent	Number	Percent	Number	Percent
All	305,124	119,153	72982	23.92	89095	29.2	97537	31.97
Congestive heart failure	80,763	23,250	23,250	28.79	29,023	35.94	31,964	39.58
Chronic obstructive pulmonary disease	49,604	14,350	14,350	28.93	17,952	36.19	19,808	39.93
Depression	33,247	9,231	9,231	27.76	11,303	34	12,457	37.47
Any chronic illness (Hopkins definition)	120,620	32,577	32,577	27.01	40,320	33.43	44,390	36.8

Instead of indicators for all other chronic diseases, the estimated models for the specific chronic illness subgroups included a variable for the count of chronic conditions. This is designed to capture the effect within a disease group of having co-occurring disorders.

For beneficiaries with COPD, age and sex have impacts similar to those found for the full study group (Table 16). Beneficiaries with more hospitalizations in the previous year are more likely to be readmitted. The coefficients for the care continuity variables are not significant at conventional levels.

Table 16: Cox Proportional Hazard Regression for Risk of First Same-diagnosis Readmission, Beneficiaries with Chronic Obstructive Pulmonary Disease with Hospitalization in 2004

Variable	Estimate	Standard Error	p-value	Degrees of Freedom
Age	0.006	0.001	<.0001	1.006
Male	-0.010	0.0145	<.0001.	1.011
Race/ethnicity				
Black	-0.01	0.031	0.74	0.99
Latino	0.042	0.0612	0.49	1.043
Other race/ethnicity	-0.022	0.0611	0.72	0.978
Chronic condition count	-0.0005	0.0032	0.14	0.995
Continuity of Care				
High	-0.014	0.0318	0.66	0.99
Medium	-0.015	0.0155	0.34	0.99
Number of Hospitalizations, 2003				
One	0.071	0.0183	<.0001	1.073
Two	0.108	0.0232	<.0001	1.114
Three	0.142	0.0307	<.0001	1.152
Four or more	0.272	0.0342	<.0001	1.312
Test	Chi Square	Degrees of Freedom	p value	
Likelihood Ratio	174.1400	12	<.0001	
Score	172.3754	12	<.0001	
Wald	172.0427	12	<.0001	
Number	38,921			

Includes State Fixed Effects

The results for CHF are also quite similar to the full sample results, showing modest effects for age and black race/ethnicity and large effects for previous hospitalizations (Table 17). For beneficiaries with CHF, high care continuity is associated with increased probability of readmissions, but medium continuity is not.

Table 17: Cox Proportional Hazard Regression for Risk of First Same-diagnosis Readmission, Beneficiaries with Congestive Heart Failure (CHF) with Hospitalization in 2004

Variable	Estimate	Standard Error	p-value	Odds Ratio
Age	0.0112	0.001	<.0001	1.011
Male	0.0057	0.015	0.7	1.006
Race/ethnicity				
Black	-0.0635	0.0268	0.02	0.938
Latino	-0.0043	0.0555	0.94	0.996
Other race/ethnicity	0.0689	0.0588	0.24	1.071
Chronic condition count	-0.0083	0.0035	0.02	0.992
Continuity of Care				
High	0.1059	0.0329	<.0001	1.112
Medium	0.0229	0.0156	0.14	1.023
Number of Hospitalizations, 2003				
One	0.0969	0.0195	<.0001	1.102
Two	0.1346	0.0234	<.0001	1.144
Three	0.1184	0.0296	<.0001	1.126
Four or more	0.2092	0.0319	<.0001	1.233
Test	Chi Square	Degrees of Freedom	p value	
Likelihood Ratio	298.2806	12	<.0001	
Score	299.7803	12	<.0001	
Wald	299.2363	12	<.0001	
Number	40,437			

State Fixed Effects

The analysis for beneficiaries with depression shows that those who are older and males have a higher probability of readmission (Table 18). Consistent with the findings for the full study group, beneficiaries with more hospitalizations in the previous year also have a higher probability of readmission. Both high and medium care continuity are associated with slightly reduced probability of readmissions (10 percent lower probability for those with high continuity and 5 percent lower probability for those with medium continuity).

Table 18: Cox Proportional Hazard Regression for Risk of First Same-diagnosis Readmission, Beneficiaries with Depression with Hospitalization in 2004

Variable	Estimate	Standard Error	p-value	Odds Ratio
Age	0.0079	0.001	<.0001	1.008
Male	0.0402	0.0172	0.02	1.041
Race/ethnicity				
Black	-0.0434	0.0365	0.23	0.958
Latino	0.0051	0.0536	0.92	1.005
Other race/ethnicity	0.0607	0.0663	0.36	1.063
Chronic condition count	0.0078	0.0035	0.02	1.008
Continuity of Care				
High	-0.1086	0.0338	<.0001	0.897
Medium	-0.0502	0.0167	<.0001	0.951
Number of Hospitalizations, 2003				
One	0.0532	0.0205	0.01	1.055
Two	0.1326	0.0275	<.0001	1.142
Three	0.1455	0.0362	<.0001	1.157
Four or more	0.2195	0.0396	<.0001	1.245
Test	Chi Square	Degrees of Freedom	p value	
Likelihood Ratio	216.7969	12	<.0001	
Score	214.3404	12	<.0001	
Wald	213.7630	12	<.0001	
Number of observations	31,709			

State Fixed Effects

For the beneficiaries who meet the criteria for an overall definition of chronic illness, age and sex are both significantly associated with higher probability of readmission (Table 19). Those who are Black are estimated to have a lower probability of readmission relative to the White reference group. Past hospitalizations are associated with an increased risk of readmission while high and medium care continuity are associated with a reduced risk.

Table 19: Cox Proportional Hazard Regression for Risk of First Same-diagnosis Readmission, Beneficiaries with All Chronic Conditions with Hospitalization in 2004

Parameter	Estimate	Standard Error	p-value	Odds Ratio
Age	0.0079	0.0005	<.0001	1.008
Male	0.0155	0.008	0.05	1.016
Race/ethnicity				
Black	-0.0332	0.016	0.04	0.967
Latino	-0.0053	0.0303	0.86	0.995
Other race/ethnicity	0.0356	0.031	0.25	1.036
Chronic condition count	-0.0082	0.0018	<.0001	0.992
Continuity of Care				
High	-0.0886	0.0164	<.0001	1.093
Medium	-0.0349	0.0087	<.0001	1.036
Number of Hospitalizations, 2003				
One	0.0689	0.0106	<.0001	0.933
Two	0.1068	0.0144	<.0001	0.899
Three	0.1239	0.0202	<.0001	0.883
Four or more	0.2037	0.0229	<.0001	0.816
Test	Chi Square	Degrees of Freedom	p value	
Likelihood Ratio	634.3004	12	<.0001	
Score	629.3005	12	<.0001	
Wald	628.0832	12	<.0001	
Number	114,695			

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