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Using Healthcare Data to Inform Health Policy: Quantifying Cardiovascular Disease Risk and Assessing 30-Day Readmission Measures

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USING HEALTHCARE DATA TO INFORM HEALTH POLICY: QUANTIFYING CARDIOVASCULAR DISEASE RISK AND ASSESSING 30-DAY READMISSION MEASURES

A Dissertation Presented

By

HASSAN FOUAYZI

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CLINICAL AND POPULATION HEALTH RESEARCH

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This work was undertaken in the Graduate School of Biomedical Sciences
Clinical and population health research

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ABSTRACT

Health policy makers are struggling to manage health care and spending. To identify strategies for improving health quality and reducing health spending, policy makers need to first understand health risks and outcomes. Despite lacking some desirable clinical detail, existing health care databases, such as national health surveys and claims and enrollment data for insured populations, are often rich in information relating patient characteristics to heath risks and outcomes. They typically encompass more inclusive populations than can feasibly be achieved with new data collection and are valuable resources for informing health policy. This dissertation illustrates how the Medicare Current Beneficiary Survey (MCBS) and MassHealth data can be used to develop models that provide useful estimates of risks and health quality measures. It provides insights into: 1) the benefits of a proxy for the Framingham cardiovascular disease (CVD) risk score, that relies only on variables available in the MCBS, to target health interventions to policy-relevant subgroups, such as elderly Medicare beneficiaries, based on their risk of developing CVD, 2) the importance of setting appropriate risk-adjusted quality of care standards for accountable care organizations (ACOs) based on the characteristics of their enrolled members, and 3) the outsized effect of high- frequency hospital users on re-admission measures and possibly other quality measures. This work develops tools that can be used to identify and support care of vulnerable patients to both improve their health outcomes and reduce spending – an important step on the road to health equity.

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LIST OF ABBREVIATIONS

ACA	Affordable Care Act
ACO	Accountable Care Organizations
ACS	American Community Survey
ADL	Activities of Daily Living
AIC	Akaike's Information Criterion
BIC	Bayesian Information Criterion
CHIP	Children's Health Insurance Program
CI	Confidence Interval
CMS	Centers for Medicare And Medicaid Services
HCC	Diagnostic Cost Group Hierarchical Condition Category
CVD	Cardiovascular Disease
FFS	Fee-For-Service
FRS	Framingham Risk Score
HEDIS	Healthcare Effectiveness Data and Information Set
HR	Hazard Ratio
ICC	Intraclass Correlation Coefficient
ICD	International Classification of Disease
IDI	The Integrated Discrimination Improvement
MCBS	Medicare Current Beneficiary Survey
NCQA	National Committee for Quality Assurance
NRI	Net Reclassification Improvement
NSS	Neighborhood Stress Score
PCC	Primary Care Clinician
SUD	Substance Use Disorders
SD	Standard Deviation
SDH	Social Determinants of Health
SMI	Serious Mental Illness

PREFACE

Some of the work presented in this dissertation will be published or currently under review.

Chapter II:

Fouayzi H, Rosen AK, Ash AS.

A cardiovascular disease risk prediction algorithm for use with the Medicare current beneficiary survey. Journal of Health Services Research (under review)

Chapter III:

Fouayzi H, Ash AS.

Improving performance on health quality measures by accounting for morbidity and social determinants of health: an illustration in 30-day readmissions (Prepared for submission)

Chapter IV:

Fouayzi H, Zhang B, Ash AS.

Should high-frequency hospital users be excluded from 30-day readmission quality measures? (Prepared for submission)

CHAPTER I:
INTRODUCTION

1.1 Specific Aims

The United States spends more per capita on health care than any other nation, while having the lowest life expectancy and some of the worst health outcomes among high-income nations. [1,2] It is critical to consider optimal allocation of the limited resources and set up priorities for health quality improvement. One strategy to curb health care spending while improving health quality is to identify the relatively small portion of patients with costly chronic conditions, such as cardiovascular disease (CVD), that account for a large share of spending. It is estimated that only about 5% percent of the U.S. population is responsible for almost 50% percent of all spending. [3] Hence, efficient population-based health interventions targeted at high-risk patients to prevent, manage, and reduce the burden of morbidity and mortality associated with expensive diseases could lead to both savings and better health.

Another strategy to reduce health spending and improve health quality is to shift from volume-based payment models, such as fee-for-service (FFS) to value-based models, such as patient-centered medical homes, value-based purchasing programs, and accountable care organizations (ACOs). Traditional FFS payment, where healthcare providers are reimbursed by payers (e.g.; Medicare, MassHealth, private insurance companies) based on the number and nature of services provided, has led to ever-increasing costs for an aging population with a substantial burden of debilitating illnesses and disabilities. Moreover, the FFS structure encourages overutilization of medical services by physicians and patients, which drives up healthcare spending. A key goal of the Affordable Care Act (ACA), enacted in 2010, is to encourage groups of doctors, hospitals, and other health care providers to contract together in networks, such as ACOs, to provide comprehensive, effective, efficient, safe and timely care to their enrolled populations. It is hoped that ACOs, by coordinating care for their members, can improve quality while reducing spending. [4,5] Payers pay ACOs to cover a defined set of services for the members they enroll. ACOs are then held responsible for providing those services, and for the overall health of their members. To judge the care provided by ACOs, payers develop quality measures and reward ACOs for delivering high quality and efficient health care, often giving them an opportunity to share in any resulting savings. [6] ACOs may also be ineligible for shared savings or even responsible to pay penalties when they do not meet quality benchmarks. [7–9] Hence, ACOs' profits are linked to the quality of health outcomes and efficiency rather than the volume of services delivered to their members.

Whether health policy makers or payers seek to identify subgroups at high risk for an expensive disease or judge the quality of care offered by an ACO to their enrollees, they need to capture health risks and outcomes accurately. Even though the use of electronic health records, which contain massive amounts of these data collected from patients, health providers, and insurance companies, has increased over time; some direct measures may still be hard and expensive to abstract, such as those entered in free-text format. Moreover, acquiring specific risk and outcome information through questionnaires may limit the number and kinds of individuals that are included in a study, which could threaten the validity and reliability of findings. Existing health care databases are important resources for health policy makers and payers. These datasets are relatively less expensive, more readily available, include larger and more diverse populations, and allow for a broader range of analyses for addressing health policy questions than would typically be obtainable with data newly gathered for a specific study. Despite lacking some desirable clinical detail, existing health care databases are often rich in information relating patient characteristics to heath risks and outcomes.

Two important types of existing databases are claims data for insured populations and national health surveys. Claims are transactions between patients and healthcare providers (e.g. hospitals, pharmacies, other medical professionals) that are submitted for payment to public and private payers. National surveys, on the other hand, are representative samples of the U.S. population or specific subgroups and may sometimes be designed for specific research areas. For instance, the Medicare Current Beneficiary Survey (MCBS) is a nationally representative probability sample of Medicare beneficiaries sponsored by the Centers for Medicare and Medicaid Services (CMS). [10] Another national database is the American Community Survey (ACS), an ongoing survey conducted by the U.S. Census Bureau. [11] It is a premier source for detailed information such as education, income, language proficiency, disability, employment, and housing characteristics (measured for groups of people who live close to each other).

In this dissertation, we build models on existing databases that can help health policy makers improve equity and efficiency. The three specific aims of this dissertation are:

1) To develop and validate a CVD risk prediction tool to better identify at-risk elderly Medicare subpopulations who are most likely to benefit from cost-effective interventions for prevention and /or management of CVD.

2) To illustrate the value of risk adjusting quality measures using morbidity and social determinants of health (SDH) factors, using the example of 30-day hospital readmission rates.

3) To describe the characteristics of high-frequency hospital users (4 or more hospital visits per year) and to assess the impact of their inclusion or exclusion on a 30-day readmission quality measure.

The purpose of the first aim was to develop a 3-year CVD risk score to use with the MCBS to identify at-risk Medicare beneficiaries aged 65 years and older to understand the extent to which effective targeting of interventions to high-risk people could improve outcomes or reduce costs. Our risk score uses variables readily available in MCBS, thereby providing an easy-to-implement enhancement to this important national data resource. This score may offer new opportunities for quantifying and monitoring CVD and its substantial effect on mortality, disability, and spending in Medicare beneficiaries. We hypothesized that our CVD risk score could improve CVD event prediction in the MCBS and provide insights for researchers and policy makers into how to target effective health interventions to Medicare subgroups, depending upon their CVD risk.

The purpose of the second aim was to show how assessing health quality without accounting for patient-mix differences among ACOs (i.e. risk adjustment), can unfairly harm ACOs that disproportionally serve vulnerable populations. [7–9] We used 30-day hospital readmission rate as an example, as high rates of readmission are often taken as a measure of poor quality of care and lowering these rates is thus seen as a good way to reduce health spending without harming health. [12] We estimated regression models predicting 30-day readmission rates from diagnoses and SDH factors using data from MassHealth, the Massachusetts Medicaid and Children's Health Insurance Program. We compared these models' predicted rates with actual readmission rates for MassHealth managed care eligible population ages 18-64 and for subgroups of interest. We hypothesized that risk adjusting 30-day readmission rates for medical morbidity and SDH risk factors could allow for fairer comparisons across ACOs that appropriately account for the challenges and complexities inherent in caring for vulnerable patients.

The goals of the third aim were to 1) better understand which MassHealth patients may be at risk for frequent hospital use and highest likelihood of readmission after hospitalization and 2) evaluate the extent to which including or excluding high-frequency users from the 30-day readmission measure changes its rate and variance. A better understanding of which patients may be at risk for frequent hospital use is important because many of their initial hospitalizations could perhaps be prevented through more effective and targeted interventions. Moreover, a better understanding of which patients are most likely to be readmitted after hospitalization may enable clinicians, ACOs, payers, and policy makers to focus efforts on patients who will benefit most from heath interventions shortly before or after hospital discharge. We hypothesized that a small group of MassHealth beneficiaries are responsible for disproportionate hospitalization use and have an outsized effect on 30-day readmission and its variability.

1.2 Background and Significance

1.2.1 A CVD risk score that uses MCBS allows for a broader range of analyses for addressing health policy questions

Policy makers increasingly rely on nationally representative datasets, such as MCBS, to assess the impact of alternate health interventions. MCBS contains a wealth of information for health policy research related to expensive chronic diseases and conditions such as CVD. More than one in three adults currently has CVD in the United States; [13] this number will likely increase as the U.S. population ages. CVD is the leading cause of death and a major cause of disability. [14] Identifying individuals at high risk for CVD-related events, and their substantial effect on mortality and disability, is a priority. Older Americans at the highest risk of a CVD event – most of whom are Medicare beneficiaries will benefit most from targeted health interventions.

The Framingham Risk Score (FRS), the most widely used tool for estimating 10-year CVD risk, is powerful for classifying people according to their risk of a major CVD event. The traditional risk factors in the sex-specific FRS models for predicting CVD events are age, total cholesterol, high-density lipoprotein (HDL) cholesterol, systolic blood pressure (SBP), antihypertensive medication use, current smoking, and diabetes status. [15] Unfortunately, MCBS does not record either cholesterol or SBP measures. This makes MCBS less useful for studying distinct CVD risk subgroups – what treatments they receive and outcomes they experience. The MCBS allows for a broader range of analyses for addressing public health and policy questions than would be possible using either survey or Medicare data alone. [10,16] Not only does the MCBS include a nationally representative sample of the US elderly, a high proportion of whom live with chronic conditions, it also contains information on health outcomes, use of health services, expenditures, and sources of payment. [10] The ability to predict CVD risk for MCBS respondents would make MCBS even more valuable for research and policy forecasting. To demonstrate the value of being able to calculate CVD risk within MCBS, we give an example of an important study where the authors used information on beneficiaries with CVD risk to examine the feasibility of a value-based insurance design intervention. [17] Value-based insurance design provides financial incentives to increase medication adherence in subpopulations where adherence is expected to yield particularly high health benefits and long-term cost savings. Findings from this study suggest that those at higher risk of CVD benefited more from reducing statin co-payments. [17] Our goal was to develop a proxy for the FRS that relies only on variables available in the MCBS, to improve the ability to measure CVD risk in this national survey dataset. This tool is intended for health policy development not for helping individual patients and clinicians decide on lifestyle modifications and/or CVD therapies.

1.2.2 Risk adjustment of 30-day readmission may be beneficial for vulnerable populations and the ACOs that serve them

Risk adjustment of quality measures is an approach intended to “level the playing field” by accounting for patient-mix differences among hospitals and health plans, so that health outcomes can be compared appropriately despite differences in risk. If the 30-day re-hospitalization rate for hospital A is 15% and that for hospital B is 20%, it is tempting to conclude that hospital B provides poorer quality care. However, if hospital B attracts patients at substantially higher risk for re-hospitalization, a 20% readmission rate could reflect the effect of delivering excellent care to a population for whom an even higher readmission rate was expected. Risk adjustment is important for health quality measures, because patients' health outcomes are usually driven not by quality of care alone, but also by patient characteristics, such as age, gender, chronic conditions, and SDH problems. ACOs that disproportionally serve and care for beneficiaries with high levels of morbidity burden and social risk factors are likely to perform poorly on ACO quality measures that are not risk adjusted, and may face unfair financial penalties. [18–20] This may translate into reluctance of ACOs to care for these beneficiaries, possibly increasing health disparities. In contrast, risk adjusted quality measures help protect ACOs that disproportionally serve medically and socially complex patients from unfair quality penalties. Plans with exceptionally vulnerable patients can use the extra dollars that risk adjustment may provide, for example, to design and implement interventions to deliver better care for their members, which could lead to better health for their high-risk members.

In this dissertation, we illustrate the value of risk adjustment in the example of a 30-day readmission measure for a health plan, since this outcome has been frequently used to measure and compare the performance of hospitals and is now coming into use for plans. [21] The goal is to encourage more attentive post-acute care and to reduce overall health care spending. [22] Under the Affordable Care Act, the Centers for Medicare and

Medicaid Services (CMS) penalizes hospitals for excessive unplanned readmissions[9]. The CMS has been publicly reporting risk-adjusted readmission rates for acute heart failure, pneumonia, and myocardial infarction for several years. [23] However, its risk-adjustment models rely primarily on morbidity burden and do not account for other risk factors such as SDH variables. [24–26] We are aware of two studies that examined the impact of adjustment for social risk factors on readmission measure when comparing hospitals.[27,28] However, these studies found inconsistent results, used limited SDH factors, and focused on Medicare elderly population with acute myocardial infarction, heart failure, or pneumonia only. Here, we examined all cause adult 30-day readmission rate as a measure of health plan quality in an entire Medicaid population, and using both medical and SDH factors, most notably serious mental illness and substance use disorder variables.

1.2.3 High frequency hospital users may have an outsized effect on 30-day readmission and its variability

Like other quality measures, 30-day readmission is based on clinical guidelines that apply to the general population or specified subgroups. However, even among targeted subpopulations, such as patients hospitalized for specific conditions, a small subgroup of individuals who frequently use hospitals may add an undesirable amount of volatility to the 30-day readmission rate. All-cause readmission as a quality measure is being extended to ACOs. [29] While it may be reasonable to hold hospitals accountable for problems that patients experience within 30 days after discharge, which could reflect poor hospital care and too-early transition to the outpatient setting[30], a readmission measure may be less suitable for comparing ACOs. Doing so may significantly impact the results and decisions about health care improvement intended by these organizations and their payers. For instance, ACOs that disproportionally serve more patients with medical and social risk factors that typically lead to frequent hospitalization are likely to face financial penalties for high readmission rates. [7–9] This may translate into reluctance of some ACOs to care for beneficiaries with high risk of hospitalization and could exacerbate existing health disparities. Excluding high-frequency hospital users from the readmission measure could lead payers and ACOs to focus more on patients with lower risk of hospitalization who may benefit more from this quality measure. In addition, and more importantly, payers and ACOs could redirect resources and efforts to avoiding preventable hospitalizations in the first place, improving care transitions and follow-up after discharge for the relatively rare people who are high-frequency users of hospitals and generate a highly disproportionate share of readmissions.

1.3 Data Used in The Dissertation

The first aim of this dissertation used MCBS to develop and validate the new CVD risk score that added predictors, such as morbidity burden and functional limitation, to those standard CVD Framingham risk score predictors that also could be identified in MCBS. The MCBS is a nationally representative probability sample of Medicare beneficiaries sponsored by the CMS; it combines information from Medicare claims data with in-person survey instruments and provides a comprehensive picture of the use of health services, expenditures, and sources of payment for the Medicare population. [10,31] The MCBS uses a rotating panel design, with each patient interviewed three times per year for four years, providing three full calendar years of data per respondent. The target sample size for an annual MCBS sample is 12,000 beneficiaries.

The second and third aims of this dissertation used 2015 and 2016 claims and enrollment data from MassHealth. In Massachusetts, MassHealth combines both Medicaid and the Children's Health Insurance Program (CHIP). Massachusetts established MassHealth in July 1997 to extend Medicaid eligibility to families and childless adults whose incomes fall below 200% and 133% of the federal poverty level, respectively. Starting in 2018, more than 1.2 million "managed care eligible" MassHealth members may choose their health care from 17 statewide ACOs, two managed care organizations, or MassHealth's primary care clinician (PCC) plan, for which the State reimburses providers directly. [32] In 2015, MassHealth was the primary payer for 70.4% of its membership and a secondary payer for eligible residents with other primary insurance coverage.

1.4 Summary

This dissertation illustrates how statistical models can be used with existing databases to provide reasonable estimates of risks and health quality outcomes to inform health policy. These models are valuable tools which can be applied or adapted by policy makers, payers, ACOs, and others to identify, facilitate, and support care of specific vulnerable patients to improve their health outcomes. Such modeling is an important step on the road to improved health equity and reduced spending.

CHAPTER II:
A CARDIOVASCULAR DISEASE RISK PREDICTION ALGORITHM FOR USE WITH THE MEDICARE CURRENT BENEFICIARY SURVEY

ABSTRACT

OBJECTIVE: To develop a new CVD risk score, similar to the Framingham Risk Score (FRS), that can be calculated using the Medicare Current Beneficiary Survey (MCBS) data.

DATA SOURCES: We studied 17,056 community-dwelling Medicare beneficiaries aged 65 years or older without pre-existing CVD using 1999-2009 MCBS data.

STUDY DESIGN: We developed and validated a new CVD risk score (MCBS-FRS) that added predictors, such as morbidity burden and functional limitation, to those standard CVD FRS predictors that also could be identified in MCBS. We then compared its performance to a modification of the FRS (modified-FRS) that had previously been used in MCBS.

DATA COLLECTION*:* We obtained risk factors from both survey and claims data. We used claims data to derive "CVD event within 3 years" following the FRS definition.

PRINCIPAL FINDINGS: Our new MCBS-FRS predicted 3-year CVD events better than the modified-FRS. The actual CVD event percentages for those with the highest 5 and 10 percent of MCBS-FRS predicted risk were 9.1% and 10.1%, while those for the modified FRS were 7.5% and 8.1%, respectively.

CONCLUSIONS: Our new MCBS-FRS risk score can be calculated in MCBS, thereby extending the survey's ability to better inform health policy and health services research alike.

2.1 Introduction

Policy makers and researchers increasingly rely on the Medicare Current Beneficiary Survey (MCBS), a nationally representative dataset, for exploring the potential benefit of policy changes on health and health care spending. This survey contains a wealth of information for health policy-related research on chronic diseases and conditions such as cardiovascular disease (CVD). CVD is a highly prevalent chronic disease in older Americans – most of whom are Medicare beneficiaries. More than 1 in 3 adults in the United States currently has CVD; [13] this number will likely increase as the U.S. population ages. CVD is the leading cause of death and a major cause of disability. [33] Identifying individuals at high risk for CVD-related events, and their substantial effect on mortality, disability, and spending is a priority.

The Framingham Risk Score (FRS) is a powerful tool for classifying individuals according to their 10-year CVD risk. It was developed using clinical data collected in the Framingham Heart Study. [15] The FRS performs well in terms of discrimination with C statistics ranging from 0.76 in men to 0.79 in women. Traditional risk factors in the sex-specific FRS models for predicting CVD events are age, total cholesterol, high-density lipoprotein (HDL) cholesterol, systolic blood pressure (SBP), antihypertensive medication use, current smoking, and diabetes status. In addition to these main sex-specific FRS models, simplified sex-specific FRS models, that use office-based predictors that are routinely obtained in primary care and incorporate body mass index instead of cholesterol, are also available. They also have a good discriminatory power with C statistics of 0.75 for men and 0.79 for women. Unfortunately, neither the main nor the simplified FRS can be calculated in MCBS because it does not record either cholesterol or SBP measures. This makes MCBS less useful for studying distinct CVD risk subgroups – what treatments they receive and outcomes they experience.

We were motivated by our presumption of a need to have a CVD prediction tool that can accommodate MCBS; which includes the type of information that is most likely to be available to health policy makers and researchers. We sought to develop a proxy for the FRS that would enable policy makers and health services researchers to identify high-risk subpopulations for CVD events using measurements readily available in MCBS. This tool is intended for health policy development only, not for helping individual patients and clinicians decide on lifestyle modifications and/or CVD therapies. We hypothesized that this new CVD risk score, developed on and relying only on data available in the MCBS, could potentially improve CVD event prediction and provide insights for researchers and policy makers into the potential benefits from targeting health interventions to policy-relevant subgroups, such as elderly Medicare beneficiaries, based on their risk of developing CVD.

2.2 Methods

To our knowledge, only 1 study has attempted to proxy the original FRS using MCBS data (in the absence of cholesterol and systolic blood pressure information). [17] Davidoff and colleagues began with the simplified version of the FRS, which relies on systolic blood pressure values, but not cholesterol. They then imputed systolic blood pressure using 140mmHg for beneficiaries with untreated hypertension and 120 mmHg for those with treated hypertension. Our purpose was to apply Davidoff's method to compute CVD risk in MCBS and suggest an improvement by adopting a somewhat different approach, developing a new CVD Risk score by adding other relevant health information from MCBS, rather than imputing clinical measurements that were unavailable. We hypothesized that our new (MCBS-FRS) risk score would predict CVD events better than the modified FRS used by Davidoff and colleagues.

2.2.1 Study data

The MCBS is a nationally representative probability sample of Medicare beneficiaries sponsored by the Centers for Medicare and Medicaid Services (CMS); it combines information from Medicare claims data with in-person survey instruments and provides a comprehensive picture of health services use, expenditures, and sources of payment for the Medicare population. [10,31] The MCBS uses a rotating panel design, with each patient interviewed 3 times per year for 4 years, providing 3 full calendar years of data per respondent. The target sample size for an annual MCBS sample is 12,000 beneficiaries.

2.2.2 Study sample

Our study sample included community-dwelling individuals aged 65 years or older from 1999-2009 MCBS data. We excluded patients with a prior history of CVD (e.g., myocardial infarction, stroke) as the FRS is designed to predict CVD risk in those without pre-existing CVD. We also excluded non-Fee-for-Service (FFS) Medicare beneficiaries, since their data are incomplete. We created separate cohorts based on the first year that respondents were observed in the MCBS. Follow-up data (for years 2 and 3) were used to identify respondents who had a CVD event and to calculate time to CVD event, death, or end of observation. To increase our study sample, we also included the cohort from 1999 who was in their second year of MCBS in that year, using year 1999 for their baseline data and year 2000 for potential occurrence of their CVD event.

Beneficiaries who entered the survey in 2009 had no follow-up data and were therefore excluded. As noted, we also excluded MCBS beneficiaries with pre-existing CVD in their first year in MCBS. We identified these individuals through claims for chronic CVD events using the CVD definition from the Framingham Heart Study (coronary heart disease, cerebrovascular disease, peripheral artery disease, and heart failure) [34–39] (see Table 2.1).

2.2.3 Dependent variable

The CVD outcome was defined during the follow-up period (years 2 and 3 of the survey) as at least 1 discharge claim with a principal diagnosis of peripheral artery disease or heart failure, or a discharge claim with a diagnosis for MI or stroke in any position; or any claim (inpatient or outpatient) with a procedure code for CABG, PTCA, carotid endarterectomy, or carotid stenting [34–39] (see Table 2.1).

2.2.4 Independent variables

Our CVD risk model included predictors from the original FRS model: age (continuous), gender (female, male), diabetes status (yes, no), smoking status (never smoker, former smoker, current smoker), hypertension status (yes, no), and BMI (continuous), as well as additional risk factors that we hypothesized might be related to CVD events and were available in MCBS. These included self-reported health status (fair/poor, good/excellent), education (more than high school degree, high school degree, no high school degree), income ($25,000 or less, more than $25,000), and race/ethnicity (Hispanic, non-Hispanic black, non-Hispanic white, other). We also included other predictors such as number of activities of daily living (ADL) (range: 0-6), the NAGI score (a measure of health status and independence for the elderly, ranging from 0 to 5 limitations) [40], Medicaid eligibility (yes/no), and morbidity burden (calculated using the Diagnostic Cost Group Hierarchical Condition Category (CMS-HCC) classification system) . [41] The HCCs are used to calculate a single risk score for each individual based on inpatient and outpatient diagnoses from medical claims, with sicker individuals receiving higher scores. All independent variables were measured in the beneficiary's baseline year.

2.2.5 Analyses

We started with bivariate analyses to assess the relationship between each of the above variables and experiencing a CVD event (yes/no). We then used cox proportional hazards regression analysis to obtain hazard ratios in the presence of more than 1 variable. To select the best CVD risk regression model, we used a stepwise approach. We started with a full model that included predictors from the original FRS model that are available in MCBS (i.e. age, gender, diabetes status, smoking status, hypertension, and BMI); these were forced into the model; we also included the potential predictors mentioned above whose P-values were $\leq$ 0.20 in bivariate analyses (which might become statistically significant when combined with other predictors). We used adjusted Wald tests to exclude potential predictors that did not improve model fit. After obtaining a final main effects model, we tested each predictor that had been dropped initially either in bivariate or multivariate analyses and potential interactions to examine whether their inclusion/exclusion improved model fit, using the Bayesian information criterion (BIC) statistic that penalizes adding variables that do not improve predictions. We tested our CVD risk model using 10-fold cross-validation which allowed us to use the whole sample for model building. [42,43]To assess the performance of our MCBS-FRS and compare it to the modified FRS used by Davidoff and colleagues, we calculated C statistics and examined calibration plots.

We also performed sensitivity analyses to assess the robustness of our model with a different specification using logistic regression instead of cox proportional hazards regression. In addition, we used risk reclassification analysis to assess the performance of the regression models. [44,45] With this method, individuals were categorized into CVD risk categories (low versus high risk) to identify which model (i.e. the MCBS-FRS or the modified FRS) moves individuals who had a CVD event during follow up to the higher CVD risk category and those who didn’t experience a CVD event to a lower risk category. Details of this method are reported in appendix 2.1.

We used sampling weights, clustering, and stratification parameters to account for the complex survey sample design. Analyses were performed with SAS version 9.3 (SAS Institute Inc, Cary, NC) and Stata version 11 (StataCorp, College Station, TX).

2.3 Results

Table 2.2 describes the MCBS participants. Fifty-nine percent were female; 58% were between 65 and 74 years of age. About five percent (4.87%) of MCBS beneficiaries had at least 1 CVD event during follow-up.

Table 2.3 shows the predictors of CVD retained in our final MCBS-FRS model. Each 1-year increase in age was associated with a 5% increase in the risk of a CVD event (hazard ratio (HR) =1.05; 95% confidence interval (CI) =1.04-1.06). Females had 23% lower risk of having a CVD event compared to men (HR=0.77; 95% CI=0.65-0.91). Individuals with diabetes had a 73% higher risk of CVD events than their non-diabetic counterparts (HR=1.73; 95% CI=1.47-2.04). Current smokers had twice the rate of a CVD event than never smokers (HR=1.87; 95% CI=1.24-1.70). Increases in morbidity burden and functional limitation scores were also associated with increases in the probability of having a CVD event (HR=1.22; 95% CI=1.10-1.35 and HR=1.12; 95% CI=1.06-1.18, respectively).

The C statistic of the MCBS-FRS was 0.68 (Table 2.3), an improvement of 0.06 over Davidoff's modified FRS (C=0.62), and it held up on validation (C = 0.67). More importantly, this model was well calibrated and discriminated better in identifying high- and low-CVD risk individuals than the modified FRS (Figure 2.1). The actual CVD event percentages for the 5 and 10 percent with the highest MCBS-FRS predicted risk were 9.1% and 10.1%, while those for the modified FRS were 7.5% and 8.1%, respectively compared to the actual at random CVD rate of 4.9%.

Results of the sensitivity analyses are reported in Table A.1 and Table A.2. Briefly, the regression coefficients obtained from the logistic regression were very similar to those obtained from the cox proportional model. In addition, the net reclassification index for the new MCBS-FRS model was 9.22% which means that the addition of other predictors improved the classification for a net of 9 % of beneficiaries. The integrated discrimination improvement was 2.35 which suggests an improvement of 235% in the discrimination of the MCBS-FRS compared to the modified FRS model.

2.4 Discussion

Our goal was to develop a CVD risk score that could be applied to elderly Medicare beneficiaries using MCBS data. Our new model had a lower C statistic of 0.68 compared to C statistics ranging from 0.75 to 0.79 for the original FRS. [15] This was expected since the original FRS was based on clinical predictors and was developed on a population very different from our MCBS sample. Although its discrimination was modest, the C statistic of our risk score was comparable to what was found in a validation of a CVD risk score among elderly Medicare enrollees in the REGARDS study, a population similar to that of the MCBS. [46,47] Furthermore, our MCBS-FRS outperformed a modified version of the FRS that had been used previously with MCBS. [17] Our findings are consistent with the established literature in this area regarding the importance of specific CVD risk factors: age, gender, diabetes, hypertension, smoking, and BMI. [15,48–51] We also demonstrated that both measures of total disease burden and functional status may partially substitute for unavailable clinical and laboratory information, since they also predict future CVD events in the elderly. Indeed, many studies have found that morbidity burden and functional status independently contribute to health outcomes in elderly patients. [52–55]

Our CVD risk equation allows for a broader range of analyses for addressing public health and policy questions than would not be possible using either survey or Medicare data alone. [16,31] Not only does the MCBS include a nationally representative sample of the US elderly, a high proportion of whom live with chronic conditions, it also contains a wealth of information on health outcomes, use of health services, expenditures, and sources of payment. [31] The study by Davidoff et al [17] demonstrates the value of being able to calculate CVD risk within MCBS. The authors used information on beneficiaries with CVD risk to demonstrate the feasibility of a value-based insurance design intervention. Value-based insurance design provides financial incentives to increase medication adherence in subpopulations where adherence is expected to yield particularly high health benefits and long-term cost savings. Davidoff et al found that those at higher risk of CVD benefited more from reducing statin co-payments. [17]

Researchers and policy makers will often seek to identify high-risk subpopulations to help design efficient population-based health interventions. However, many nationally representative datasets lack the necessary clinical and laboratory data needed for calculating the original FRS. Hence, having a good CVD risk predictor that can be calculated in rich national databases allows us to estimate the added value of targeting interventions to those subpopulations at higher CVD risk. Many studies suggest that high-CVD risk patients require interventions that focus on long-term CVD therapies and lifestyle changes, including diet, physical activity, and smoking cessation. However, several studies have found cost-related underutilization of CVD medications. [56,57] Appropriately identifying high-risk patients in MCBS, which contains a wealth of information on expenditures and payments is valuable in designing interventions that focus on reducing out-of-pocket costs, such as value-based insurance designs (which many studies have found successful in increasing medication adherence). [58–62] This will help increase the proportion of Medicare patients that meet recommended cholesterol and blood pressure goals. These well-targeted interventions could also reduce the burden of morbidity and mortality associated with CVD and decrease health care spending, since CVD is one of the costliest diseases and only about 5% percent of the U.S. population, most of which is elderly, is responsible for almost 50% percent of all spending. [63]

The original FRS was developed on a mostly white, homogeneous population of individuals aged 30-74 years; hence it may underestimate or overestimate CVD risk in other populations, such as individuals with diabetes or other ethnic or racial groups. [64–68] Our MCBS sample included elderly beneficiaries from all race/ethnicity groups who had a much higher risk of CVD and other comorbid conditions than the FRS population. When applied to other groups, the original CVD FRS may perform better after recalibration (taking into account differences in the prevalence of risk factors and rates of developing CVD). We were able to improve the ability to predict CVD risk among the elderly MCBS beneficiaries by recalibrating the coefficients of established CVD risk factors (i.e. gender, diabetes, hypertension, smoking, and BMI). Our method of refitting the model in new data (rather than simply using the coefficients of the risk factors in the FRS) and including other risk factors, such as morbidity and functional limitation, could be replicated to develop specific case-mix modified Framingham scores that may be more appropriate for specific databases of specific populations. Our use of cross-validation, that allowed the entire sample to be in model development, and sensitivity analyses to demonstrate that our new model is robust and reliable, are also worth emulating.

Our study has limitations. First, we used survey and claims data to develop our model. These data are generally thought to be less accurate than the clinical and laboratory data used in the original FRS. However, our goal was to build an “FRS-like” CVD risk score that relies only on information available in MCBS. Second, the FRS was developed using a 10-year follow-up period that was not available for MCBS; our MCBS-FRS score predicts CVD events within a 2-year follow-up period. However, identifying individuals at higher CVD risk over a relatively short-time period is also important for more timely interventions. Intensive early follow-up and more frequent surveillance may improve health and offset future costs associated with avoidable health care utilization in this high-risk population. Moreover, even though only about 4.9% of our study sample had events with 2 years of follow-up, there were enough CVD events to build a stable and credible model. Furthermore, since MCBS beneficiaries identified by our CVD risk algorithm can be easily linked to Medicare claims data, future studies may easily evaluate their long-term CVD health outcomes. Third, the predictors in the MCBS-FRS score, except for the HCC disease burden score, were all self-reported, and therefore subject to reporting or recall bias. Fourth, we identified CVD outcomes based on claims data, which may include “rule-out” diagnosis codes for CVD. [69,70] However, for the major CVD events of AMI and stroke we used ICD-9-CM codes that are specific to new events (see Table 2.1), mitigating the potential for overestimating CVD outcomes. Finally, our results may be representative of the Medicare FFS population only. However, complete claims information is required to accurately perform our analyses as is usually done in studies of MCBS that are based on analysis of claims data.

2.5 Conclusion

We were able to generate a relatively powerful CVD risk score that can be computed in MCBS, enhancing the survey’s value for health policy and health services research. This CVD risk score, requiring data that is more readily available than what is needed to calculate the original FRS, may be similarly effective in helping us learn how to reduce CVD events and may allow for a more nuanced examination of the costs and benefits of well-targeted health care interventions to improve the health of high-risk groups. Future research should externally validate our MCBS-FRS risk score and examine its potential to appropriately identify subgroups of subpopulations at high risk of CVD for whom targeted interventions may be particularly valuable in preventing heart attacks, strokes and pre-mature cardiovascular death.

Table 2.1: Diagnosis and procedure codes to identify cardiovascular disease using MCBS claims data

	ICD-9-CM diagnosis codes	**ICD-9-CM procedure and CPT codes**
Prevalent CVD*		
Coronary heart disease	410.xx (at least one diagnosis code in one inpatient or 2 outpatient/physician claims in any dx position)	CABG: 36.1x, 33510-33536 PTCA: 00.66, 36.01, 36.02, 36.05, 36.06, 36.07, 36.09, 92995, 92996, G0290, G0291, 92980-92984 (at least one procedure code in any inpatient or outpatient/physician claims)
Peripheral artery disease	440.2 (at least one diagnosis code in one inpatient or 2 outpatient/physician claims in any dx position)	
Heart failure	428.0, 428.1, 428.9, 404.13, 404.93, 428.20-428.23, 428.30-428.33, 428.40-428.43 (at least one diagnosis code in one inpatient or 2 outpatient/physician claims in any dx position)	
Cerebrovascular disease	433.xx, 434.xx, 436.xx, 435.xx, 438.xx (at least one diagnosis code in one inpatient or 2 outpatient/physician claims in any dx position)	Carotid endarterectomy or carotid stenting: 38.12, 00.63, 35301, 37205, 37206, 37215, 37216 (at least one procedure code in any inpatient or outpatient/physician claims)
Incident CVD**		
Coronary heart disease	410.xx except 410.x2 in any inpatient diagnosis	CABG: 36.1x, 33510-33536 PTCA: 00.66, 36.01, 36.02, 36.05, 36.06, 36.07, 36.09, 92995, 92996, G0290, G0291, 92980-92984 (at least one procedure code in any inpatient or outpatient/physician claims)

	ICD-9-CM diagnosis codes	ICD-9-CM procedure and CPT codes
Peripheral artery disease	440.2 in principal discharge diagnosis and admission type is urgent or emergent	
Heart failure	428.0, 428.1, 428.9, 404.13, 404.93, 428.20-428.23, 428.30-428.33, 428.40-428.43 in principal discharge diagnosis	
Cerebrovascular disease	433.x1 or 434.x1 or 436.xx in any inpatient diagnosis	Carotid endarterectomy or carotid stenting: 38.12, 00.63, 35301, 37205, 37206, 37215, 37216 (at least one procedure code in any inpatient or outpatient/physician claims)

MCBS*= Medicare Current Beneficiary Survey.* ***CVD****=cardiovascular disease.* ***ICD-9-CM*** *= International Classification of Diseases, Ninth Revision, Clinical Modification.* ***CPT****=Current Procedural Terminology.* ***CABG****= Coronary artery bypass graft surgery.* ***PTCA*** *= Percutaneous transluminal coronary angioplasty.*

** Medicare beneficiaries with prevalent CVD in year 1 of the MCBS were identified and then excluded as the original Framingham risk equations are designed to predict CVD risk in those without pre-existing CVD.*

*** Incident CVD was the outcome and was measured in years 2 and 3 of the MCBS among Medicare beneficiaries with no evidence of pre-existing CVD.*

Table 2.2: Baseline characteristics of the study population

Characteristics of MCBS respondents	(%)
Total number*	17,056 (weighted to represent 63,996,916 patients) (100%)
Age	
65-74	58.03
75-84	33.49
85-plus	8.48
Race/ethnicity	
Hispanic	6.09
Non-Hispanic black	7.33
Non-Hispanic white	81.86
Other	4.72
Gender	
Female	58.89
Marital Status	
Married	57.23
Selected health conditions (CVD risk factors)	
Diabetes	16.21
Hypertension	55.77
Current smoking	
Non-smoker	42.90
Former smoker	45.20
Current smoker	11.90
BMI categories	
Underweight	2.15
Normal	36.09
Obese	22.12
Overweight	39.65
Poor or fair health status (versus good/excellent)	15.43
HCC score; mean (SD)[!]	0.80 (0.61)
NAGI score; mean (SD)~	1.80 (1.57)

Characteristics of MCBS respondents	(%)
Education	
More than HS degree	43.65
HS degree	30.01
No HS degree	26.34
Income	
$25,000 or less	50.89
More than $25,000	49.11

Source: authors' calculations using MCBS data.

MCBS*= Medicare Current Beneficiary Survey.* ***HCC****: The Centers for Medicare & Medicaid Services (CMS) Diagnostic Cost Group Hierarchical Condition Category classification system. For some variables, small numbers of respondents had unknown values and are not shown.*

** Fee-for-Service (FFS) community-dwelling beneficiaries first observed in the MCBS between 1999 and 2008 who did not have claims for pre-existing CVD in baseline year (i.e. coronary heart disease, intermittent claudication, congestive heart failure, stroke or transient ischemic attack).*

! HCC score measures morbidity burden. The higher the score, the sicker the individual is.

~ NAGI is a measure of health status and independence for the elderly. NAGI scores range from 0 to 5 and evaluate a patient's difficulty in performing 5 activities, including stooping, handling small objects, and carrying and lifting weights greater than 10 pounds. The higher the score, the more dependent a patient is.

Table 2.3: Predictors of 3-year CVD event among MCBS beneficiaries

	Hazard Ratio (95% CI)
Established Framingham score predictors	
Age (per year)	1.05 (1.04-1.06)
Gender (female)	0.77 (0.65-0.91)
Diabetes status (yes)	1.73 (1.47-2.04)
Smoking status	
Never smoker	Reference
Former smoker	1.24 (1.04-1.49)
Current smoker	1.87 (1.45-2.42)
Hypertension (yes)	1.45 (1.24-1.70)
BMI	1.02 (1.00-1.04)
Additional predictors	
HCC morbidity burden score	1.22 (1.10-1.35)
NAGI score	1.12 (1.06-1.18)
C statistic	67.71
C statistic after 10-fold cross validation	67.21

Source: authors' calculations using MCBS data.

MCBS*= Medicare Current Beneficiary Survey.* ***CVD****=cardiovascular disease.* ***HCC****: The Centers for Medicare & Medicaid Services (CMS) Diagnostic Cost Group Hierarchical Condition Category classification system.*

Data used in these analyses were for Fee-for-Service community-dwelling elderly beneficiaries first observed in the MCBS between 1999 and 2008 who did not have claims for pre-existing CVD in baseline year (i.e. coronary heart disease, intermittent claudication, congestive heart failure, stroke or transient ischemic attack). The CVD outcome was defined in years 2 or 3 of MCBS by claims for acute CVD event. N(unweighted/weighted) = 16,867/63,208,832

This model included the following covariates: age (continuous), gender (female), diabetes status (yes), smoking status (never smoker, former smoker, and current smoker), hypertension (yes), BMI (continuous), the hierarchical condition category (HCC) morbidity burden score (range=0-12), and the NAGI score (measure of health status and independence for the elderly, range=0-5).

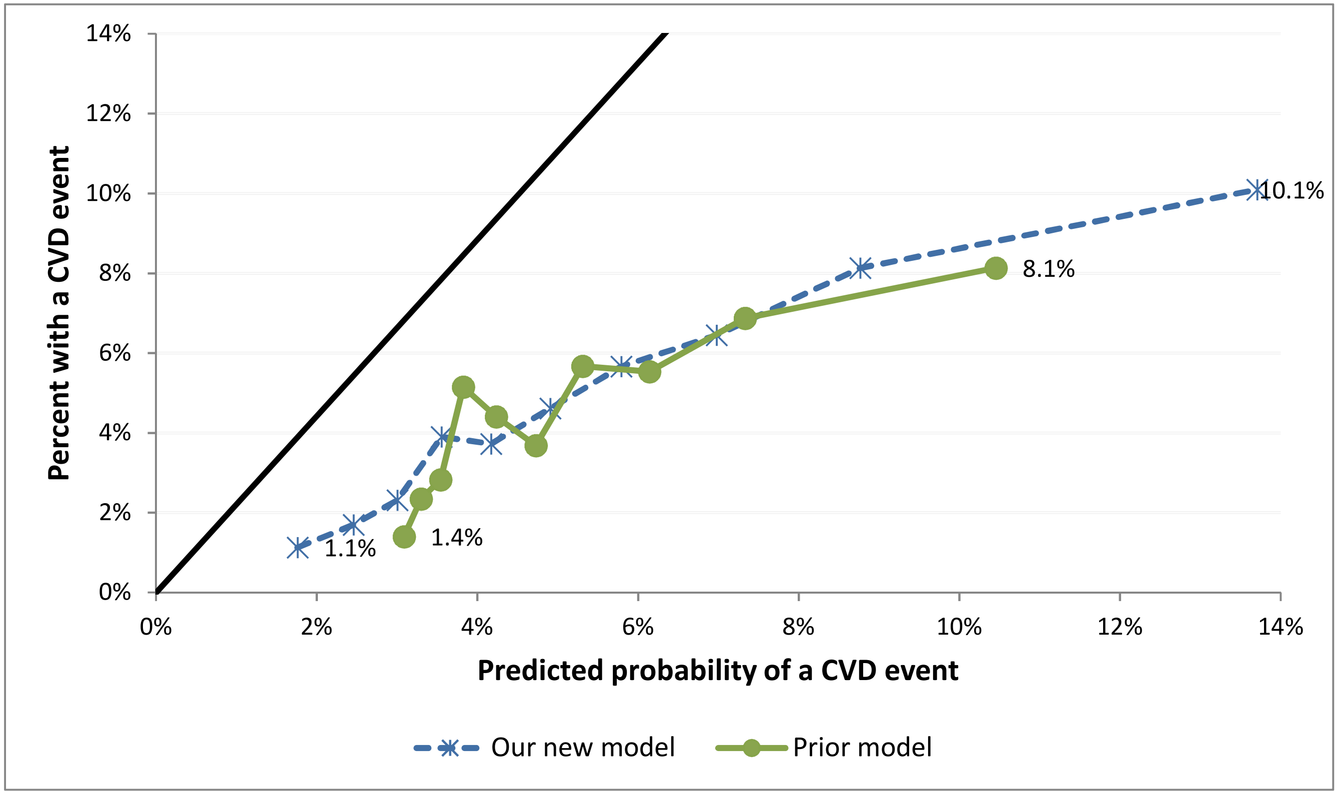
The 3-year MCBS-based CVD risk can be calculated by the following equation:

Probability of CVD event=1-0.99959^exp(Xβ)

where

$X\beta = 0.05*(\text{age}) - 0.27*(\text{female}=1) + 0.02*(\text{BMI}) + 0.37*(\text{with hypertension}) + 0.22*(\text{former smoker}) + 0.63*(\text{current smoker}) + 0.55*(\text{with diabetes}) + 0.20*(\text{HCC score}) + 0.11*(\text{NAGI score})$

Figure 2.1: Calibration and discrimination of the new MCBS-based model and the prior modified Framingham CVD Risk score in predicting a CVD event among MCBS beneficiaries



MCBS*= Medicare Current Beneficiary Survey.* ***CVD****=cardiovascular disease.* ***FRS****= Framingham Risk Score. Markers are deciles of predicted probabilities from each model. Graphs based on 16,867 observations (weighted to represent 63,208,832 people).*

The MCBS-based new model shows better calibration (closer to the 45-degree line) and better discrimination (its lowest decile of risk has lower risk (1.1% vs. 1.4%) and its highest decile of risk has higher risk (10.1% vs. 8.1%) of CVD events than the modified FRS.
Our new model is MCBS-based and included the following covariates: age (continuous), gender (female), diabetes status (yes), smoking status (never smoker, former smoker, and current smoker), hypertension (yes), BMI (continuous), the Centers for Medicare & Medicaid Services Diagnostic Cost Group Hierarchical Condition Category (HCC) morbidity burden score (range 0-12), and the NAGI score (measure of health status and independence for the elderly, range=0-5).
The prior model is the modified FRS and was calculated based on the original FRS assuming that MCBS respondents with hypertension had an untreated systolic blood pressure of 140mmHg while respondents without hypertension had a treated systolic blood pressure of 120 mmHg.

CHAPTER III:
IMPROVING PERFORMANCE ON HEALTH QUALITY MEASURES BY ACCOUNTING FOR MORBIDITY AND SOCIAL DETERMINANTS OF HEALTH: AN ILLUSTRATION IN 30-DAY READMISSIONS

ABSTRACT

IMPORTANCE: Risk-adjusting health quality measures for medical morbidity and social determinants of health (SDH) may allow for more accurate comparisons across accountable care organizations (ACOs) by more fully accounting for the challenges and complexities inherent in caring for vulnerable patients.

OBJECTIVE: To illustrate the value of risk adjusting quality measures for morbidity and SDH factors, using the example of 30-day readmission rates.

DESIGN, SETTING, AND PARTICIPANTS: Using data from MassHealth, the Massachusetts Medicaid and Children's Health Insurance Program, we estimated increasingly complex models predicting 30-day readmission using patient demographics, medical diagnoses and SDH factors as predictors. We compared these models' predicted rates with actual readmission rates for subgroups of interest for 74,704 hospital stays among 42,638 MassHealth managed care eligible members ages 18-64.

EXPOSURES: Predictors in the diagnosis-based model were: age, sex, and diagnoses from claims summarized via CMS's Hierarchical Condition Category (CMS-HCC) score. Our SDH model added predictors for behavioral health issues and for housing instability, disability, and neighborhood-level stressors.

MAIN OUTCOMES AND MEASURES: Model goodness of fit, discriminatory power, and predictive ratio: actual 30-day readmission rate divided by model-predicted rate; a ratio close to 1 indicates a good fit between actual and predicted outcomes; higher ratios indicate worse outcomes (more readmissions than expected).

RESULTS: We predicted readmission well with only age, sex, and morbidity (C=0.67), but better after adding SDH factors (C=0.69). Readmission rates for subgroups with the least or most morbidity burden improved from being 51% less and 58% more than predicted respectively without adjustment to only 2% more than predicted (i.e.; predictive ratio=1.02) after adjusting for age, sex, morbidity, and SDH factors. Observed readmission rates for people with serious mental illness and substance abuse were 15% and 21% higher than average, respectively. Predictions based on age, sex, morbidity and SDH factors brought predictive ratios for these subgroups to 1. Observed rates for residents of the most stressed neighborhoods were 8% higher than those in the least stressed neighborhoods. Our richest risk adjustment model captured most of this difference. Moreover, risk adjustment for morbidity and SDH factors reduced the 37% higher than average readmission rates to only 14% more than expected for enrollees who used long-term services and supports and fully accounted for the 25% higher than average readmission rates for patients with a disability. Risk adjusting for age, sex, morbidity and SDH factors reduced differences between the actual readmission rates of some pseudo- (realistically simulated) ACO populations and what was expected.

CONCLUSIONS AND RELEVANCE: Rich risk adjustment models can accurately predict readmissions for subgroups with above-average morbidity burden and SDH risk factors. Without risk adjustment, an ACO that cares for beneficiaries with high levels of morbidity and SDH risk is likely to be penalized, creating a reluctance to care for such patients that could increase health disparities. Not only do payers need to set appropriate risk-adjusted quality of care standards for all patient subgroups, they should provide

ACOs with support to encourage them to enroll and provide excellent care for at-risk subpopulations.

3.1 Introduction

Accountable care organizations (ACOs) are groups of doctors, hospitals, and other health care providers who contract together to provide comprehensive, effective, efficient, safe and timely care to their enrolled population. By coordinating care for their members, ACOs also aim to reduce spending.[4,5] Payers (e.g. Medicare, Medicaid, private insurances) reward ACOs for delivering high quality and efficient health care, providing them with an opportunity to share in the savings. [6,71]

Incentives for ACOs are based on measures of health quality for patients overall. Payers may choose to focus on a specific subgroup of the population (e.g. those who have had a myocardial infarction), to obtain estimates of health quality differences across ACOs. However, a subgroup of patients selected for health quality comparison across ACOs may have characteristics that differ between ACOs, undermining the validity of the comparison. ACOs that serve a given population may differ on important characteristics such as morbidities and social determinants of health (SDH) factors (e.g. housing instability, behavioral health issues, disability, and neighborhood-level stressors). There is growing evidence that SDH factors play a major role in worse health outcomes and higher spending.[27,72–79] An ACO that cares for many beneficiaries with morbidity burden and social risk factors may have worse performance on ACO quality measures and may be less eligible for the shared savings or even responsible to pay penalties to the payer when they do not meet a quality benchmark. This may translate into reluctance of ACOs to care for beneficiaries with multiple morbidities and SDH risk factors.

Risk adjustment of quality measures is an approach intended to "level the playing field" by accounting for patient-mix differences among ACOs. The goal of this paper is to illustrate the value of adjusting quality measures for age, gender, morbidities and SDH factors. We used 30-day readmission rate as an example, as high rates of readmission are often taken as a measure of poor quality of care and lowering these rates may serve as a good opportunity to reduce health spending [12].

The Centers for Medicare and Medicaid Services (CMS) has been publicly reporting risk-adjusted readmission rates for acute heart failure, pneumonia, and myocardial infarction since 2009. [23] However, its risk-adjustment models rely primarily on morbidity burden and do not account for other risk factors such as SDH variables. [24–26] We are aware of two studies that examined the impact of adjustment for social risk factors on readmission measure when comparing hospitals.[27,28] However, these studies found inconsistent results, used limited SDH factors, and focused on Medicare elderly population with acute myocardial infarction, heart failure, or pneumonia only. Here, we examined all cause adult 30-day readmission rate as a measure of health plan quality in an entire Medicaid population, and using both medical and SDH factors, most notably serious mental illness and substance use disorder variables. We hypothesized that risk adjusting 30-day readmission rates for SDH risk factors in addition to medical morbidity may allow for more accurate comparisons across ACOs that appropriately account for the challenges and complexities inherent in caring for vulnerable patients.

3.2 Methods

3.2.1 Study data

We used claims and enrollment data from MassHealth, Massachusetts' combined Medicaid and Children's Health Insurance Program (CHIP). Massachusetts established MassHealth in July 1997 to extend Medicaid eligibility to families and childless adults whose incomes fell below 200% and 133% of the federal poverty level, respectively. More than 1.2 million MassHealth members are now managed care eligible and may choose their health care from 17 statewide ACOs, two managed care organizations, or MassHealth's primary care clinician (PCC) plan, for which the State reimburses providers directly. [32] To measure 30-day readmission, we used 2016 data for MassHealth managed care eligible enrollees. We assigned enrollees to 17 pseudo- (realistically simulated) ACOs which we created by applying MassHealth's assignment algorithm to historic member claims and encounters; all have at least 5,000 members. Actual ACO attribution only took effect in 2018. We then assigned the remaining members to the other two groups: managed care organization or PCC plan. Because adjustment for the readmission measure requires a one-year lookback period for enrollment in Medicaid and for measuring morbidity [27,80], 2015 data from the year prior to hospitalization of MassHealth beneficiaries were also used.

3.2.2 Study sample

We followed strict definitions for eligibility criteria and the measure, based on MassHealth ACO Quality Measurement Program designed by the National Committee for Quality Assurance (NCQA). [81] NCQA developed the Healthcare Effectiveness Data and Information Set (HEDIS) standardized performance measures widely used for evaluating quality of care delivered by health care organizations. Members were eligible for this study if they had at least one inpatient stay between January 1st and December 1st, 2016. We only included hospitalizations for members who were continuously enrolled in MassHealth for 365 days (with at most one 45-day gap) prior to the discharge date through 30 days after the discharge date. [27,80,81] We excluded hospitalizations for females with a principal diagnosis of pregnancy or of a condition originating in the perinatal period and for members who had a planned hospital stay (e.g. transplantation, chemotherapy, rehabilitation) within 30 days [27,81]. Finally, we excluded members younger than 18 or older than 64. We allowed members to contribute multiple hospital stays to the analyses. Our final study sample included 74,706 unique hospitalizations among 42,794 MassHealth members (figure 3.1). We used these hospitalizations (hereafter referred to as index hospitalization stays) as the denominator for calculating all cause 30-day readmission rates.

3.2.3 Outcome measure:

Our dependent variable was 30-day readmission for any diagnosis. For each index hospitalization stay, we determined if any of the other subsequent inpatient stays for the corresponding member had an admission date within 30 days after the index discharge date. For members with multiple hospitalizations during the study period, we included each index hospitalization discharge and followed it for 30 days.

3.2.4 Covariates:

We considered three types of covariates. The first group of variables were age and gender which we coded in 12 categories (Table 3.1). The second group of factors measured morbidity burden using the CMS's Hierarchical Condition Category (CMS-

HCC) model in the year prior to index hospitalization. The CMS-HCC model calculates expected costs from age, sex, and diagnoses grouped into condition categories with hierarchies [82]. When two conditions within the same disease hierarchy co-exist, the lower-ranked diagnosis is ignored. For instance, a member with claims for both diabetes with chronic complications and diabetes without complication is only assigned the highest and most costly condition (i.e.; diabetes with chronic complications). While originally developed to predict costs, the CMS-HCC model has been widely used to measure total morbidity burden. The third group of variables encompassed SDH factors including behavioral health issues (i.e. serious mental illness and substance use disorder), disability, housing instability, and neighborhood-level stressors. We used SDH factors during the measurement year 2016. For members missing 2016 SDH data, which constituted about 1.8% of our sample, we included their 2015 SDH information. We used two indicators for serious mental illness and substance use disorder based on condition categories created with the diagnosis-based Diagnostic Cost Group Hierarchical Condition Category software (DxCG-HCC) [41] (Appendix 3.1). MassHealth routinely uses the DxCG-HCC software to adjust payments to Medicaid managed care organizations. This model is similar to the CMS-HCC model except that it creates indicators for up to 394 medical condition categories instead of 189. Disability was created based on entitlement and qualification for specialized services for mental health or developmental disabilities. Housing problems were identified by unstable housing (≥3 addresses within a year) and through an international classification of disease (ICD) code indicating homelessness (Appendix 3.1). Neighborhood-level stressors were summarised by a neighborhood stress score (NSS) derived from a principal components analysis; the NSS is calculated at the US Census-block-group level from seven neighbourhood-level indicators of economic stress available through the American Community Survey [83] (Appendix 3.1).

3.2.5 Statistical analyses

We compared index hospitalization stays with readmission within 30 days to those without using Chi-squared or Student t tests. We then generated model-predicted 30-day readmission rates (i.e. risk adjusted rates). A model-predicted readmission rate is the expected average of readmission for patients with characteristics that are beyond the control of an ACO such as age, gender, medical problems, and SDH factors. We estimated a series of "nested" (increasingly complex) multivariable logistic models. First, we adjusted the readmission rates for age, sex, and morbidity burden only. Second, we added the behavioral health variables: serious mental illness and substance use disorder. Third, we added the remaining SDH factors (i.e. disability, housing problem, NSS). To compare the goodness of fit among the models, we used the Akaike's information criterion (AIC) that penalizes adding variables that do not improve predictions. To assess the discriminatory power of the models, we calculated the C statistic representing the area under the receiver operating characteristic curve. A value of 0.5 indicates no ability to discriminate; higher values close to 1.0 indicate a better model fit. Finally, we compared the risk adjustment models, examining how well they fit race-, morbidity-, and SDH-defined subgroups using the predictive ratio: the group's average actual (observed) 30-

day readmission rate divided by its average model-predicted (expected) rate. A predictive ratio closer to 1 indicates accurate prediction with higher ratios considered worse.

We used hierarchical generalized linear models to account for clustering of index hospitalizations within patients and patients within ACOs. Clustering may result in potential violation of the assumption of independence required in many statistical tests and generalized linear models. Variation in hospital readmission may be smaller between hospitalizations attributed to the same patient or same ACO than between hospitalizations attributed to different patients or different ACOs. Controlling for clustering leads to more precise estimates. All analyses were carried out using the SAS package version 9.4 (SAS Institute, Cary NC, USA) and Stata software version 12 (Stata Corporation., College Station, TX, USA).

3.3 Results

Index hospitalization stays with 30-day readmission significantly differed from those without readmission on all demographic, morbidity, and SDH variables (Table 3.1). For instance, discharges from index hospitalizations that were followed by readmission within 30 days were more likely among older male patients (35.8% vs 30.30% compared to those without readmission) and among sicker patients (mean morbidity scores of 3.5, SD=2.5 vs 2.4, SD=2.0). Index hospitalizations with 30-day readmission were more likely among patients with serious mental illness (80.7% vs 66.6% for those without readmission) and substance use disorder (74.4% vs 57.7%). Index hospitalizations with 30-day readmission were also more likely among patients with housing problems (32.9% vs 25.1%) and living in most stressed neighborhoods 25.7 % vs 24.8%).

Table 3.2 shows that we can predict readmission well with only age, sex, and morbidity in risk adjustment models (AIC=69,776, C=0.67), but better with the addition of behavioral health predictors and other SDH factors (AIC=69,029, C=0.69). Predictive ratios were closer to 1 (i.e.; predicted readmission rates were closer to actual rates) as we moved from the non-adjusted model to the richer risk adjustment model with age, sex, morbidity, and SDH factors as predictors. For example, the actual readmission rate for patients with housing problems was 23% higher than average without adjustment (i.e.; predictive ratio=1.23), 16% higher after adjusting the predicted rate for age, sex, and morbidity, 12% higher with additional adjustment for behavioral health issues, and equal to predicted after adjustment for age, sex, medical, and all SDH factors.

The expected 30-day readmission rates predicted by each risk adjustment model, were generally close to actual rates for racial subgroups (Table 3.2). However, expected rates were not close to actual rates for subgroups with the least or most morbidity burden, for whom rates improved from being 51% less and 58% more than predicted respectively without adjustment to only 2% more than predicted after adjusting for age, sex, morbidity, behavioral health issues, and other SDH factors. Readmission rates for people with serious mental illness and substance abuse were 15% and 21% higher than average without adjustment, respectively. Taking into account age, sex, morbidity and all SDH factors corrected predicted readmission rates, yielding predictive ratios equal to 1. Readmission rates for residents of the most stressed neighborhoods were 8% higher than those in the least stressed neighborhoods (22.7/21.0 = 1.08). Our richest risk adjustment model captured most of this difference. Moreover, risk adjustment for age, sex, morbidity and SDH factors reduced the 37% higher than expected readmission rates to only 14% for enrollees who used long-term services and supports and eliminated the 25% higher than expected readmission rates for patients with a disability. Table 3.2 also shows that risk adjusting for age, sex, morbidity and SDH factors reduced differences between the actual readmission rates of some pseudo- (realistically simulated) ACO populations and what was expected.

3.4 Discussion

We risk adjusted 30-day readmission measure for age, sex, morbidity burden and SDH factors improving goodness of fit and discriminatory power overall and dramatically improving the match between actual and expected readmission rates for several subgroups of vulnerable MassHealth managed care eligible members. These members, whose readmission rates are much higher than expected before risk adjustment, are patients who have high morbidity levels, disability, behavioral health problems, and housing issues. Our results are consistent with prior studies demonstrating the association between SDH factors and readmission. [7–12] Moreover, our findings are analogous and consistent with results of a payment model that adjusted for SDH variables in addition to medical diagnoses and which was implemented by MassHealth in 2016 to meet the needs of socially disadvantaged beneficiaries[83].

This study illustrates how a quality measure that does not account for age, sex, morbidity burden, and SDH factors can seriously affect some vulnerable populations. This may generate unfair financial stress for ACOs that disproportionally serve and care for these enrollees. Such ACOs may be less eligible for the shared savings or even responsible to pay a portion of losses to payers when they fail to meet a quality threshold.[7,8] This systematic penalty may make ACOs reluctant to care for such beneficiaries, possibly leading to increased health disparities. Hence, risk adjusting quality measures may protect ACOs that disproportionally serve medically and socially complex patients from unfair quality penalties that would otherwise make them ineligible for shared savings. These extra dollars may, for instance, help design and implement interventions to facilitate and improve care for vulnerable populations; this may incentivize ACOs to overcome barriers to better health outcomes for high-risk populations.

Health quality models such as ours may be used by policy makers, payers, and ACOs to identify morbidity and SDH subgroups such as those defined in this study or other potential subgroups with issues requiring distinct programs to reduce disparities. Payers may want to examine quality measures for subgroups of patients based on SDH factors in addition to calculating a single measure for all members or subsets with specific medical conditions. They may choose to set different quality improvement standards for subgroups of vulnerable patients for whom caring may be complex and difficult, and for whom current outcomes are worse than average. Moreover, payers may need to provide ACOs additional special rewards and support as incentives to enroll and care for medically and socially complex subpopulations. Supporting ACOs to collaborate with social services and community associations may also facilitate and improve access to and engagement with health care for these vulnerable patients. For instance, payers may give ACOs that serve patients from distressed neighborhoods extra resources to design and support interventions for finding housing, helping with transportation, or linking medically complex patients to community health workers to help them address the main causes of their recurrent health issues. [83] Programs that reward improvements in heath quality for disadvantaged groups and payment arrangements that support ACO development in disadvantaged communities may be necessary since the most vulnerable members remained underrepresented in managed care programs. [83] The goal is to reduce health disparities while avoiding inappropriately penalizing ACOs that disproportionally serve medically and socially complex patients.

This study has limitations. First, it seems likely that a model that could account for additional important social risk factors, such as social support, health literacy, English proficiency, and functional status – would perform better [24,25,84]. However, we could use only readily available predictors. MassHealth may need to work with ACOs and other state entities, such as social and housing services, to obtain other factors to augment their data. Having additional factors available in the future will add value to analyses that address important health policy questions. Second, to improve the precision of our prediction models, we controlled for clustering of hospitalizations within patients and patients within ACOs and other settings that we assigned based on an algorithmic attribution. However, our ACO attribution may differ from actual member attribution or assignment of ACOs that went into effect later in 2018. Finally, our study was limited by a geographically constrained population that included MassHealth members only. Priorities and support given to advance coverage, access, health outcomes, and efficiency goals may differ from state to state. Hence, our findings may not generalize to other states, programs, and populations.

Despite these limitations, this is the first study to risk-adjust a quality measure using a broader group of SDH factors, most notably health behavioral variables. In addition, this study used MassHealth, a large statewide healthcare database. In 2015, MassHealth was the primary payer for 70.4% of its membership and a secondary payer for eligible residents with other primary insurance coverage, which represented 28.3% of total MassHealth membership. We were able to identify medically and socially disadvantaged Massachusetts Medicaid beneficiaries whose needs should be addressed immediately to improve health quality overall, reduce health disparities, and decrease spending.

3.5 Conclusion

Our comprehensive medical and SDH-based risk adjustment model development can be replicated by others to facilitate and support care of vulnerable patients by improving hospital readmission and other quality measures. Such modeling is an important step on the road to improved health equity.

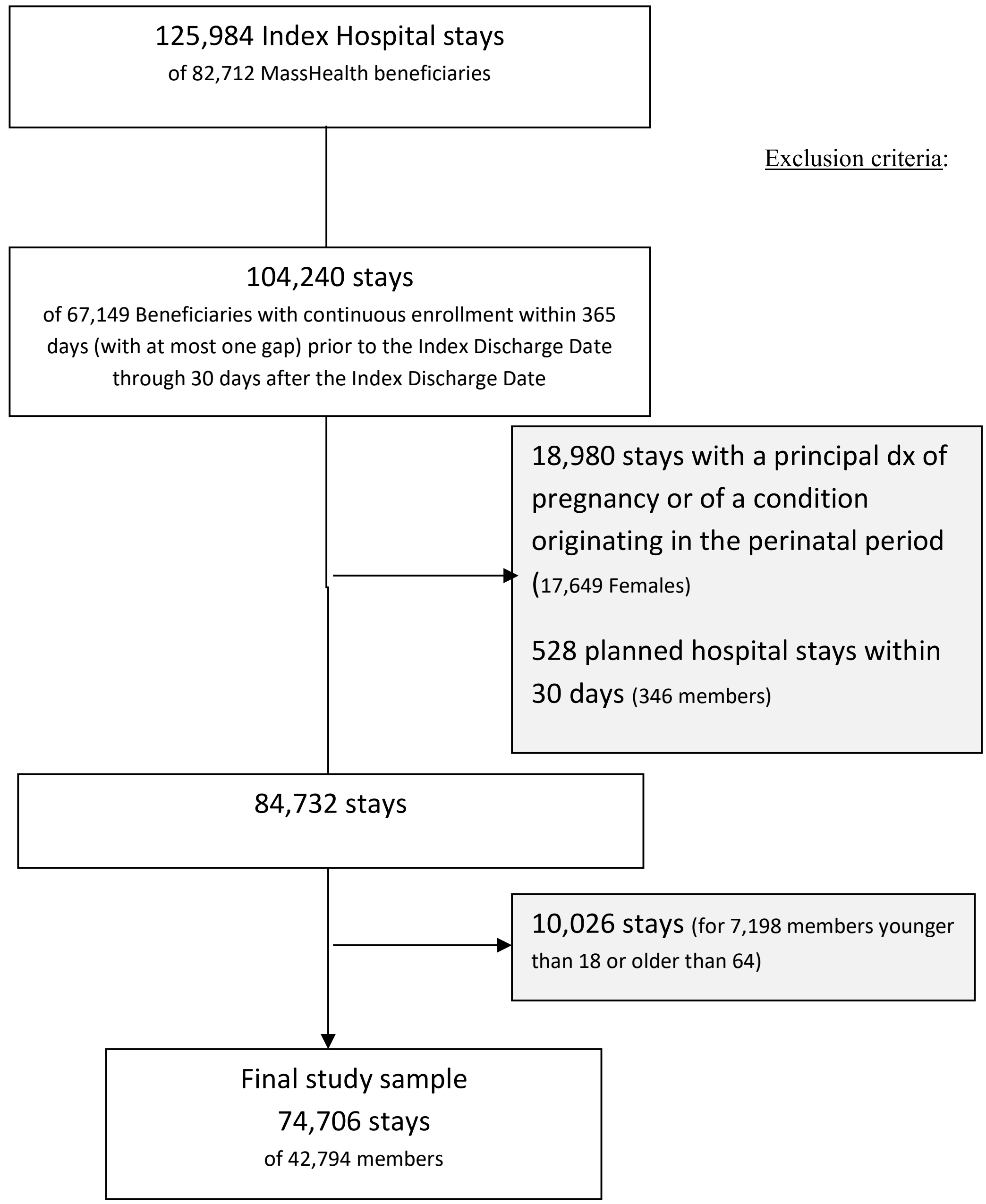


Figure 3.1: Study population flow chart, hospital stays between Jan 1st and Dec 1st, 2016 among MassHealth managed care eligible enrollees

Table 3.1: Baseline Characteristics of index Hospital Discharges by 30-Day Re-admission

	Readmitted		Not Readmitted		P- value [a]
	#	%	#	%	
Total	16,485	22.1%	58,221	77.9%	
Age/gender at discharge					0.000
18-24 Female	748	4.5%	2,720	4.7%	
25-34 Female	1,699	10.3%	6,276	10.8%	
35-44 Female	1,436	8.7%	5,828	10.0%	
45-54 Female	1,902	11.5%	7,628	13.1%	
55-59 Female	977	5.9%	3,806	6.5%	
60-64 Female	754	4.6%	3,329	5.7%	
18-24 Male	666	4.0%	2,488	4.3%	
25-34 Male	1,712	10.4%	5,602	9.6%	
35-44 Male	1,897	11.5%	5,463	9.4%	
45-54 Male	2,613	15.9%	7,742	13.3%	
55-59 Male	1,178	7.1%	3,975	6.8%	
60-64 Male	903	5.5%	3,364	5.8%	
Race/Ethnicity					0.000
White/Non-Hispanic	8,074	49.0%	28,345	48.7%	
Black/Non-Hispanic	1,384	8.4%	5,155	8.9%	
Hispanic	1,003	6.1%	4,240	7.3%	
Other non-Hispanic	284	1.7%	1,385	2.4%	
Missing/unknown	5,740	34.8%	19,096	32.8%	
HCC morbidity burden, mean (SD)	3.5	2.5	2.4	2.0	0.000
Behavioral health					
Serious mental illness	13,306	80.7%	38,779	66.6%	0.000
Substance use disorder	12,257	74.4%	33,580	57.7%	

	Readmitted		Not Readmitted		P- value [a]
	#	%	#	%	
Any LTSS use	7,593	46.1%	17,430	29.9%	0.000
Disability status [b]	7,115	43.2%	18,567	31.9%	0.000
Housing problems [c]	5,417	32.9%	14,593	25.1%	0.000
Neighborhood stress score quartile [d]					0.000
Least stressed neighborhood quartile	3,908	23.7%	14,734	25.3%	
Most stressed neighborhood quartile	4,230	25.7%	14,426	24.8%	

Source: Authors' calculations using data on 74,706 hospitalizations between Jan 1st and Dec 1st, 2016 of 42,794 MassHealth managed care eligible adult members.
*Abbreviations: **HCC**, the CMS-HCC diagnosis-based Hierarchical Condition Category; **SD**, standard deviation; **LTSS**, long-term services and supports.*
[a] *P values based on Chi-squared and Student t tests.*
[b] *based on entitlement and qualification for specialized services for mental health or developmental disabilities in 2016.*
[c] *defined as 3+ distinct addresses or homelessness (Z59.0) on claims or encounter records during 2016.*
[d] *measure summarizing seven neighborhood-level indicators of economic stress using US Census block groups.*

Table 3.2: Rates and Predictive Ratios for models predicting 30-day readmission among subpopulations [a]

Subgroups/Models	# of eligible hospital discharges (%)		Observed readmission rate	No adjustment	Risk adjustment for age, sex, and morbidity (1)		(1) + serious mental illness and substance use disorder (2)		(2) + disability, neighborhood-level stressors, and housing issues	
				Predictive ratio [b c]	Expected readmission rate	Predictive ratio	Expected readmission rate	Predictive ratio	Expected readmission rate	Predictive ratio
All	74,706	100.0%	22.1%	1.00	22.1%	1.00	22.1%	1.00	22.1%	1.00
Race/ethnicity subgroups										
Black	6,539	8.8%	21.2%	0.96	21.9%	0.97	21.1%	1.00	21.5%	0.99
White	36,419	48.7%	22.2%	1.00	22.1%	1.00	22.5%	0.99	22.4%	0.99
Hispanic	5,243	7.0%	19.1%	0.86	22.1%	0.86	21.6%	0.88	22.2%	0.86
Other	1,669	2.2%	17.0%	0.77	19.7%	0.86	17.7%	0.96	17.4%	0.98
Missing Unknown	24,836	33.2%	23.1%	1.05	22.2%	1.04	22.1%	1.05	22.0%	1.05
Any LTSS use	25,023	33.5%	30.3%	1.37	26.5%	1.14	26.3%	1.15	26.6%	1.14
Disability	25,682	34.4%	27.7%	1.25	24.5%	1.13	25.1%	1.10	27.7%	1.00
Morbidity burden										
Lowest morbidity burden quartile	19,008	25.4%	11.3%	0.51	11.6%	0.97	11.2%	1.01	11.1%	1.02
Highest morbidity burden quartile	18,681	25.0%	35.0%	1.58	34.9%	1.00	35.0%	1.00	34.4%	1.02

Subgroups/Models	# of eligible hospital discharges (%)		Observed readmission rate	No adjustment	Risk adjustment for age, sex, and morbidity (1)		(1) + serious mental illness and substance use disorder (2)		(2) + disability, neighborhood-level stressors, and housing issues	
				Predictive ratio [b c]	Expected readmission rate	Predictive ratio	Expected readmission rate	Predictive ratio	Expected readmission rate	Predictive ratio
Behavioral health										
Serious mental illness	52,085	69.7%	25.5%	1.15	23.2%	1.10	25.5%	1.00	25.6%	1.00
Substance use disorder	45,837	61.4%	26.7%	1.21	24.2%	1.10	26.7%	1.00	26.7%	1.00
Housing										
Housing problem	20,010	26.8%	27.1%	1.23	23.4%	1.16	24.3%	1.12	27.1%	1.00
Least stressed neighborhood quartile [d]	18,642	25.0%	21.0%	0.95	21.5%	0.98	21.4%	0.98	20.9%	1.00
Most stressed neighborhood quartile	18,656	25.0%	22.7%	1.03	22.6%	1.00	22.7%	1.00	22.9%	0.99
Select pseudo ACOs [e]										
ACO_1	1,800-8,000	*****	23.5%	1.06	21.6%	1.09	22.2%	1.06	22.6%	1.04
ACO_2	1,800-8,000	*****	22.3%	1.01	22.2%	1.01	22.4%	1.00	22.2%	1.00
ACO_3	>8,000	*****	24.6%	1.11	23.0%	1.07	23.5%	1.05	23.9%	1.03
ACO_4	>8,000	*****	24.3%	1.10	22.2%	1.09	22.7%	1.07	22.8%	1.07
Model performance										
AIC				71,908	69,776		69,208		69,029	
C statistic*100				50.00	66.65		68.26		68.78	

Source: Authors' calculations using data on 74,706 hospitalizations between Jan 1st and Dec 1st, 2016 of 42,794 MassHealth managed care eligible adult members.

*Abbreviations: **AIC**, Akaike's information criterion; **LTSS**, long-term services and supports; **ACO**, accountable care organization*

[a] *Estimates are based on hierarchical generalized linear models with a logit link and a binomial distribution*

[b] ***Predictive ratio** is the group's average actual (observed) 30-day readmission rate divided by its average model-predicted (expected) rate. Ratios close to 1 reflect good model fit.*

[c] ***Predictive ratio with no adjustment** is obtained by dividing actual rate by grand mean of rate for the whole sample.*

[d] ***Neighborhood stress*** *measure summarizes seven neighborhood-level indicators of economic stress using US Census block groups.*
[e] ***Pseudo ACOs*** *are created by applying MassHealth's assignment algorithm to historic member claims and encounters. Actual ACO attribution only took effect in 2018; numbers categorized or masked for confidentiality.*
Morbidity burden *is measured using the CMS-HCC diagnosis-based Hierarchical Condition Category score.*
Disability status *is Medicaid entitlement for disability or qualification for specialized services for mental health or developmental disabilities in 2016.*
Housing problem *is defined as 3+ distinct addresses or homelessness (Z59.0) on claims or encounter records during 2016.*

CHAPTER IV: SHOULD HIGH-FREQUENCY HOSPITAL USERS BE EXCLUDED FROM 30-DAY READMISSION QUALITY MEASURES?

ABSTRACT

BACKGROUND: Thirty-day readmission rate is a popular metric for measuring the performance of hospitals, health plans, and accountable care organizations (ACOs). Like other quality measures, it is based on clinical guidelines that apply to the general population or specified subgroups. However, even in a targeted subpopulation, a few patients who frequently use hospitals may add unwanted volatility to a readmission measure.

OBJECTIVES: We sought to describe the characteristics of MassHealth members who are high-frequency hospital users (with 4 or more hospital visits per year) and to assess the impact of their inclusion or exclusion on 30-day readmission.

METHODS: We studied managed care eligible MassHealth patients with at least one acute inpatient stay during 2016. We assessed demographics, morbidity burden, and social determinant of health factors for both high-frequency hospital users and low-frequency users. We then evaluated the extent to which the inclusion or exclusion of high-frequency users from the 30-day readmission measure changes its rate and its variance.

RESULTS: Of the 42,794 unique patients with at least one acute hospitalization in 2016, only 8.7% were high-frequency hospital users, contributing 30.2% of all hospital visits. These patients were more likely to be male (77.1% vs. 50.0%), 35 years or older (72.1% vs. 69.7%), with high morbidity burden (CMS-HCC score of 3.3 (SD=2.2) vs. 1.9 (SD=1.5) for low-frequency users of hospitals), and with significant social determinant of

health factors (33.1% with housing problems, 44.1% disabled, 83.2% with serious mental illness, 77.1% with substance abuse disorder, and 25.3% living in most stressed neighborhoods compared to 22.0%, 27.3%, 60.2%, 50.0%, 24.5% for low-frequency users of hospitals respectively). Their readmission rate was 50.7% compared to 9.7% for other patients. These patients also contributed 72.0% of the variance in 30-day readmission which is due to clustering of hospitalizations within patients.

CONCLUSIONS: Despite their small proportion, high-frequency hospital users have a huge impact on 30-readmission rates. Excluding these patients from readmission and other quality measures could benefit medically and socially complex patients and the ACOs that disproportionally serve them.

4.1 Introduction

Thirty-day readmission rate is commonly used to measure and compare the performance of hospitals and to encourage more attentive post-acute care and reduced health care spending. Under the Affordable Care Act, the Centers for Medicare and Medicaid Services (CMS) penalizes hospitals for excessive unplanned readmissions[9]. Like other quality measures, 30-day readmission is based on clinical guidelines that apply to the general population or specified subgroups. The CMS has been publicly reporting readmission rates for acute heart failure, pneumonia, and myocardial infarction for several years[23]. However, even among targeted subpopulations, such as patients hospitalized for these conditions, a small subgroup of individuals who frequently use hospitals may add undesirable amounts of volatility to the 30-day readmission rate.

All-cause unplanned readmission as a quality measure is being extended to accountable care organizations (ACOs)[29] . While it may be reasonable to hold hospitals accountable for problems that patients experience within 30 days after discharge, which could reflect poor hospital care or a too-early transition to an outpatient setting[30], a readmission measure may be less suitable for comparing ACOs. Doing so may significantly impact the results and decisions about health care improvement intended by these organizations and their payers. For instance, ACOs that disproportionally serve more patients with medical and social risk factors that typically lead to frequent hospitalization may face financial penalties for high readmission rates. This may translate into reluctance of some ACOs to care for beneficiaries with high risk of hospitalization and could exacerbate existing health disparities. Excluding high-frequency hospital users from the readmission measure, could lead payers and ACOs to focus more on patients with lower risk of hospitalization who may benefit more from this quality measure. In addition, and more importantly, payers and ACOs could redirect resources and efforts to avoiding preventable hospitalizations in the first place, improving care transitions, and bettering follow-up after discharge for the relatively few high-frequency users of hospitals, who are responsible for a disproportionate share of readmissions.

We sought to describe the characteristics of MassHealth beneficiaries who are high-frequency hospital users (who visit the hospitals 4 or more times per year) and their patterns of hospital use and readmissions. We also evaluated the extent to which the inclusion or exclusion of high-frequency users from the 30-day readmission measure changes its rate and its variance.

4.2 Methods

4.2.1 Study data

We used claims and enrollment data from MassHealth, Massachusetts' combined Medicaid and Children's Health Insurance Program (CHIP). Massachusetts established MassHealth in July 1997 to extend Medicaid eligibility to families and childless adults whose incomes fell below 200% and 133% of the federal poverty level, respectively. More than 1.2 million MassHealth members are now managed care eligible and may choose their health care from 17 statewide ACOs, two managed care organizations, or MassHealth's primary care clinician (PCC) plan, for which the State reimburses providers directly. [32] To measure 30-day readmission, we used 2016 data for MassHealth managed care eligible enrollees. We assigned enrollees to 17 pseudo- (realistically simulated) ACOs which we created by applying MassHealth's assignment algorithm to historic member claims and encounters; all have at least 5,000 members. Actual ACO attribution only took effect in 2018. We then assigned the remaining members to the other two groups: managed care organization or PCC plan. Because adjustment for the readmission measure requires a one-year lookback period for enrollment in Medicaid and for measuring morbidity [27,80], 2015 data from the year prior to hospitalization of MassHealth beneficiaries were also used.

4.2.2 Study sample

We followed strict definitions for eligibility criteria and the 30-day readmission measurement. based on MassHealth ACO Quality Measurement Program designed by the National Committee for Quality Assurance (NCQA). [81] NCQA developed the Healthcare Effectiveness Data and Information Set (HEDIS) standardized performance measures widely used for evaluating quality of care delivered by health care organizations. Members were eligible for this study if they had at least one inpatient stay between January 1st and December 1st, 2016. We only included hospitalizations for members who were continuously enrolled in MassHealth for 365 days (with at most one 45-day gap) prior to the discharge date through 30 days after the discharge date. [27,80,81] We excluded hospitalizations for females with a principal diagnosis of pregnancy or of a condition originating in the perinatal period and for members who had a planned hospital stay (e.g. transplantation, chemotherapy, rehabilitation) within 30 days [27,81]. Finally, we excluded members younger than 18 or older than 64. We allowed members to contribute multiple hospital stays to the analyses. Our final study sample included 74,706 unique hospitalizations among 42,794 MassHealth members (figure 3.1). We used these hospitalizations (hereafter referred to as index hospitalization stays) as the denominator for calculating all cause 30-day readmission rates.

4.2.3 Outcome measures:

Our two main outcome measures were hospitalization (as defined and described above) and 30-day readmission for any diagnosis. For each index hospitalization stay, we determined if any other acute inpatient stay for that member had an admission date within 30 days after the index discharge date. For members with multiple hospitalizations during the study period, we included each index hospitalization discharge and followed it for 30 days.

4.2.4 Covariates:

We considered three types of covariates. The first group of variables were age and gender. The second group of factors measured morbidity burden using the CMS's Hierarchical Condition Category (CMS-HCC) model in the year prior to index hospitalization. The CMS-HCC model calculates expected costs from age, sex, and diagnoses grouped into condition categories with hierarchies [82]. When two conditions within the same disease hierarchy co-exist, the lower-ranked diagnosis is ignored. For instance, a member with claims for both diabetes with chronic complications and diabetes without complication is only assigned the highest and most costly condition (i.e.; diabetes with chronic complications). While originally developed to predict costs, the CMS-HCC model has been widely used to measure total morbidity burden. The third group of variables encompassed SDH factors including behavioral health issues (i.e. serious mental illness and substance use disorder), disability, housing instability, and neighborhood-level stressors. We used SDH factors during the measurement year 2016. For members missing 2016 SDH data, which constituted about 1.8% of our sample, we included their 2015 SDH information. We used two indicators for serious mental illness and substance use disorder based on condition categories created with the diagnosis-based Diagnostic Cost Group Hierarchical Condition Category software (DxCG-HCC) [41] (Appendix 3.1). MassHealth routinely uses the DxCG-HCC software to adjust payments to Medicaid managed care organizations. This model is similar to the CMS-HCC model except that it creates indicators for up to 394 medical condition categories instead of 189. Disability was created based on entitlement and qualification for specialized services for mental health or developmental disabilities. Housing problems were identified by unstable housing (≥3 addresses within a year) and through an international classification of disease (ICD) code indicating homelessness (Appendix 3.1). Neighborhood-level stressors were summarised by a neighborhood stress score (NSS) derived from a principal components analysis; the NSS is calculated at the US Census-block-group level from seven neighbourhood-level indicators of economic stress available through the American Community Survey [83] (Appendix 3.1).

4.2.5 Statistical analyses

First, we used Chi-squared and Student t tests to assess the association between each covariate and high hospitalization use (4 or more eligible hospitalizations in 2016). Second, we assessed the distribution of hospitalizations and 30-day readmission rates.

Third, we investigated the effect of including/excluding high-frequency users from the 30-day readmission measure on its variance.

Because some patients have multiple hospitalizations and each ACO serves a unique set of patients, we used hierarchical generalized linear models. Clustering may result in potential violation of the assumption of independence required in many statistical tests and generalized linear models. Variation in hospital readmission may be smaller between hospitalizations attributed to the same patient or same ACO than between hospitalizations attributed to different patients or different ACOs. Controlling for clustering leads to more precise estimates. We estimated the intraclass correlation coefficient (ICC), which is the ratio of the between-cluster variance that is accounted for by clustering to the total variance in 30-day readmission. We attributed the variance in 30-day readmissions to three levels: ACOs, patients, and hospitalizations. Hospitalization-level ICC is the residual variance after the ACO level and patient level variances have been accounted for. We ran 2 logistic models with random effects only (unadjusted) to estimate the total variance at each of the 2 ACO- and patient-levels. The first model included all patients while the second excluded high-frequency hospital users. Finally, to assess whether some of the variance at the ACO- and patient-levels can be attributed to patient characteristics, we re-ran these 2 models adding the fixed effects for 12 age/sex categories, morbidity, serious mental illness, substance use disorder, disability, neighborhood- level stressors, and housing issues [85]. All analyses were carried out using the SAS package version 9.4 (SAS Institute, Cary NC, USA) and Stata software version 12 (Stata Corporation., College Station, TX, USA).

4.3 Results

Of the 42,794 unique patients with at least one acute hospitalization in 2016, only 3,728 (8.7%) were high-frequency hospital users, contributing 22,586 (30.2%) of all hospital visits (Table 4.1). These patients were more likely to be male (77.1% vs. 50.0%), 35 years or older (72.1% vs. 69.7%), with high morbidity burden (CMS-HCC score of 3.3 (SD=2.2) vs. 1.9 (SD=1.5) for low-frequency users of hospitals), and with significant social determinant of health factors (33.1% with housing problems, 44.1% disabled, 83.2% with serious mental illness, 77.1% with substance abuse disorder, and 25.3% living in most stressed neighborhoods compared to 22.0%, 27.3%, 60.2%, 50.0%, 24.5% for low-frequency users of hospitals respectively).

The readmission rate for high-frequency hospital users was 50.7% in contrast to 9.7% for other patients. By excluding high-frequency hospital users from the readmission measure, the overall readmission rate was cut by more than half (9.7% vs. 22.1% including all patients) (data not shown).

Table 4.2 provides the composition of variance in 30-day readmission attributed to clustering at the ACO level and at the patient level: 35.0% of the total variance in 30-day readmission was between patients; multiple hospitalizations within one patient were more similar than among random patients. However, this estimate dropped to only 9.8% after excluding high-frequency users, suggesting that this group of patients is responsible for 72.0% of the variance in 30-day readmission which is due to nesting of hospitalizations within patients ([35.0 -9.8]/ 35.0). On the other hand, the proportion of variance explained by the ACO level pales in comparison to that attributed to the patient level (ICC of 0.3% or less before or after excluding high-frequency users). Furthermore, whether we excluded high-frequency hospital users from the 30-day readmission measure, ICC was always lower in the adjusted models than in the unadjusted models. That is, risk adjusting 30-day readmission by taking into account patient characteristics also decreases variability in this measure, making it more stable.

4.4 Discussion

We found that a small group of MassHealth beneficiaries are responsible for disproportionate hospitalization use and have an outsized effect on 30-day readmission and its variability. These beneficiaries are sicker than other patients, with significant mental illness, drug dependence abuse, and housing issues. A better understanding of which patients may be at risk for frequent hospital use is important because many of their initial hospitalizations could perhaps be prevented through more effective and targeted interventions. Moreover, a better understanding of which patients are at highest likelihood of readmission after hospitalization may enable clinicians, ACOS, and policy makers to focus efforts on patients who will benefit the most from heath interventions after hospitalization.

The 30-day readmission measure may have less utility for judging ACOs than hospitals. ACOs that disproportionally serve many high-frequency hospital users may be disproportionately affected by facing penalties for having high readmission rates. [7,8] On the contrary, these ACOs are the ones that are in need of extra money to spend on caring for the medically and socially complex subpopulations they serve who use hospitals more frequently than others. One way to avoid penalties for these ACOs is to exclude high-frequency users from the 30-day readmission measure. This will decrease the heterogeneity of the population targeted by the readmission measure to keep only patients who are most likely to benefit from its improvement. Moreover, given finite resources, it is reasonable for ACOs to focus efforts on enrollees with greater likelihood of hospitalization and readmission to improve health quality overall and reduce spending. First, ACOs may focus more on characterizing which hospitalizations may be preventable and on designing health programs that enroll and most benefit these high-risk patients such as individualized patient care plans, coordinated care, and improvement of discharge summaries. [86–88] Second, designing and implementing comprehensive social programs for the high-frequency hospital use subpopulation are particularly beneficial given this population's prevalence of mental illness, drug abuse, and housing issues. [89,90]

This study has limitations. First, it seems likely that a model that could account for additional important social risk factors, such as social support, health literacy, English proficiency, and functional status – would perform better [24,25,84]. However, we could use only readily available predictors. MassHealth may need to work with ACOs and other state entities, such as social and housing services, to obtain other factors to augment their data. Having additional factors available in the future will add value to analyses that address important health policy questions. Second, to improve the precision of our prediction models, we controlled for clustering of hospitalizations within patients and patients within ACOs and other settings that we assigned based on an algorithmic attribution. However, our ACO attribution may differ from actual member attribution or assignment of ACOs that went into effect later in 2018. Finally, our study was limited by a geographically constrained population that included MassHealth members only. Priorities and support given to advance coverage, access, health outcomes, and efficiency goals may differ from state to state. Hence, our findings may not generalize to other states, programs, and populations.

4.5 Conclusion

High-frequency hospital users have many medical morbidities and significant psychiatric, substance abuse, and housing problems. Despite their small numbers, they exert a large influence on 30-readmission rates, this raises questions about how to fairly judge readmissions for them and the ACOs that disproportionally serve them. This study suggests that it might be wise to exclude high-frequency users from the re-admission measure, and possibly from other quality measures.

Table 4.1: Characteristics of MassHealth enrollees with at least one acute inpatient stay in 2016

	>= 4 hospitalizations		1-3 hospitalizations		P- value [a]
	#	%	#	%	
Total number of enrollees (%)	3,728	100.0%	39,066	100.0%	
Total number of hospitalizations (%)	22,586	100.0%	52,120	100.0%	
Male	2,873	77.1%	19,533	50.0%	0.000
Category of age					
18-34	1,041	27.9%	11,815	30.2%	0.000
35-54	1,829	49.1%	17,427	44.6%	
55-64	858	23.0%	9,824	25.1%	
Race/Ethnicity					
White/Non-Hispanic	1,817	48.7%	18,920	48.4%	0.000
Black/Non-Hispanic	337	9.0%	3,469	8.9%	
Hispanic	219	5.9%	2,988	7.6%	
Other non-Hispanic	60	1.6%	1,035	2.6%	
Missing/unknown	1,295	34.7%	12,654	32.4%	
HCC morbidity burden, mean (SD)	3.3	2.2	1.9	1.5	0.000
Housing problems [b]	1,233	33.1%	8,614	22.0%	0.000
Disability [c]	1,643	44.1%	10,682	27.3%	0.000

	>= 4 hospitalizations #	%	1-3 hospitalizations #	%	P- value [a]
Serious mental illness	3,103	83.2%	23,513	60.2%	0.000
Substance use disorder	2,873	77.1%	19,533	50.0%	0.000
Any LTSS use	1,769	47.5%	9,265	23.7%	0.000
Neighborhood stress score quartile [d]					
Least stressed neighborhood quartile	891	23.9%	10,063	25.8%	0.002
Most stressed neighborhood quartile	942	25.3%	9,586	24.5%	

Source: Authors' calculations using data on 74,706 hospitalizations between Jan 1st and Dec 1st, 2016 of 42,794 MassHealth managed care eligible adult members.

*Abbreviations: **HCC**, Morbidity burden measured using the CMS-HCC diagnosis-based Hierarchical Condition Category score; **LTSS**, long-term services and supports; **SD**, standard deviation.*

[a] *Chi-square or Student t test.*

[b] ***Housing problem** is defined as 3+ distinct addresses or homelessness (Z59.0) on claims or encounter records during 2016.*

[c] ***Disability status** is Medicaid entitlement for disability or qualification for specialized services for mental health or developmental disabilities in 2016.*

[d] ***Neighborhood stress** measure summarizes seven neighborhood-level indicators of economic stress using US Census block groups.*

Table 4.2: Variance decomposition statistics for 30-day readmission

	Patient-level ICC	Pseudo ACO [a]-level ICC
Unadjusted		
All enrollees	35.0% (33.7%-36.3%)	0.2% (0.1%-0.7%)
Low-frequency hospital users only	9.8% (7.5%-12.9%)	0.3% (0.1%-1.0%)
Adjusted		
All enrollees	26.8% (25.6%-28.1%)	0.1% (0.0%-0.6%)
Low-frequency hospital users only	6.1% (3.8%-9.5%)	0.2% (0.1%-1.0%)

Source: Authors' calculations using data on 74,706 hospitalizations between Jan 1st and Dec 1st, 2016 of 42,794 MassHealth managed care eligible adult members.

*Abbreviations: **ACO**, accountable care organization; **ICC**, intraclass correlation coefficient.*

[a] Pseudo ACOs are created by applying MassHealth's assignment algorithm to historic member claims and encounters. Actual ACO attribution only took effect in 2018.

Estimates are based on hierarchical generalized linear models with a logit link and a binomial distribution. Unadjusted models include random effects only. Adjusted models added fixed effects for age, sex, morbidity, serious mental illness, substance use disorder, disability, neighborhood- level stressors, and housing issues.

CHAPTER V
CONCLUSIONS AND DISCUSSION

5.1 Summary of Findings

In this dissertation, we 1) developed and validated a new CVD risk score, similar to the Framingham Risk Score relying only on data available in the MCBS that could be applied to specific subgroups, such as elderly Medicare beneficiaries (**aim 1**); 2) illustrated the value of risk adjusting quality measures using morbidity and social determinants of health (SDH) factors based on 30-day readmission rates (**aim 2**); and 3) described the characteristics of MassHealth members who are high-frequency hospital users and assessed the impact of their inclusion or exclusion on the 30-day readmission measure (**aim 3**).

Aim 1:

We showed that existing data on morbidity and functional limitation may partially substitute for unavailable direct measures such as clinical and laboratory information in MCBS to evaluate CVD risks. Our MCBS-FRS predicted 3-year CVD events better than a modification of the FRS that had previously been used in MCBS. The actual CVD event percentages for those with the highest 5 and 10 percent of MCBS-FRS predicted risk were 9.1% and 10.1%; analogous numbers based on the (previously used) modified FRS were lower: 7.5% and 8.1%, respectively. Our CVD risk equation is important because it allows for a broader range of analyses for addressing public health and policy questions than would not be possible using either survey or Medicare data alone. [10,16] Not only does the MCBS include a nationally representative sample of the US elderly, a high proportion of whom live with chronic conditions, it also contains a wealth of information on health outcomes, use of health services, expenditures, and sources of payment. [10]

Moreover, our method of refitting the model in new data (rather than simply using the coefficients of the risk factors in the FRS) and including other risk factors, such as morbidity and functional limitation, could be replicated to develop specific case-mix modified Framingham scores that may be more appropriate for specific databases of specific populations.

Aim 2:

We used MassHealth claims and enrollment data to measure morbidity burden [82] and social determinant of health factors such as behavioral health issues (i.e. serious mental illness and substance use disorder), disability, and housing instability. We also used census data to compute a social stress neighborhood stress score at the US Census-block-group level from seven neighborhood-level indicators of economic stress available through the American Community Survey. [11] We then illustrated the value of risk adjusting quality measures for morbidity and SDH factors using all cause 30-day re-admission rate as an example. We were able to dramatically improve the match between actual and expected readmission rates for several subgroups of vulnerable MassHealth members. These include members with high morbidity levels, with a disability, with behavioral health problems, and those with housing issues. We showed that not adjusting quality measures' performance for morbidities and SDH factors may harm some vulnerable populations and the ACOs that serve them. [7,8] Our comprehensive medical and SDH-based model development can be replicated by others to facilitate and support care of vulnerable patients. Such modeling is an important step on the road to improved health equity.

Aim 3:

With the same data used for aim 2, we described the characteristics of MassHealth members who are high-frequency hospital users and assessed the impact of their inclusion or exclusion on the 30-day readmission measure. We found that 30-day readmission rates increase sharply with numbers of hospitalizations per patient. Thus, a small group of MassHealth beneficiaries are responsible for disproportionate hospitalization use and have an outsized effect on 30-day readmission and its variability. These beneficiaries are sicker than other patients, with significant mental illness, drug dependence abuse, and housing issues. A better understanding of which patients may be at risk for frequent hospital use is important because many of their initial hospitalizations could perhaps be prevented through more effective and targeted interventions. Moreover, a better understanding of which patients are at highest likelihood of readmission after hospitalization may enable clinicians, ACOs, and policy makers to focus efforts on patients who will benefit the most from heath interventions after hospitalization. Our study suggests that it might be wise to exclude high-frequency users from the re-admission measure, and possibly from other quality measures. Doing so will benefit both medically and socially complex patients and the ACOs that disproportionally serve them.

5.2 Limitations and Strengths

Our aim 1 study has several limitations that must be acknowledged. First, we used survey and claims data to develop our MCBS CVD risk model. These data are generally thought to be less accurate than the clinical and laboratory data used in the original FRS. However, our goal was to build an "FRS-like" CVD risk score that relies only on information available in MCBS. Second, the FRS was developed using a 10-year follow-up period that was not available for MCBS; our MCBS-FRS score predicts CVD events within a 2-year follow-up period. However, identifying individuals at higher CVD risk over a relatively short-time period is also important for more timely interventions. Intensive early follow-up and more frequent surveillance may improve health and offset future costs associated with avoidable health care utilization in this high-risk population. Moreover, even though only about 4.40% of our study sample had events within 2 years of follow-up, there were enough CVD events to build a stable and credible model. Furthermore, since MCBS beneficiaries identified by our CVD risk algorithm can be easily linked to Medicare claims data, future studies may easily evaluate their long-term CVD health outcomes. Third, the predictors in the MCBS-FRS score, except for the HCC disease burden score, were all self-reported, and therefore subject to reporting or recall bias. Fourth, we identified CVD outcomes based on claims data, which may include "rule-out" diagnosis codes for CVD. [69] [70] However, for the major CVD events of AMI and stroke, we used ICD-9-CM codes that are specific to new events, mitigating the potential for overestimating CVD outcomes. Finally, our results may be representative of the Medicare FFS population only. However, complete claims information is required to accurately perform our analyses as is usually done in studies of MCBS that are based on analysis of claims data. Despite these limitations, we were able to generate a relatively powerful CVD risk score that can be computed in MCBS, enhancing the survey's value for health policy and health services research. This CVD risk score, requiring data that are more readily available than what is needed to calculate the original FRS, may be similarly effective in helping us learn how to reduce CVD events and may allow for a more nuanced examination of the costs and benefits of well-targeted health care interventions that may be particularly valuable in preventing, managing, and reducing the burden of morbidity and mortality associated with CVD.

Our aim 2 and aim 3 studies also have some limitations. First, it seems likely that a model that could account for additional important social risk factors, such as social support, health literacy, English proficiency, and functional status – would perform better.[24,25,84] However, we could use only readily available predictors. MassHealth may need to work with ACOs, managed care organizations, and other state entities, such as social and housing services, to obtain other factors to augment their data. Having additional factors available in the future will add great value to these types of analyses and others that address important health policy questions. Second, to improve the precision of our prediction models, we controlled for clustering of hospitalizations within patients and patients within ACOs that we assigned based on an algorithmic attribution using historic member claims and encounters. However, our ACO attribution may differ from actual member attribution or assignment under current ACO models that went into effect in 2018. Third, our study was limited by a geographically constrained population that included MassHealth members only. Priorities and support given to advance coverage, access, health outcomes, and efficiency goals expressed by the ACA, may differ from state to state. Hence, our findings may not generalize to other states, programs, and populations. Despite these limitations, this is the first study to risk-adjust a quality measure using a broader group of SDH factors, most notably health behavioral variables. In addition, this study used MassHealth, a large statewide healthcare database. In 2015, MassHealth was the primary payer for 70.4% of its membership and a secondary payer for eligible residents with other primary insurance coverage, which represented 28.3% of total MassHealth membership. We were able to identify medically and socially disadvantaged Massachusetts Medicaid beneficiaries whose needs should be addressed immediately to improve health quality overall, reduce health disparities, and decrease spending.

5.3 Implications and Future Directions

This dissertation uses available existing databases, making research easier and less expensive to perform and findings more reliable and generalizable to the data study population compared to newly collected data. Most importantly, this dissertation was able to examine potential areas of intervention, such as morbidity and social factors to improve hospital readmission and other quality measures and identify vulnerable populations to facilitate and support caring for them.

5.3.1 Controversy regarding risk adjusting quality measures:

Poorer quality ranking of an ACO that disproportionally serves patients with high morbidity levels and with SDH factors may be due to the complexity of these patients and the challenge of caring for them. Not risk adjusting performance quality measures penalizes ACOs that serve high-risk populations. Moreover, ACOs may not get the support needed to continue to care for these vulnerable subpopulations, hence they may be reluctant to care for them. However, some worry that risk adjustment will “forgive” ACOs for delivering worse care to these high-risk patients. Under this theory, one assumes that differences in quality of health care between ACOs may be due to poor performance of their providers and staff. However, this may not be true since these differences may be due to the difficulty to care for vulnerable patients. Another argument against risk adjusting quality measures is that doing so will mask health disparities, making it less likely that they are identified and reduce them. However, not risk adjusting also does nothing to reveal disparities. If reducing disparities is a goal, it must be separately targeted as an outcome of interest. Despite the controversy, this dissertation shows that patient characteristics, such as age, sex, morbidities and SDH factors are important drivers of readmissions; adjusting for them may help fairly judging readmissions for vulnerable patients and the ACOs that disproportionally serve them. Risk adjusting quality measures may protect ACOs that disproportionally serve medically and socially complex patients from unfair quality penalties that would otherwise make them ineligible for shared savings. These extra dollars may, for instance, help them design and implement interventions to facilitate and better the care for vulnerable populations. The goal is to incentivize ACOs to overcome barriers to better health outcomes for high-risk populations and reduce health disparities.

5.3.2 About hospital readmission measure:

Although they are considered good quality metrics and are commonly used, readmission measures should include two important aspects: 1) readmissions that are related to index hospitalization discharges versus those that are unrelated and 2) readmissions that are preventable. [22,91,92] One systematic review has found that between 5% to 79% of readmission could be considered preventable. [22] More research needs to be done to accurately identify which readmissions are preventable so that focus will be on reducing avoidable 30-day readmissions. Moreover, some hospitals and ACOs may have high readmission rates only because they may have lower mortality rates or may provide easy access to care compared to others with lower readmission rates. [8] Furthermore, patients may prefer having a few consecutive hospitalizations with a few days or weeks in between during the whole year rather than being hospitalized regularly every three months or so; this may not translate as a good quality of care from the perspective of a hospital or an ACO. Finally, condition-specific readmission measures and those for specific settings may help assess quality of care better than all-cause readmission measures. As suggested in this dissertation, specific 30-day readmission measures for vulnerable patients with disabilities, or behavioral health problems, and those with housing issues could be very helpful in improving health quality and reducing health disparities. [93] Despite the limitations of the 30-day readmission measure, risk adjusting it or any other quality measure for risk factors can still be useful in identifying vulnerable subpopulations who are most likely to incur high costs and have issues that need to be addressed with distinct programs.

5.4 Final Conclusions

This dissertation illustrates how statistical models can be used with existing databases to provide reasonable estimates of risks and health outcomes in a way than can inform health policy. Results from this dissertation provide insights for policy makers and researchers into:

1) the potential benefits of a proxy for the Framingham cardiovascular disease (CVD) risk score, that relies only on variables available in the MCBS, to target health interventions to policy-relevant subgroups, such as elderly Medicare beneficiaries based on their risk of developing CVD

2) the benefits of setting appropriate risk-adjusted quality of care standards for subpopulations while providing ACOs with additional support to enroll, facilitate, and provide excellent care for at-risk subgroups

3) the outsized effect of high-frequency hospital users on re-admission rates that raises questions about how to fairly judge readmissions for medically and socially complex patients and the ACOs that disproportionally serve them.

The models in this dissertation are great tools which can be replicated by policy makers, payers, ACOs, and others to identify, facilitate, and support care of high risk and specific vulnerable patients by improving their health outcomes. Such modeling is an important step on the road to improved health equity and reduced spending.

APPENDICES

APPENDICES FOR CHAPTER I: A CARDIOVASCULAR DISEASE RISK PREDICTION ALGORITHM FOR USE WITH THE MEDICARE CURRENT BENEFICIARY SURVEY

Table A.1: Predictors of 3-year CVD event among MCBS beneficiaries using logistic regression

	Odds Ratio (95% CI)
Established Framingham score predictors	
Age (per year)	1.04 (1.03-1.06)
Gender (female)	0.78 (0.65-0.92)
Diabetes status (yes)	1.73 (1.46-2.05)
Smoking status	
Never smoker	Reference
Former smoker	1.31 (1.08-1.58)
Current smoker	1.99 (1.52-2.60)
Hypertension (yes)	1.46 (1.24-1.71)
BMI	1.02 (1.00-1.03)
Additional predictors	
HCC morbidity burden score~	1.22 (1.10-1.34)
NAGI score!	1.10 (1.04-1.16)
C statistic	67.07
C statistic after 10-fold cross validation	66.37

Source: authors' calculations using MCBS data.
MCBS*= Medicare Current Beneficiary Survey.* ***CVD****=cardiovascular disease.*
Data used in these analyses were for Fee-for-Service (FFS) community-dwelling elderly beneficiaries first observed in the MCBS between 1999 and 2008 who did not have claims for pre-existing CVD in baseline year (i.e. coronary heart disease, intermittent claudication, congestive heart failure, stroke or transient ischemic attack). The CVD outcome was defined in years 2 or 3 of MCBS by claims for acute CVD event.
This model included the following covariates: age (continuous), gender (female), diabetes status (yes), smoking status (never smoker, former smoker, and current smoker), hypertension (yes), BMI (continuous), the hierarchical condition category (HCC) morbidity burden score (range=0-12), and the NAGI score (measure of health status and independence for the elderly, range=0-5).
N(unweighted/weighted) = 16,867/63,208,832

Appendix 2.1: Risk reclassification analysis

We first categorized our 3-year CVD risk as less than 6% (low risk) and 6% or more (high risk) based on our assessment of the specificity and sensitivity plots against possible probability cut-offs. We then computed the Net Reclassification Improvement (NRI). The NRI for a new model is the difference in proportions of individuals who moved up and down risk categories compared to a reduced or a prior model. It is the sum of the reclassification improvement among beneficiaries who experienced the CVD event and the reclassification improvement among those who didn't. For individuals who had a CVD event, we assigned 1 for upward reclassification (move to a higher CVD risk category), -1 for downward and 0 for people who did not change their risk category. The opposite was done for beneficiaries who didn't have a CVD event. We then summed these individual scores and divided by numbers of people in each group. We also assessed the ability of the additional predictors (i.e. morbidity and limitation variables) in the new model compared to the modified FRS model to improve the discrimination between CVD cases and non-cases by computing the Integrated Discrimination Improvement (IDI). IDI can be seen as a continuous version of the NRI with probability differences used instead of categories. The larger the IDI, the better is the ability of the additional predictors to improve the discrimination.

Table A.2: Risk reclassification from the prior modified Framingham model to the new model for predicting a CVD event among MCBS beneficiaries

	New model[&]		
Prior model (reference)[*]	Low risk (<6%)	High risk (>=6%)	Total
Beneficiaries who experienced a CVD event [a] (4.87%)			
Low risk (<6%)	40.13%	21.55%	61.68%
High risk (>=6%)	8.52%	29.80%	38.32%
Total	48.65%	51.35%	100.00%
Beneficiaries who did not experience a CVD event (95.13%)			
Low risk (<6%)	64.67%	11.97%	76.64%
High risk (>=6%)	8.16%	15.20%	23.36%
Total	72.83%	27.17%	100.00%

MCBS*= Medicare Current Beneficiary Survey. Table based on 16,867 observations (weighted to represent 63,208,832 people).*
[&]Our new model is MCBS-based and included the following covariates: age (continuous), gender (female), diabetes status (yes), smoking status (never smoker, former smoker, and current smoker), hypertension (yes), BMI (continuous), the hierarchical condition category (HCC) morbidity burden score (range 0-12), and the NAGI score (measure of health status and independence for the elderly, range=0-5).
** The prior model is the modified FRS and was calculated based on the original FRS assuming that MCBS respondents with hypertension had an untreated SBP of 140mmHg while respondents without hypertension had a treated SBP of 120 mmHg.*
➔ *Of the beneficiaries who had a CVD event, 21.55% moved to higher CVD risk category while 8.52% moved to lower CVD risk category, with a 13.03% (i.e. 21.55-08.52%) reclassification improvement.*
On the other hand, 8.16% of individuals who didn't have a CVD event moved to lower CVD risk category while 11.97% moved to higher CVD risk category giving a -3.81% (8.16-11.97%) reclassification index. The net reclassification index (NRI) for the new model was

9.22% (13.03-3.81%) which means that the addition of other predictors improved the classification for a net of 9 % of beneficiaries.

The Integrated Discrimination Improvement (IDI) was 2.35 which suggests an improvement of 235% in the discrimination of the full model with the additional baseline predictors.

APPENDICES FOR CHAPTER II: IMPROVING PERFORMANCE ON HEALTH QUALITY MEASURES BY ACCOUNTING FOR MORBIDITY AND SOCIAL DETERMINANTS OF HEALTH: AN ILLUSTRATION IN 30-DAY READMISSIONS

Table A.3: Odds ratios of increasingly complex models predicting 30-day readmission

	Risk adjustment for age, sex, and morbidity (1)	(1) + serious mental illness and substance use disorder (2)	(2) + disability, neighborhood- level stressors, and housing issues
	Odds Ratio [a] (95% confidence interval)	Odds Ratio (95% confidence interval)	Odds Ratio (95% confidence interval)
Age/gender at discharge			
18-24 Female	Ref	Ref	Ref
25-34 Female	1.00 (0.84, 1.19)	0.91 (0.77, 1.08)	0.91 (0.76, 1.08)
35-44 Female	0.81 (0.70, 0.94)	0.75 (0.65, 0.86)	0.76 (0.65, 0.87)
45-54 Female	0.95 (0.82, 1.10)	0.80 (0.69, 0.93)	0.82 (0.71, 0.95)
55-59 Female	0.72 (0.62, 0.83)	0.68 (0.58, 0.78)	0.68 (0.59, 0.78)
60-64 Female	0.86 (0.75, 1.00)	0.75 (0.65, 0.87)	0.77 (0.67, 0.89)
18-24 Male	0.58 (0.51, 0.67)	0.57 (0.49, 0.65)	0.56 (0.49, 0.65)
25-34 Male	0.73 (0.63, 0.84)	0.67 (0.58, 0.77)	0.68 (0.59, 0.78)
35-44 Male	0.56 (0.48, 0.66)	0.58 (0.49, 0.68)	0.57 (0.49, 0.67)
45-54 Male	0.58 (0.50, 0.68)	0.60 (0.51, 0.70)	0.60 (0.51, 0.70)
55-59 Male	0.48 (0.41, 0.57)	0.54 (0.46, 0.64)	0.54 (0.45, 0.63)
60-64 Male	0.52 (0.44, 0.61)	0.57 (0.48, 0.67)	0.57 (0.48, 0.67)
Morbidity burden (log-transformed)	2.22 (2.14, 2.30)	2.04 (1.97, 2.12)	1.99 (1.91, 2.06)
Behavioral health			
Serious mental illness		1.67 (1.57, 1.77)	1.60 (1.50, 1.70)
Substance use disorder		1.49 (1.41, 1.58)	1.46 (1.38, 1.55)
Disability status [b]			1.29 (1.22, 1.36)

	Risk adjustment for age, sex, and morbidity (1)	(1) + serious mental illness and substance use disorder (2)	(2) + disability, neighborhood- level stressors, and housing issues
	Odds Ratio [a] (95% confidence interval)	Odds Ratio (95% confidence interval)	Odds Ratio (95% confidence interval)
Housing			
Housing problem [c]			1.27 (1.20, 1.34)
Neighborhood stress score [d]			0.99 (0.98, 1.00)
Model performance			
AIC	69,925	69,335	69,089
C statistic*100	66.6	68.26	68.77

Source: Authors' calculations using data on 74,706 hospitalizations between Jan 1st and Dec 1st, 2016 of 42,794 MassHealth managed care eligible adult members.

Abbreviations: ***AIC****, Akaike's information criterion;* ***ACO****, accountable care organization.*

[a] *Estimates are based on hierarchical generalized linear models with a logit link and a binomial distribution.*

[b] *based on entitlement and qualification for specialized services for mental health or developmental disabilities in 2016*

[c] *defined as 3+ distinct addresses or homelessness (Z59.0) on claims or encounter records during 2016.*

[d] *measure summarizing seven neighborhood-level indicators of economic stress using US Census block groups.*

Appendix 3.1: Variable definitions

Serious mental illness and substance use disorders were based on the diagnosis-based Hierarchical Condition Category (DxCG-HCC):
<u>Serious mental illness:</u>
Acute Paranoid Reaction and Confusion
Schizophrenia
Other Nonorganic Psychosis
Delusional Disorder and Paranoid States
Bipolar Disorder
Major Depression
<u>Substance use disorders:</u>
Drug Induced Hallucinations, Delusions, and Delirium
Withdrawal and Other Specified Drug-Induced Mental Disorders
Drug Dependence
Drug Abuse without Dependence, Except Alcohol and Tobacco
Alcohol Psychosis
Alcohol Dependence
Alcohol Abuse, Without Dependence

Housing problems were identified as unstable housing and through international classification of disease (ICD) codes:
<u>Unstable housing:</u>
Defined as 3 or more distinct addresses during 12-month
<u>Homelessness:</u>
Presence of at least one ICD10 code Z59.0 for homelessness in claims or encounter records during 12-month

Neighborhood Stress Score was derived from principal components analysis that identified seven neighborhood-level indicators of economic stress using US Census block groups with American Community Survey
The Neighborhood Stress Score (NSS) is a composite measure of economic stress which summarizes seven census variables that were identified in a principal components analysis on 2013 Massachusetts Medicaid data. The NSS was derived from addresses that were geocoded at the census block group level. It was developed by Dr Arlene Ash and colleagues at the University of Massachusetts Medical School as part of a project to incorporate social determinants of health (SDH) variables into risk adjustment of global payment models for MassHealth.

Census variables in the NSS:
% of families with incomes < 100% of FPL
% < 200% of FPL
% of adults who are unemployed

% of households receiving public assistance
% of households with no car
% of households with children and a single parent
% of people age 25 or older who have no HS degree.

APPENDICES FOR CHAPTER III: SHOULD HIGH-FREQUENCY HOSPITAL USERS BE EXCLUDED FROM 30-DAY READMISSION QUALITY MEASURES?

Table A.4: Risk adjusted odds ratios for 30-day readmission

	Odds Ratio (95% confidence interval)
Age/gender at discharge	
18-24 Female	Ref
25-34 Female	0.91 (0.76, 1.08)
35-44 Female	0.76 (0.65, 0.87)
45-54 Female	0.82 (0.71, 0.95)
55-59 Female	0.68 (0.59, 0.78)
60-64 Female	0.77 (0.67, 0.89)
18-24 Male	0.56 (0.49, 0.65)
25-34 Male	0.68 (0.59, 0.78)
35-44 Male	0.57 (0.49, 0.67)
45-54 Male	0.60 (0.51, 0.70)
55-59 Male	0.54 (0.45, 0.63)
60-64 Male	0.57 (0.48, 0.67)
Morbidity burden (log-transformed)	1.99 (1.91, 2.06)
Behavioral health	
Serious mental illness	1.60 (1.50, 1.70)
Substance use disorder	1.46 (1.38, 1.55)
Disability status	1.29 (1.22, 1.36)
Housing	
Housing problem	1.27 (1.20, 1.34)
Neighborhood stress score	0.99 (0.98, 1.00)
Model performance	
C statistic*100	68.77

Source: Authors' calculations using data on 74,706 hospitalizations between Jan 1st and Dec 1st, 2016 of 42,794 MassHealth managed care eligible adult members.

Abbreviations: ***AIC****, Akaike's information criterion;* ***ACO****, accountable care organization.*
[a] *Estimates are based on hierarchical generalized linear models with a logit link and a binomial distribution.*
[b] *based on entitlement and qualification for specialized services for mental health or developmental disabilities in 2016.*
[c] *defined as 3+ distinct addresses or homelessness (Z59.0) on claims or encounter records during 2016.*
[d] *measure summarizing seven neighborhood-level indicators of economic stress using US Census block groups.*

REFERENCES

1. World Health Organization. TheWorld Health Report 2000: Health Systems, Improving Performance. https://www.who.int/whr/2000/en/whr00_en.pdf%0D. Published 2000. Accessed April 2, 2019.
2. Papanicolas I, Woskie LR, Jha AK. Health care spending in the United States and other high-income countries. *JAMA - J Am Med Assoc*. 2018. doi:10.1001/jama.2018.1150
3. National Institute For Health Care Management. Understanding U.S. health care spending. https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&cad=rja&uact=8&ved=2ahUKEwjyrf3w2rHhAhVow1kKHWo8CaIQFjAAegQIARAB&url=https%3A%2F%2Fwww.nihcm.org%2Fimages%2Fstories%2FNIHCM-CostBrief-Email.pdf&usg=AOvVaw1e1PzwlkwVt5IU2PyCLili. Accessed February 4, 2019.
4. McClellan M, McKethan AN, Lewis JL, Roski J, Fisher ES. A national strategy to put accountable care into practice. *Health Aff*. 2010. doi:10.1377/hlthaff.2010.0194
5. Casalino L, Gillies RR, Shortell SM, et al. External incentives, information technology, and organized processes to improve health care quality for patients with chronic diseases. *J Am Med Assoc*. 2003. doi:10.1001/jama.289.4.434
6. Medicare Program. *Medicare Shared Savings Program: Accountable Care Organizations; Final Rule, 42 CFR Part 425.*; 2011.
7. Joynt KE, Jha AK. Characteristics of hospitals receiving penalties under the hospital readmissions reduction program. *JAMA - J Am Med Assoc*. 2013. doi:10.1001/jama.2012.94856
8. Joynt KE, Jha AK. Thirty-Day Readmissions — Truth and Consequences. *N Engl J Med*. 2012. doi:10.1056/nejmp1201598
9. Medicaid C for M and, Reduction SR, (HRRP) P. https://www.cms.gov/medicare/medicare-fee-for-service-payment/acuteinpatientpps/readmissions-reduction-program.html. Accessed April 2, 2016.
10. Medicare & Medicaid Services. The Medicare Current Beneficiary Survey. https://www.cms.gov/Research-Statistics-Data-and-Systems/Research/MCBS/. Accessed February 4, 2019.
11. U.S. Census Bureau. The American Community Survey (ACS). https://www.census.gov/programs-surveys/acs/. Accessed February 4, 2019.
12. Hansen LO, Young RS, Hinami K, Leung A, Williams M V. Interventions to reduce 30-day rehospitalization: A systematic review. *Ann Intern Med*. 2011. doi:10.7326/0003-4819-155-8-201110180-00008
13. Benjamin EJ, Blaha MJ, Chiuve SE, et al. Heart Disease and Stroke Statistics’2017 Update: A Report from the American Heart Association. *Circulation*. 2017. doi:10.1161/CIR.0000000000000485
14. Roger VL, Go AS, Lloyd-Jones DM, et al. Heart disease and stroke statistics-2011

update: A report from the American Heart Association. *Circulation*. 2011;123(4). doi:10.1161/CIR.0b013e3182009701

15. D'Agostino RB, Vasan RS, Pencina MJ, et al. General cardiovascular risk profile for use in primary care: The Framingham heart study. *Circulation*. 2008;117(6):743-753. doi:10.1161/CIRCULATIONAHA.107.699579
16. Eppig FJ, Chulis GS. Matching MCBS (Medicare Current Beneficiary Survey) and Medicare data: the best of both worlds. *Health Care Financ Rev*. 1997.
17. Davidoff A, Lopert R, Stuart B, Shaffer T, Lloyd JT, Shoemaker JS. Simulated value-based insurance design applied to statin use by medicare beneficiaries with diabetes. *Value Heal*. 2012. doi:10.1016/j.jval.2012.01.008
18. Lipstein SH, Dunagan WC. The Risks of Not Adjusting Performance Measures for Sociodemographic Factors. *Ann Intern Med*. 2014. doi:10.7326/m14-1601
19. Glance LG, Kellermann AL, Osler TM, Li Y, Li W, Dick AW. Impact of risk adjustment for socioeconomic status on risk-adjusted surgical readmission rates. *Ann Surg*. 2016. doi:10.1097/SLA.0000000000001363
20. Joynt KE, De Lew N, Sheingold SH, Conway PH, Goodrich K, Epstein AM. Should Medicare Value-Based Purchasing Take Social Risk into Account? *N Engl J Med*. 2016. doi:10.1056/nejmp1616278
21. Star Ratings. Medicare.gov. https://www.medicare.gov/find-a-plan/staticpages/rating/planrating-help.aspx?AspxAutoDetectCookieSupport=1.
22. Van Walraven C, Bennett C, Jennings A, Austin PC, Forster AJ. Proportion of hospital readmissions deemed avoidable: A systematic review. *CMAJ*. 2011. doi:10.1503/cmaj.101860
23. Quality Net Org. QualityNet. http://www.qualitynet.org/dcs/ContentServer?c=Page&pagename=QnetPublic%2FPage%2FQnetTier3&cid=1219069855841. Published 2018. Accessed April 2, 2019.
24. Kansagara D, Englander H, Salanitro A, et al. Risk prediction models for hospital readmission: A systematic review. *JAMA - J Am Med Assoc*. 2011. doi:10.1001/jama.2011.1515
25. Joynt KE, Jha AK. A Path Forward on Medicare Readmissions. *N Engl J Med*. 2013. doi:10.1056/NEJMp1300122
26. Calvillo-King L, Arnold D, Eubank KJ, Lo M, Yunyongying P, Stieglitz H, Halm EA. Impact of social factors on risk of readmission or mortality in pneumonia and heart failure: Systematic review. *J Gen Intern Med*. 2013. doi:http://dx.doi.org/10.1007/s11606-012-2235-x
27. Joynt Maddox, KE, Reidhead, M, Hu, J et al. Adjusting for social risk factors impacts performance and penalties in the hospital readmissions reduction program. *Heal Serv Res*. 2019;54:327– 336.
28. Bernheim SM, Parzynski CS, Horwitz L, et al. Accounting For Patients' Socioeconomic Status Does Not Change Hospital Readmission Rates. *Health Aff*. 2016. doi:10.1377/hlthaff.2015.0394
29. Care RIA, Quality organization 2016 program, Specifications measure narrative. https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&cad=rj

a&uact=8&ved=2ahUKEwjtwLC57KfgAhXuct8KHY9IAqUQFjAAegQIChAC&url=https%3A%2F%2Fwww.cms.gov%2FMedicare%2FMedicare-Fee-for-Service-Payment%2Fsharedsavingsprogram%2FDownloads%2F2016-ACO-Narr. Accessed April 2, 2019.

30. Methodology C for M and MSM. https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/HospitalQualityInits/Measure-Methodology.html. Accessed April 2, 2019.
31. Adler GS. A profile of the Medicare Current Beneficiary Survey. *Health Care Financ Rev*. 1994;15(4):153-163.
32. Mass.gov. The Executive Office of Health and Human Services. MassHealth Launches Restructuring To Improve Health Outcomes for 1.2 Million Members. https://www.mass.gov/news/masshealth-launches-restructuring-to-improve-health-outcomes-for-12-million-members.
33. Roger VL, Go AS, Lloyd-Jones DM, et al. Heart disease and stroke statistics-2011 update: A report from the American Heart Association. *Circulation*. 2011. doi:10.1161/CIR.0b013e3182009701
34. Sacks NC, Ash AS, Ghosh K, Rosen AK, Wong JB, Rosen AB. Trends in acute myocardial infarction hospitalizations: Are we seeing the whole picture? *Am Heart J*. 2015. doi:10.1016/j.ahj.2015.09.009
35. Matlock DD, Groeneveld PW, Sidney S, et al. Geographic variation in cardiovascular procedure use among medicare fee-for-service vs medicare advantage beneficiaries. *JAMA - J Am Med Assoc*. 2013. doi:10.1001/jama.2013.7837
36. Rowe VL, Weaver FA, Lane JS, Etzioni DA. Racial and ethnic differences in patterns of treatment for acute peripheral arterial disease in the United States, 1998-2006. *J Vasc Surg*. 2010. doi:10.1016/j.jvs.2009.09.066
37. Chen J, Normand SLT, Wang Y, Krumholz HM. National and regional trends in heart failure hospitalization and mortality rates for medicare beneficiaries, 1998-2008. *JAMA - J Am Med Assoc*. 2011. doi:10.1001/jama.2011.1474
38. McDonald RJ, Kallmes DF, Cloft HJ. Comparison of hospitalization costs and medicare payments for carotid endarterectomy and carotid stenting in asymptomatic patients. *Am J Neuroradiol*. 2012. doi:10.3174/ajnr.A2791
39. Andrade SE, Harrold LR, Tjia J, et al. A systematic review of validated methods for identifying cerebrovascular accident or transient ischemic attack using administrative data. *Pharmacoepidemiol Drug Saf*. 2012. doi:10.1002/pds.2312
40. Nagi SZ. An epidemiology of disability among adults in the United States. *Milbank Mem Fund Q Health Soc*. 1976;54(4):439-467.
41. Ash AS, Ellis RP, Pope GC, et al. Using diagnoses to describe populations and predict costs. *Health Care Financ Rev*. 2000;21(3):7-28. doi:Article
42. Gould MK, Fletcher J, Iannettoni MD, et al. Evaluation of patients with pulmonary nodules: When is it lung cancer? ACCP evidence-based clinical practice guidelines (2nd edition). Chest. 2007;132(3 SUPPL.). doi:10.1378/chest.07-1353.
43. Efron B TR. *An Introduction to the Bootstrap*. Boca Raton, FL: Chapman and Hall; 1993.

44. Pencina MJ, D'Agostino RB, D'Agostino RB, Vasan RS. Evaluating the added predictive ability of a new marker: from area under the ROC curve to reclassification and beyond. *Stat Med*. 2008. doi:10.1002/sim.2929
45. Achhra AC, Amin J, Sabin C, et al. Reclassification of risk of death with the knowledge of D-dimer in a cohort of treated HIV-infected individuals. *AIDS*. 2012. doi:10.1097/QAD.0b013e328355d659
46. Goff DC, Lloyd-Jones DM, Bennett G, et al. 2013 ACC/AHA guideline on the assessment of cardiovascular risk: A report of the American college of cardiology/American heart association task force on practice guidelines. *J Am Coll Cardiol*. 2014. doi:10.1016/j.jacc.2013.11.005
47. Muntner P, Colantonio LD, Cushman M, et al. Validation of the atherosclerotic cardiovascular disease Pooled Cohort risk equations. *JAMA - J Am Med Assoc*. 2014. doi:10.1001/jama.2014.2630
48. Gaziano TA, Young CR, Fitzmaurice G, Atwood S, Gaziano JM. Laboratory-based versus non-laboratory-based method for assessment of cardiovascular disease risk: the NHANES I Follow-up Study cohort. *Lancet*. 2008. doi:10.1016/S0140-6736(08)60418-3
49. Vaidya D, Yanek LR, Moy TF, Pearson TA, Becker LC, Becker DM. Incidence of Coronary Artery Disease in Siblings of Patients With Premature Coronary Artery Disease: 10 Years of Follow-up. *Am J Cardiol*. 2007. doi:10.1016/j.amjcard.2007.06.031
50. Ho PM, Bryson CL, Rumsfeld JS. Medication adherence: Its importance in cardiovascular outcomes. *Circulation*. 2009;119(23):3028-3035. doi:10.1161/CIRCULATIONAHA.108.768986
51. Miyasaka Y, Barnes ME, Gersh BJ, et al. Coronary Ischemic Events after First Atrial Fibrillation: Risk and Survival. *Am J Med*. 2007. doi:10.1016/j.amjmed.2006.06.042
52. Extermann M, Overcash J, Lyman GH, Parr J, Balducci L. Comorbidity and functional status are independent in older cancer patients. *J Clin Oncol*. 1998. doi:10.1200/JCO.1998.16.4.1582
53. Parmelee PA, Thuras PD, Katz IR, Lawton MP. Validation of the Cumulative Illness Rating Scale in a Geriatric Residential Population. *J Am Geriatr Soc*. 1995. doi:10.1111/j.1532-5415.1995.tb06377.x
54. Waldman E, Potter JF. A prospective evaluation of the cumulative illness rating scale. *Aging Clin Exp Res*. 1992. doi:10.1007/BF03324087
55. Keller BK, Potter JF. Predictors of mortality in outpatient Geriatric Evaluation and Management clinic patients. *Journals Gerontol*. 1994. doi:10.1093/geronj/49.6.M246
56. Osterberg L, Blaschke T. Drug Therapy: Adherence to Medication. *N Engl J Med*. 2005;353:487-497. doi:10.1056/NEJMra050100
57. Cramer JA. A Systematic Review of Adherence with Medications for Diabetes. *Diabetes Care*. 2004. doi:10.2337/diacare.27.5.1218
58. Zeng F, An JJ, Scully R, Barrington C, Patel B V., Nichol MB. The impact of value-based benefit design on adherence to diabetes medications: A propensity

score-weighted difference in difference evaluation. *Value Heal*. 2010. doi:10.1111/j.1524-4733.2010.00730.x

59. Choudhry NK, Fischer MA, Avorn J, et al. At pitney bowes, value-based insurance design cut copayments and increased drug adherence. *Health Aff*. 2010. doi:10.1377/hlthaff.2010.0336
60. Maciejewski ML, Farley JF, Parker J, Wansink D. Copayment reductions generate greater medication adherence in targeted patients. *Health Aff*. 2010. doi:10.1377/hlthaff.2010.0571
61. Mahoney JJ. Reducing patient drug acquisition costs can lower diabetes health claims. *Am J Manag Care*. 2005.
62. Rosen AB, Hamel MB, Weinstein MC, Cutler DM, Fendrick AM, Vijan S. Cost-effectiveness of full medicare coverage of angiotensin-converting enzyme inhibitors for beneficiaries with diabetes. *Ann Intern Med*. 2005;143(2). doi:10.1016/j.accreview.2005.09.019
63. National Institute For Health Care Management. Understanding U.S. health care spending. https://www.nihcm.org/images/stories/NIHCM-CostBrief-Email.pdf. Accessed October 6, 2018.
64. Guzder RN, Gatling W, Mullee MA, Mehta RL, Byrne CD. Prognostic value of the Framingham cardiovascular risk equation and the UKPDS risk engine for coronary heart disease in newly diagnosed Type 2 diabetes: Results from a United Kingdom study. *Diabet Med*. 2005. doi:10.1111/j.1464-5491.2005.01494.x
65. McEwan P, Williams JE, Griffiths JD, et al. Evaluating the performance of the Framingham risk equations in a population with diabetes. *Diabet Med*. 2004. doi:10.1111/j.1464-5491.2004.01139.x
66. Stevens RJ, Coleman RL, Holman RR. Framingham risk equations underestimate coronary heart disease risk in diabetes [4]. *Diabet Med*. 2005. doi:10.1111/j.1464-5491.2005.01387.x
67. D'Agostino, Sr RB, Grundy S, Sullivan LM, Wilson P, for the CHD Risk Prediction Group for the CRP. Validation of the Framingham Coronary Heart Disease Prediction Scores. *JAMA*. 2001. doi:10.1001/jama.286.2.180
68. Sacco RL, Khatri M, Rundek T, et al. Improving Global Vascular Risk Prediction With Behavioral and Anthropometric Factors. The Multiethnic NOMAS (Northern Manhattan Cohort Study). *J Am Coll Cardiol*. 2009. doi:10.1016/j.jacc.2009.07.047
69. P. BB and J. How Healthcare Studies Use Claims Data. *Open Heal Serv Policy J*. 2011;4.1:26–29.
70. Duncan I. Mining Health Claims Data for Assessing Patient Risk. In: ; 2012. doi:10.1007/978-3-642-23151-3_4
71. Kocher RP, Adashi EY. Hospital readmissions and the affordable care act: Paying for coordinated quality care. *JAMA - J Am Med Assoc*. 2011. doi:10.1001/jama.2011.1561
72. Zuckerman RB, Sheingold SH, Orav EJ, Ruhter J, Epstein AM. Readmissions, Observation, and the Hospital Readmissions Reduction Program. *N Engl J Med*. 2016. doi:10.1056/NEJMsa1513024

73. Medicare Payment Advisory Commission. *Report to the Congress: Medicare and the Health Care Delivery System*.(2013).
74. Barnett ML, Hsu J, Michael McWilliams J. Patient characteristics and differences in hospital readmission rates. *JAMA Intern Med*. 2015. doi:10.1001/jamainternmed.2015.4660
75. Hu J, Gonsahn MD, Nerenz DR. Socioeconomic status and readmissions: Evidence from an urban teaching hospital. *Health Aff*. 2014. doi:10.1377/hlthaff.2013.0816
76. Hu J, Kind AJH, Nerenz D. Area Deprivation Index Predicts Readmission Risk at an Urban Teaching Hospital. *Am J Med Qual*. 2018. doi:10.1177/1062860617753063
77. Loignon C, Fortin M, Bedos C, et al. Providing care to vulnerable populations: A qualitative study among GPs working in deprived areas in Montreal, Canada. *Fam Pract*. 2015. doi:10.1093/fampra/cmu094
78. Kind AJH, Jencks S, Brock J, et al. Neighborhood Socioeconomic Disadvantage and 30-Day Rehospitalization. *Ann Intern Med*. 2014. doi:10.7326/M13-2946
79. Arbaje AI, Wolff JL, Yu Q, Powe NR, Anderson GF, Boult C. Postdischarge environmental and socioeconomic factors and the likelihood of early hospital readmission among community-dwelling medicare beneficiaries. *Gerontologist*. 2008. doi:10.1093/geront/48.4.495
80. YNHHSC/CORE. 2018 Condition-Specific Measures Updates and Specifications Report Hospital-Level 30-Day Risk-Standardized Readmission Measures. http://www.qualitynet.org/dcs/ContentServer?cid=1219069855841&pagename=QnetPublic%2FPage%2FQnetTier3&c=Page.
81. NCQA. The National Committee for Quality Assurance. https://www.ncqa.org/. Accessed April 2, 2019.
82. Centers for Medicare & Medicaid Services. https://www.cms.gov/Medicare/Health-Plans/MedicareAdvtgSpecRateStats/Risk-Adjustors.html.
83. Ash AS, Mick EO, Ellis RP, Kiefe CI, Allison JJ, Clark MA. Social determinants of health in managed care payment formulas. *JAMA Intern Med*. 2017. doi:10.1001/jamainternmed.2017.3317
84. Calvillo-King L, Arnold D, Eubank KJ, et al. Impact of social factors on risk of readmission or mortality in pneumonia and heart failure: Systematic review. *J Gen Intern Med*. 2013. doi:10.1007/s11606-012-2235-x
85. Sall L, Hayward RD, Fessler MM EE. Between-hospital and between-neighbourhood variance in trauma outcomes: cross-sectional observational evidence from the Detroit metropolitan area. *BMJ Open*. 2018;8(11):e022.
86. Kripalani S, Theobald CN, Anctil B, Vasilevskis EE. Reducing Hospital Readmission Rates: Current Strategies and Future Directions. *Annu Rev Med*. 2013. doi:10.1146/annurev-med-022613-090415
87. Naylor MD, Brooten D, Campbell R, et al. Comprehensive discharge planning and home follow-up of hospitalized elders: A randomized clinical trial. *J Am Med Assoc*. 1999. doi:10.1001/jama.281.7.613

88. Naylor M, Brooten D, Jones R, Lavizzo-Mourey R, Mezey M, Pauly M. Comprehensive discharge planning for the hospitalized elderly: A randomized clinical trial. *Ann Intern Med*. 1994. doi:10.7326/0003-4819-120-12-199406150-00005
89. Carroll KM, Onken LS. Behavioral therapies for drug abuse. *Am J Psychiatry*. 2005. doi:10.1176/appi.ajp.162.8.1452
90. Corrigan PW, Shapiro JR. Measuring the impact of programs that challenge the public stigma of mental illness. *Clin Psychol Rev*. 2010. doi:10.1016/j.cpr.2010.06.004
91. Goldfield NI, McCullough EC, Hughes JS, et al. Identifying potentially preventable readmissions. *Health Care Financ Rev*. 2008.
92. Mull HJ, Chen Q, O'Brien WJ, et al. Comparing 2 methods of assessing 30-day readmissions: What is the impact on hospital profiling in the veterans health administration? *Med Care*. 2013. doi:10.1097/MLR.0b013e31829019a4
93. Williams DR, Costa M V, Odunlami AO, Mohammed SA. Moving Upstream: How Interventions That Address the Social Determinants of Health Can Improve Health and Reduce Disparities. *J Public Health Manag Pract.* 2008. doi:10.1097/01.PHH.0000338382.36695.42.