Quality Reporting System Risk Adjustment Assessment

REPORT TO THE MINNESOTA LEGISLATURE

Minnesota Department *of* Health

HEALTH ECONOMICS PROGRAM

Quality Reporting System Risk Adjustment Assessment

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MDH
Minnesota
Department
of Health

PROTECTING, MAINTAINING AND IMPROVING THE HEALTH OF ALL MINNESOTANS

March 23, 2017

The Honorable Jim Abeler
Chair, Human Services Reform Finance and Policy Committee
Minnesota Senate
Room 3215, Minnesota Senate Building
95 University Avenue W.
Saint Paul, MN 55155

The Honorable Michelle Benson
Chair, Health, Human Services Policy and Finance Committee
Minnesota Senate
Room 3109, Minnesota Senate Building
95 University Avenue W.
Saint Paul, MN 55155

The Honorable Joe Schomacker
Chair, Health, Human Services Reform Committee
Minnesota House of Representatives
Room 509, State Office Building
100 Rev. Dr. Martin Luther King Jr. Blvd.
Saint Paul, MN 55155-1606

The Honorable Matt Dean
Chair, Health, Human Services Finance Committee
Minnesota House of Representatives
Room 401, State Office Building
100 Rev. Dr. Martin Luther King Jr. Blvd.
Saint Paul, MN 55155

Dear Senator Abeler, Senator Benson, Representative Schomacker, and Representative Dean:

As required by 2014 Minnesota Laws, chapter 312, article 23, section 10, this report presents findings from a study by the Minnesota Department of Health about assessing the risk adjustment methodology used for the Minnesota Statewide Quality Reporting and Measurement System (Quality Reporting System).

This study was prompted by concerns among safety net providers about the potential unintended consequences associated with the use of quality measures that don't fully consider factors associated with patient complexity in new, value-based payment models.

MDH conducted:

- A review of reports and peer reviewed literature related to quality measurement and risk adjustment that includes socio-demographic factors;

- Consultation with stakeholders, including safety net providers that primarily serve communities and patient populations with health disparities, health care purchasers, providers, and quality measurement organizations;
- An empirical analysis with researchers from the University of Minnesota to risk adjust quality measure data using socio-demographic factors; and
- An environmental scan of local and national quality measure risk adjustment activities.

Eliminating health disparities and creating a culture of health equity in which all individuals have the opportunity to be healthy is among MDH's highest priorities. We know that patient socio-demographic factors matter in the assessment of provider performance, but we still don't know the relationships between these factors and performance outcomes. This report attempts to explain some of that complexity, and lays out a series of policy options that offer ways to minimize harms to providers who serve patients that experience health disparities, while allowing us to continue to identify and reduce disparities in patient outcomes. These options will help us continue to move forward—together with our partners that provide and pay for health care, and publicly report outcomes—in improving our approach to risk adjusting quality measures and accounting for patient socio-demographic factors in quality measurement.

If you have questions or concerns regarding this study, please contact Stefan Gildemeister, the State Health Economist, at 651-201-3554 or Stefan.Gildemeister@state.mn.us.

Sincerely,

Edward P. Ehlinger, M.D., M.S.P.H,

Commissioner of Health

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Executive Summary

Enacted in 2008, Minnesota's Health Reform Law requires the Commissioner of Health to establish a standardized set of quality measures for health care providers (i.e., physician clinics and hospitals) across Minnesota, creating a more uniform approach to quality measurement to enhance market transparency and drive health care quality improvement.[1] The standardized quality measure set is called the Minnesota Statewide Quality Reporting and Measurement System (Quality Reporting System).[2]

Because quality measures are publicly reported and can be integrated in financial incentive programs or value-based payment models, it is important that they accurately convey relative provider performance and appropriately consider providers' patient populations. One way to control for the effect of factors outside of the control of providers, including patient-related factors, is to "risk adjust" quality measure results when calculating results.

The Minnesota Department of Health (MDH) is required to risk adjust Quality Reporting System measures, and does so currently by using the type of primary health insurance payer (e.g., distinguishing between commercial insurance and Medicaid) as a proxy for income for most measures, and severity for the depression measure.

In 2014, the Minnesota Legislature directed MDH to:

- Assess whether the Quality Reporting System's risk adjustment methodology creates potential harms and unintended consequences for patient populations who experience health disparities and the providers who serve them; and
- Identify changes that may be needed to alleviate harm and unintended consequences.

Accordingly, MDH conducted a literature review, obtained stakeholder input, worked with researchers from the University of Minnesota (University) to conduct an empirical analysis, and performed an environmental scan of related local and national research activities.

MDH intentionally took a statewide perspective, rather than just narrowly looking at the program we administer, recognizing that the question of whether and how to incorporate measures of patient socio-demographic characteristics into the assessment of provider quality could have an impact beyond the limited reach of the Quality Reporting System.

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[1] Minnesota Statutes, section 62U.02.

[2] Minnesota Administrative Rules, chapter 4654.

Key Findings

- There is powerful evidence in literature and practice about how patient demographics, such as poverty and education, as well as community characteristics, including safety, transit and housing, affect people's ability to achieve and maintain good health.

- In addition, there is a growing body of evidence that suggests patient characteristics or socio-demographic factors also need to be considered more effectively when measuring the quality of care that doctors and clinics provide to patients. Yet, we lack evidence on which factors are the most relevant and how large the impact of patient characteristics is on quality measure outcomes compared to provider practice patterns or health care system characteristics.

- MDH's current risk adjustment methodology does not appear to cause financial harm to providers who serve disadvantaged populations, or their patients. This is in part because our risk-adjusted measures are currently used only in one pay-for-performance program that covers a very narrow subset of the population.

- However, safety net providers are very concerned about unintended financial and reputational consequences resulting from a greater use of quality-based payment systems without deeper risk adjustment. These providers worry that, longer-term, these consequences could impact access to care for disadvantaged populations, and they are concerned that potential improvements to the MDH risk adjustment approach would not apply to the broader market because of a lack of a uniform approach to risk adjustment in the state.

- The empirical component of the study showed *available* socio-demographic factor data that are not currently used in MDH's risk adjustment methodology do not meaningfully improve risk adjustment. To potentially improve risk adjustment, MDH and the community need new risk factor data with a strong link to quality measure outcomes and data that can be available at more detailed levels.

- Comparing the performance of clinics that see similar patients by clustering like clinics together can potentially aid in making more meaningful and fair comparisons.

- Efforts by other local and national stakeholders to investigate the role of patient socio-demographic factors in health care quality measurement—and whether and how to incorporate them in risk adjustment—will produce important insights for MDH's work and the community.

Conclusions

The question of whether and how to adjust quality performance measures in Minnesota and the nation is complex, because of the relative lack of data on patient characteristics in health care delivery; the concern that changes would mask variation in care that patients should know about; and the complexity of factors that contribute to patients reaching and maintaining good health.

Based on the findings of the study, we have concluded that changes to the MDH risk adjustment method—as currently applied to a small share of the patient population—would be premature and not produce meaningful improvements. However, we found that gains in measuring relevant concepts of patient factors that are conceptually related to provider performance, and availability of more granular data, offer opportunities for refining current risk adjustment approaches across the state. Implementing these changes over time would be most effective if there was alignment in measure risk adjustment across payers.

Although MDH will maintain its risk adjustment methodology in the Quality Incentive Payment System in the near term, we have identified a range of tools and policies that can address, in the short term, potential unintended consequences of quality measurement on safety net and other providers in Minnesota, including:

- Identifying and paying for non-medical support services that have been shown to improve patient outcomes for people who face economic and social barriers to good health;
- On a targeted basis, financially rewarding improvements in quality performance more strongly than absolute goals;
- Comparing the performance of clinics that have similar features and see similar types of patients; and
- Offering more contextual information within public reporting platforms about the unmeasured impact of patient complexity factors.

Use of these tools and policies would recognize that risk adjustment, as a technique, will always be limited in accomplishing multiple, finely targeted policy goals.

Recognizing that research and available data related to risk adjustment are rapidly evolving, and others in the market are also grappling with this issue, MDH will continue to coordinate with and learn from risk adjustment research using socio-demographic factors that others are conducting locally and nationally, and use those learnings to advance and refine the Quality Reporting System risk adjustment methodology.

Introduction

Although Minnesota ranks among the healthiest states in the nation, it simultaneously experiences significant and persistent disparities in health outcomes for some segments of the population. To eradicate these disparities, it is important for the State to foster health equity, which means creating the "conditions in which all people have the opportunity to attain their highest possible level of health," (MDH, 2014). One of the challenges related to developing and evaluating programs to address and eliminate health disparities is the relative lack of data on the manner and size of the contribution of a range of socio-demographic factors (MDH & DHS, 2011). This is largely true across all settings affecting health, including transportation and justice, but also medical care services.

With regard to the health care delivery system, Minnesota has led the nation in its efforts to measure and report on various aspects of clinical quality. After a number of years of voluntary reporting, Minnesota has required the collection of quality measurement data from physician clinics and hospitals since 2009 through the Statewide Quality Reporting and Measurement System (Quality Reporting System). (Appendix A includes more information on the history and administration of the Quality Reporting System.)

Quality measures are increasingly used by health care providers, payers, and others to help assess provider care quality. For providers who predominantly serve patient populations that experience health disparities, there is concern that they will score low on quality measures that fail to take patient characteristics (or socio-demographic factors), and the effect these characteristics can have on reaching performance goals, into account. Furthermore, when quality measures are used in value-based purchasing and pay-for-performance programs, these providers may not be eligible for performance rewards and incur financial penalties for not meeting quality measure benchmarks due to characteristics of their patient population.

Socio-demographic characteristics are important for understanding system-wide variations and disparities in quality of care because evidence shows that many of the factors that most heavily impact a person's health status exist outside of the health care system. These include factors such as race, language, income, education level, neighborhood assets, access to healthy food, and housing stability (MDH, 2014).[3] While a health care provider may not be able to directly influence many of these factors, a deeper understanding of them can impact the type of care that the provider recommends, the likelihood that the care provided will actually improve the patient's health status, or the types of supportive services that may be necessary for the patient as part of any treatment regimen. The recognition of such factors in the delivery and measurement of care has strong support in multiple sectors, including the state's largest businesses and employers, who specifically recommended expanding quality measurement to address recognized gaps and omissions as a strategy to better assess disparities.[4] Moreover, there are other factors such as co-existing conditions, severity of disease, and age of patients, that also affect the likelihood of achieving good health outcomes and delivering high-quality care, and are outside of the control of the physician.

Along with increased awareness of the socio-demographic factors that create health, there is also growing interest in accounting for socio-demographic factors in health care quality measurement and the use in value-based purchasing initiatives. One way to combine socio-demographic and other risk factors with quality measures to isolate the physician contribution to health outcomes is to use these factors to "risk adjust" quality measure results by using statistical methods to account for patient-related factors when computing quality measure scores.

Proponents of using patient socio-demographic factors to risk adjust quality measures think that doing so could provide a more fair assessment of the care quality provided by a clinic or hospital and should guard against penalizing providers who care for disadvantaged patients (NASEM, 2016a); it would also balance the playing field in provider-to-provider comparisons. Those who are skeptical of adjusting measures with patient socio-demographic factors are concerned that this adjustment may mask disparities in the provision of care and thus make it difficult to hold those providing lower quality care accountable. Additionally, critics are concerned that such adjustment may implicitly create the acceptance of a lower standard of

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[3] There is an active discussion among measurement experts, public health officials, health care providers, government representatives and others to assess what additional socio-demographic factors—whether measurable in the current environment or not—are important to our understanding of health equity or what helps ensure high quality of health care and health outcomes.

[4] Minnesota Business Partnership, Minnesota's Health Care Performance Scorecard 30, Jan. 2015, http://mnbp.com/wp-content/uploads/2015/02/MBP_HealthScorecard.pdf.

care for vulnerable patients, if it is driven by provider practices or other factors under the control of the health care delivery system.

Recognizing these issues, in 2014, the Minnesota Legislature directed the Minnesota Department of Health (MDH) to perform two tasks:

1. To assess whether the Quality Reporting System risk adjustment methodology creates potential harms and unintended consequences for patient populations who experience health disparities and the providers who serve them, and
2. To identify changes that may be needed to alleviate harm and unintended consequences (Appendix B).[5, 6]

In 2015, the Minnesota Legislature directed MDH to risk adjust quality measures for patient characteristics that are correlated with health disparities and have an impact on performance on quality measures, effective July 1, 2017.[7] Although quality measures can be used in value-based payment models, adjusting the quality performance *rate* (e.g., the percent of a population that receives optimal care for a certain condition) is distinct from risk adjusting *payment*. In parallel to the direction to MDH, the Legislature also directed the Department of Human Services (DHS) to develop a risk adjustment mechanism for payments to providers that considers the potential higher cost, complexity, and resources needed to serve patients of varying demographic characteristics.[8]

Background

Quality Measure Risk Adjustment

Quality measurement initiatives have grown from a tool that helps us collectively understand how much variation there is in health care quality and that the link between cost and quality is

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[5] Minnesota Laws 2014, chapter 312, article 23, section 10.

[6] In 2014, the Minnesota Legislature also directed MDH to develop an implementation plan for stratifying Quality Reporting System measures based on disability, race, ethnicity, language, and other socio-demographic factors that are correlated with health disparities and impact performance on quality measures (Minnesota Laws 2014, chapter 312, article 23, section 10). In early 2015, MDH submitted the plan to the Legislature, titled "Stratifying Health Care Quality Measures Using Socio-demographic Factors". In 2015, the Minnesota Legislature directed MDH to begin stratifying five clinic quality measures by race, ethnicity, preferred language and country of origin in 2016 (Minnesota Laws 2015, chapter 71, article 9, sections 4-7).

[7] Minnesota Laws 2015, chapter 71, article 9, sections 4-7.

[8] Minnesota Laws 2015, chapter 71, article 9, section 63.

a tenuous one, to seeking to ultimately improve the quality of care that providers deliver to patients.

Quality measures are specific qualitative or quantitative indicators that evaluate:

- Patient health outcomes (e.g., whether a patient’s functional status improved after surgery);
- Processes of care (e.g., whether a recommended drug was delivered);
- Structural features of health care organizations and facilities (e.g., electronic health record (EHR) adoption and provider to patient ratios);
- Patient experience, access, and safety; and
- Other results for a defined patient population.

By measuring health care quality, providers, health plans, and others can identify strengths and weaknesses in the provision of care, and develop care and system improvements to advance patient health outcomes.

Health care providers, payers, and others use quality measures in quality improvement initiatives, public reporting, and incentive programs or value-based payment arrangements. In addition, it is thought that over time, as quality measure reporting covers more services and becomes significantly more consumer-friendly, patients may consider provider performance as one factor in their decisions over where to seek care and which provider networks to choose at the point of purchasing insurance coverage.

Various clinical characteristics such as diagnoses and conditions, and patient characteristics—including illness severity, and socio-demographic factors such as poverty and race—influence health outcomes and therefore can effect quality measure results (NQF, 2014). When quality measures are influenced by factors other than the care received, they may need to be adjusted before being used in public reporting and incentive programs to avoid incorrect inferences about provider performance and enable fair comparisons.

“Risk adjustment” of quality measures is a process that controls or accounts for patient-related factors that may independently affect results of a given measure and are not randomly distributed across all providers.[9] Risk adjustment is not appropriate for all types of quality measures. Quality measures based on clinician-controlled care processes (e.g., immunizations, preventive screenings) may be ill-suited to risk adjustment, since these processes are generally not impacted by patient factors. Risk adjustment is more likely to be appropriate for patient-

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[9] Risk adjustment is also used in other contexts. For example, in epidemiology, it is used to adjust for confounding factors, such as age, when comparing death or disease rates in different populations. In the insurance industry, risk adjustment is used to assess differing patterns of utilization across population groups.

controlled processes and outcome measures that are influenced by a patient's life circumstances or environment (NQF, 2014).

While risk adjusting quality scores for patient characteristics can aid in more equitable comparisons, there are limitations to its effectiveness.

- Risk adjustment can reduce differences or variation in quality scores between providers or across patient categories. This can mask disparities in the quality of health care and disguise poor care provided to disadvantaged patients.
- Risk adjusting for certain patient characteristics can create lower standards of care for these patient groups.
- Also, risk adjustment is only possible if there is high-quality data available on the relevant risk factors, and if there is a robust understanding of what the relevant factors are and how to measure them.

Risk adjustment is distinct from the methods of stratifying quality measures by key factors. Instead of reporting an *adjusted* overall rate, reporting occurs by key factors, socio-demographic variables or peer groups to enable evaluating health care quality and compare provider performance for these groupings.[10] As such, stratification enables the identification of health care disparities for certain patient groups and it can unmask health care disparities by examining performance for groups who have been historically disadvantaged compared to groups who have not been disadvantaged. Peer grouping refers to a method of grouping providers that care for a similar mix of patients and then making performance comparisons among providers in that group. Both of these methods can complement risk adjustment and help to address its limitations. Overall, it is important to consider the objective of quality measurement (e.g., public reporting, payment, quality improvement) to determine whether to use unadjusted, adjusted, stratified, or peer grouped results.

Quality Reporting System Risk Adjustment Methodology

As part of the Commissioner of Health's responsibility to develop a standard set of quality measures and a system for offering quality incentive payments (called the Quality Incentive

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[10] "Stratification" refers to calculating health care performance scores separately for different patient groups based on some characteristic (NQF, 2014). For example, groups could be constructed based on race and performance scores computed for each group.

Payment System), the Commissioner is required to develop a risk adjustment system for measures of quality. In 2015, the Minnesota Legislature added requirements that the risk adjustment system must adjust for patient characteristics, "…that are correlated with health disparities and have an impact on performance on quality measures," beginning July 1, 2017.[11] To the extent possible, MDH is required to adjust for variations in patient population within the Quality Incentive Payment System to reduce potential incentives to health care providers to avoid high-risk patients or populations. In 2015, the Legislature further defined high-risk patients and populations to include those with risk factors related to race, ethnicity, language, country of origin, and other socio-demographic factors.

The Quality Reporting System uses a direct standardization, or "standardized mix" approach in risk adjusting physician clinic measures.[12] Under this approach, risk adjusted results show how each clinic or medical group would perform with the same, hypothetical, statewide population. Variables used for risk adjustment in the Quality Reporting System include primary payer type (as a proxy for income) for most measures, and severity for depression.[13] (Appendix C includes a detailed presentation and an illustrative example of the application of this risk adjustment methodology.) While MDH develops the risk adjustment methodology for the Quality Reporting System, it delegates the process of risk adjustment to its data collection and measure development contractor.

MDH developed its risk adjustment methodology for the Quality Reporting and Quality Incentive Payment Systems in 2009 in collaboration with a work group of experts. At that time, the workgroup concluded that, considering available data, risk adjustment by payer mix using a direct standardization methodology would offer the best available proxy for differences in the socio-demographic characteristics of clinics' patient populations. That is, by risk adjusting quality scores to account for differences to the average statewide payer mix, variations not under the control of the provider would be reasonably well adjusted and controlled for within the calculation of the measure.

MDH's aims in developing its risk adjustment methodology were to seek something that was robust, not administratively burdensome for providers, and also simple to understand for the public and for health care providers. While more sophisticated methods and models of adjusting for clinical and population differences among providers were considered at that time, and would have been possible, more comprehensive approaches would have required additional data which would have resulted in administrative burden for providers.

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[11] Minnesota Laws 2015, chapter 71, article 9, sections 4-7.

[12] MDH does not risk adjust hospital quality measures as these measures are highly aligned with federal reporting requirements and standards for adjustment, and MDH does not hold the granular data that would be needed to perform any adjustment.

[13] The primary payer type categories are private/commercial insurance, Medicare, Minnesota Health Care Programs, and uninsured/self-pay.

Over the intervening years, as MDH has worked with researchers at the University of Minnesota (University) to evaluate and test the risk adjustment approach, those same principles have applied. The University's analysis supported the continuing use of primary payer for risk adjustment, as well as support for adjusting some measures by age, gender, comorbidities, and distance of patient residence from the clinic. However, MDH maintained its practice of risk adjusting measures by primary payer type and patient severity because this sought a reasonable balance between appropriately risk adjusting quality measures and managing the administrative burden associated with data collection from providers for risk adjustment.

While risk adjustment can be an important tool for supporting informed, fair comparisons on health care quality measures, ultimately, its impact will always be limited. Currently, risk adjustment can typically only explain a fraction of differences in quality between providers—largely as a result of the state of available science and data. The data on risk factors that is currently available to such initiatives may only measure a limited set of factors affecting quality, not adequately address socio-demographic differences across patient populations or patient complexity, or find an appropriate balance between patient and provider factors.

For example, while we have documented that using primary payer can serve as a reasonable proxy for patient income and a composite of socio-economic characteristics, it is imprecise and there can be a lot of variation within categories. For instance, a community clinic's commercial health plan population may differ from a suburban clinic's commercial health plan population. Similarly, people in Medicaid represent low-income individuals with varying degrees of acculturation, language capabilities, medical care needs, and physical, psychological or psychosocial impairments. Yet, the current risk adjustment methodology implicitly treats groups within a payer category as if they are expected to have similar outcomes. As such, other tools are important to reach goals of creating transparency in health care quality, incentivizing performance improvements, and ensuring that providers of health care services to people who are impacted by health disparities are fairly compensated.

Use of Risk-adjusted Measures from the Quality Reporting System

The Minnesota Quality Incentive Payment System uses risk-adjusted Quality Reporting System measures and, at the time of this review, two payers have been the primary clients of this framework:

- The Commissioner of Management and Budget is directed to implement the Quality Incentive Payment System for the State Employee Group Insurance Program.[14]
- The Commissioner of Human Services is directed to do the same for all enrollees in state health care programs.[15]

MDH updates the system on an annual basis. The system rewards providers for one of two types of accomplishment: (1) achieving absolute performance benchmarks; or (2) improvements in performance over time. In 2015, Minnesota Management and Budget (MMB) and the Department of Human Services (DHS) paid nearly $1.3 million in incentive payments to providers in 241 clinics that achieved benchmarks or significantly improved care for diabetes, vascular disease, and depression (MDH, 2016a).[16]

Recently, the Legislature added requirements that the measures DHS uses in its performance reporting and quality improvement system must be stratified and risk adjusted as specified in the Quality Reporting System, effective January 1, 2016 and July 1, 2017, respectively.[17, 18] Other state programs choose whether to use unadjusted or adjusted quality measure results. For example, MDH's Health Care Homes and DHS's Integrated Health Partnerships programs use unadjusted measures to evaluate the performance of participating clinics.

Our understanding of the current practice by private payers or payer collaborations is that they either use unadjusted quality measure results, or results that have been adjusted by a methodology developed by a workgroup advising MN Community Measurement (MNCM), a measurement and reporting organization that partners with MDH on various aspects of quality measurement but also independently pursues public reporting (more detail is available in Appendix A).[19] For example, the Minnesota Health Action Group, which implements the Bridges to Excellence pay-for-performance system for their health care purchaser membership composed primarily by large, self-insured employers (the private sector counterpart to the

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[14] Minnesota Statutes, section 62U.02.

[15] Minnesota Statutes, section 256B.0754.

[16] There are ongoing discussions of whether the Quality Incentive Payment System (and its private sector equivalent, Bridges to Excellence) are effective quality improvement tools, and in alignment with other federal and state obligations. Should DHS and MMB ever discontinue their participation in the Quality Incentive Payment System, any impact of MDH's revisions to its risk adjustment methodology would be diminished.

[17] Minnesota Laws 2015, chapter 71, article 9, section 16, subdivision (e).

[18] In 2015, the Legislature directed DHS to establish a performance reporting and quality improvement system for medical groups and clinics providing health care services to patients enrolled in the managed care component of Minnesota Health Care Programs. Accordingly, in 2007, DHS and MNCM released their inaugural Health Care Disparities Report evaluating care provided in 2006. DHS and MNCM update and issue the disparities report annually.

[19] MNCM is an independent quality measurement organization that publicly reports a range of quality and cost measures on Minnesota clinics and hospitals on its website, http://www.MNHealthScores.org.

Quality Incentive Payment System), uses unadjusted quality measures. This group values the transparency and simplicity of using unadjusted measures.

MNCM independently reports medical group and clinic quality measure results that it risk adjusts using its own methodology through MNHealthScores.org. MNCM's risk-adjusted measures use an indirect adjustment approach under which unadjusted performance rates are compared to expected rates calculated by weighting statewide average performance to reflect a specific clinic or medical group's patient population. Website users may also view raw performance rates. Any public reporting and risk adjustment on MNHealthScores.org is not bound by methodological decisions made by MDH for the Quality Reporting System. In order not to duplicate efforts, MDH does not publicly report quality measures at the medical group and clinic levels; MDH's reporting focuses on reporting higher-level trends as part of its market study analyses (MDH, 2016b).

Minnesota Council of Health Plan representatives told MDH that health plans use unadjusted and adjusted clinic quality measures in pay-for-performance and total cost of care contracts with providers. Historically, commercial plans have not asked MDH to provide them with risk-adjusted measures from the Quality Reporting System. Instead, plans obtain measures from MNCM and use measures that they calculate from administrative (or claims) data.[20] Plans participated in the technical workgroup that MDH and MNCM convened as part of the empirical component of this assessment to test risk adjustment factors. Health plans may consider the further use of risk-adjusted measures in future versions of pay-for-performance and total cost of care contracts with providers.

Study Approach

To assess the Quality Reporting System risk adjustment methodology for the potential for harm and unintended consequences for patient populations who experience health disparities, and the providers who serve them, and to identify changes that may be needed to alleviate harm and unintended consequences as directed by the Legislature, MDH investigated the following questions:

- What is the role of socio-demographic factors in risk-adjusting quality measures in the Quality Reporting System and other settings, and who would be impacted by changes to MDH's risk adjustment methodology?

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[20] Minnesota Council of Health Plan representatives stated that when health plans use risk adjustment, they use well-established and vetted measures regionally (e.g., MNCM, MHA), nationally (e.g., National Committee for Quality Assurance, CMS, Joint Commission, Leapfrog), and then complement with plan-specific measures where gaps exist.

- What is the perspective of safety net and other providers, and health care purchasers, on quality measure risk adjustment in general and the Quality Reporting System risk adjustment methodology specifically?
- What other factors and data sources could be used to risk adjust Quality Reporting System measures, and what are the associated benefits and challenges?
- What are other local and national organizations and agencies doing to include socio-demographic and patient complexity factors in quality measure risk adjustment?

To answer these questions, MDH performed the following tasks:

Literature review. MDH reviewed research reports and peer reviewed literature related to risk adjusting health care quality measures, focusing on the evidence concerning, and choice of, socio-demographic measures.

Stakeholder input. MDH conducted interviews with a range of stakeholders.

- To ensure that the voice of providers who serve patients with health disparities was fully considered as part of this report, MDH conducted semi-structured interviews with six Minnesota Federally Qualified Health Centers (FQHC) that report to the Quality Reporting System and a safety net care system.[21]
- We met with provider and health care quality measurement industry representatives including the Safety Net Coalition, Minnesota Association of Community Health Centers (MNACHC), Minnesota Medical Association (MMA), Minnesota Hospital Association (MHA), and MN Community Measurement (MNCM).
- We sought input from individuals associated with Minnesota payers, including the Minnesota Health Action Group (MNHAG) that represents large employers, the Minnesota Council of Health Plans (MCHP), the Minnesota Department of Human Services (DHS), and the State Employee Group Insurance Program (SEGIP) within Minnesota Management and Budget (MMB).

Analysis of quality measure data. MDH worked with a contractor, the University of Minnesota (University), to conduct an empirical analysis on four quality measures. MDH obtained methodological input from a range of technical stakeholders by holding two public meetings that were convened in partnership with MNCM and the University.[22] Technical panel members

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[21] Interviewed FQHCs include: NorthPoint Health & Wellness Center-Minneapolis, Open Door Health Center-Mankato, People's Center Health Services-Minneapolis, Scenic Rivers Health Services-Cook, United Family Medicine-St. Paul, and Westside Community Health Services-St. Paul. MDH also interviewed representatives from Hennepin County Medical Center in Minneapolis, which is a safety net care system that provides care for low-income, uninsured, and vulnerable populations.

[22] At the time, MNCM was in the process of considering needed modifications to the risk adjustment methodology used by the organization in public reporting. A joint technical discussion with an overlapping panel of experts offered the opportunity for coordinated discussions about available evidence and application to a range of existing measurement approaches.

were representatives of safety net and other provider organizations, private and public health care payers, consumers, and research organizations.

Environmental scan. MDH reviewed public and private risk adjustment research underway in Minnesota and nationally to inform this assessment, and connected with a national expert who is in the process of generating firm empirical evidence on the role of patient and provider factors with regard to health quality measures.

As explained in the background, MDH's risk-adjusted quality measures have historically only been used in the Minnesota Quality Incentive Payment System, and DHS will begin to use MDH's risk-adjusted measures in its performance reporting and quality improvement system. Therefore, any changes to MDH's approach to risk adjusting quality measures would, at this point, only impact those two initiatives. However, because the question of whether and how to risk adjust quality measures has broader implications, affecting virtually all performance-based payment models, MDH took a statewide perspective in conducting its work. Additionally, MDH sought to recognize in its work the potential tension that can arise in quality measurement between holding providers harmless for factors that are outside of their control and can adversely affect patient outcomes, and not masking health disparities in care quality and outcomes for patients.

Findings

Socio-demographic Factors Matter, but Approaches to Accounting for Them in Quality Measurement Are Under Development

Socio-demographic factors that describe patients along lines of income, education, race, and ethnicity strongly impact health outcomes in complex ways. Clinical and social factors can accumulate and interact to complicate care and affect health (Shippee, Shah, May, Mair, & Montori, 2012). Higher levels of income and education are associated with longer lifespans and better health outcomes (NBER, 2003). Financial resource strain, including food and housing insecurity, is connected to poorer health (IOM, 2014). Racial and ethnic minorities are more likely to experience social disadvantage, discrimination, and poorer health outcomes (IOM, 2014; NASEM, 2016a). However, the relationships between socio-demographic factors and health outcomes are complicated by interactions between factors and variation within socio-demographic categories. For example, income is intertwined with education and race, and low-income people are a diverse group with a wide range of life experiences and health statuses.

The evidence on the factors that impact provider performance by assessing outcomes on quality measures, remains fairly limited. Some evidence is emerging from research on hospital measures about the important, but relatively modest impact of patient factors (NASEM, 2017).

Other research confirms the importance of patient factors for outpatient measures without being able to yet offer a clear picture of the precise role of separate patient factors or their impact on quality outcomes relative to physician and practice patterns (HHS, 2016). There is also little published research on the *interactions* between patient-level socio-demographic factors and provider- and system-level factors (e.g., how patient factors affect providers practice patterns, adherence to guidelines, etc.), and the impact these interactions may have on quality measure results is not understood (Fung et al., 2010; NQF, 2014).

Value-based purchasing, pay-for-performance, and public reporting initiatives, if structured appropriately, are thought to incentivize improvements in patient quality of care for the services measured, but have the potential to bring unintended consequences for populations who experience disparities and the providers who serve them if patient social risk factors play a substantial role that is not adequately taken into consideration (Bernheim, 2014; Joynt & Jha, 2013; Lipstein & Dunagan, 2014; Ryan, 2013). These unintended consequences could include:

- The reduction of payments to physicians serving disadvantaged communities;
- Providers avoiding patients perceived as likely to lower quality scores, thereby creating reduced access to health care for disadvantaged patients; and
- Financial sustainability challenges for safety net providers resulting from the perception of being lower-quality providers.

The increase in public reporting of health care quality measures and inclusion of these measures in incentive programs and advanced payment systems that reward higher performance and (potentially) penalize poor performance has raised questions about the validity and fairness of provider-to-provider comparisons and rewards and penalties. Particularly the efforts by the federal government in the use of quality-based performance measures for payment has generated interest in more robustly considering socio-demographic factors to risk adjust quality measures (NQF, 2014).

Safety Net Providers Are Concerned about Financial Penalties and Reputation

We find that MDH's current approach to risk adjusting quality measures has not produced measurable financial penalties for safety net providers. As explained in the background section of this report, MDH's risk adjusted rates are currently only used in the Quality Incentive Payment System in which two payers offer financial rewards for performance achievements, and no penalties.[23] However, safety net providers have great concerns about penalties that could be imposed in the future by local and federal payers that tie payment to performance on quality measures. These providers think that if MDH can better account for patient socio-demographic factors in its quality measure risk adjustment model, that payers outside of the Quality Incentive System may adopt MDH's approach, thereby curtailing the risk of such penalties.

For example, some of the safety net representatives who MDH interviewed shared that they have experienced financial penalties or failed to earn payouts from some DHS and federal incentive programs (these programs do not use risk-adjusted quality measures from MDH), and most were concerned about potential penalties from payers in the future. They believe that their quality measure scores may be more of a reflection of the socio-demographic characteristics of their patient populations versus deficiencies in their provision of care. Representatives of these sites believe that if public and private payers do not take their patient populations into account in risk sharing and pay-for-performance arrangements, they may not meet quality measurement benchmarks and as a result, may be penalized financially through payment reductions or withholds. Clinic representatives fear that financially penalizing community clinics who serve populations with the greatest health care needs and disparities in care outcomes may put them out of business and ultimately affect their patients and exacerbate disparities.

As public reporting becomes more common and consumer-friendly, clinics are concerned that perceptions of low quality may detract private payers from including them in network or private patients from seeking care from them. Some safety net representatives commented that they were concerned about how their clinics may be perceived by current and potential patients, peers, funders, media, and current and potential staff through public reporting platforms like MNHealthScores.org. Clinics that primarily serve patient populations that experience health disparities may show up as below average performers on public reporting venues where they are compared to clinics that serve healthier and better resourced populations. For instance, one clinic provided an example whereby one of their doctors attained good quality measure scores while working in a well-resourced clinic that served a predominantly healthy and resourced population, but when the doctor moved to the safety net clinic, her scores went down.

Safety net representatives offered a number of options for equitably assessing provider performance for payment and public reporting initiatives. In terms of local and federal value-based purchasing and pay-for-performance arrangements, representatives suggested that

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[23] Representatives of one clinic that MDH met with questioned whether MDH's current risk adjustment methodology provides an opportunity for FQHCs to participate in the Quality Incentive Payment System or whether deficiencies in risk adjustment hinder FQHC participation. In 2016, 3 out of 18 FQHCs received rewards for making significant improvements in care for diabetes, vascular disease, or depression (MNHAG, 2016).

these programs could be strengthened by comparing like providers through peer grouping, including improvement rewards, and/or risk adjusting or stratifying quality measures using patient socio-demographic factors. For example, some clinic representatives noted the peer grouping system that the federal Health Resources and Services Administration uses whereby it assesses FQHCs' performance on a set of benchmarks—including clinical quality measures—and rank-orders FQHCs according to their results. Representatives of one community clinic noted that clinics participating in DHS's Integrated Health Partnerships program may receive rewards for achieving absolute benchmarks or showing significant improvement in their unadjusted quality measure results. Additionally, payers could distinguish between the provider and patient contribution to health outcomes, and prioritize measures where the provider contribution is clear.

To publicly report quality measures, clinic representatives we spoke with thought it would be helpful if these reports provided more context for their scores such as information about their patient populations or denoting their FQHC status. They also stated that clinics could be grouped into peers so consumers could make performance comparisons among similar clinics.

The safety net representatives that MDH met with were supportive of local and national efforts to examine how to accurately and equitably measure the quality of care that community clinics provide. Most representatives thought that factoring patient socio-demographic factors—or social determinants of health—into health care quality measurement should provide a more complete picture of community clinic performance. Some representatives noted that stratifying quality measures by socio-demographic factors can help identify disparities. Representatives of most of the safety net systems we met with shared that they use their quality measure data to track performance and identify opportunities for improving care to patients, and some of these sites stratify measures themselves using socio-demographic factors such as race and gender to identify gaps in care and make improvements. One system shared that they are developing standardized screening for social determinants of health across their population.

Similarly, MMA and MHA representatives did not cite any current harms caused by MDH's risk adjustment approach. Representatives did express concern about potential harms and unintended consequences that could be caused by quality measure public reporting, value-based purchasing, and pay-for-performance initiatives that do not account for providers' patient population characteristics.

Empirical Study Shows the Limitations of Available Socio-demographic Factors in Risk Adjustment and Offers Support for Exploring Other Factors and Statistical Methods

Given the limited evidence on the importance of supplementing risk adjustment of quality measures with socio-demographic variables, MDH was interested in taking advantage of the data-rich environment in Minnesota to assess opportunities for improving the approach taken to date. MDH worked with a research team from the University of Minnesota (University) to test risk adjusting quality measures using socio-demographic factors. (See Appendix E for the full study.)

In their analysis, the University included four Quality Reporting System measures[24], patient-level and clinic-level[25] factors from the measure data, and ZIP code-level[26] data that indicated economic deprivation from the U.S. Census Bureau (see Table 1).

Table 1. Quality Measures and Risk Factors

Quality Measures	Risk Factors from Measure Data	Risk Factors from U.S. Census Bureau
Optimal Diabetes Care Optimal Vascular Care Optimal Asthma Control – Adult Colorectal Cancer Screening	Race Hispanic ethnicity Preferred language Country of origin Primary payer type Gender Age Comorbidities Clinic type Rurality	Deprivation index: ▪ Inverse median income and poverty rates ▪ Unemployment ▪ Public assistance ▪ Supplemental Nutrition Assistance Program benefits ▪ Single mother families

Quality measure data source and year: MNCM, 2014. Deprivation index data source and year: U.S. Census Bureau, 2014.

The University's primary results are as follows:

- **Socio-demographic factors such as race and ethnicity had significant relationships with the quality measures; yet, adding these socio-demographic factors to existing risk adjustment models did not substantially improve model results.** The University concluded that there is a high degree of correlation among patient characteristics such as race, ethnicity, deprivation, and primary payer type; therefore, the addition of new socio-demographic factors did not add much new explanatory information to the existing risk adjustment model, which already included primary payer type as a proxy for income. This finding is consistent with the levels of explanatory effects from patient factors found in the literature (Fung et al., 2010).

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[24] MDH selected these four quality measures for the analysis because these are the only measures for which reporting of race, ethnicity, preferred language, and country of origin variables to the Quality Reporting System will occur beginning mid-2017.

[25] Clinic-level factors included the percentage of patients that resided in the same ZIP code as the clinic, whether a clinic was a FQHC or affiliated with a critical access hospital, and whether the clinic was located in an urban, micropolitan, small town, or frontier area.

[26] The University used ZIP code-level deprivation data because the most granular geographic level of the quality measure data to which the deprivation data was linked was the patient ZIP code.

- **Comparing the performance of clinics that see similar patients by clustering like clinics together can potentially aid in making more meaningful and fair comparisons.** Including clinic clusters in performance categorization acknowledges that patients of certain demographic groups chose (or cluster at) the same clinics, and that it is, therefore, difficult to separate patient factors from clinic factors and geographic or neighborhood factors. Accounting for clustering of patients within clinics has a measureable impact on clinic rankings, and may be more influential in assessing clinic performance than risk adjustment with socio-demographic factors.

Although the empirical results are consistent with evidence from other research, some factors of the study limit the generalizability of the findings.

- **Missing or incomplete data for sociodemographic factors.** The University's analysis identified that voluntarily reported data on race and Hispanic ethnicity were systematically missing for 31 medical systems (out of a total of 160) and 119 clinics (out of a total of 733). Among the medical groups submitting data, approximately 3 percent of patients were missing race, Hispanic ethnicity, and country of origin data.[27] As such, to the extent that the missing clinics are systematically different from those that have submitted data, results cannot necessarily be generalized to all Minnesota clinics.[28]

- **There are questions about whether the concepts of race, ethnicity, preferred language, and country of origin best convey the impact of patient complexity or neighborhood effects on health and health care quality performance outcomes.** Socio-demographic data used for research on health outcomes is generally limited to elements needed to process health care transactions or those that can be easily collected in the process of health care delivery. Other patient socio-demographic factors for which either there are not available data in the patient medical record (e.g., income) or that have not yet been well articulated and tested (e.g., housing and food insecurity) could potentially add explanatory power to a risk adjustment model. However, collinearity among socio-demographic factors and the difficulty and reporting burden associated with acquiring detailed data could limit the benefits of risk adjusting measures with additional factors.

- **Effective use of secondary data on socio-demographics may imperfectly capture social complexity and the differential effects of poverty, because they cannot be used at the appropriate level of granularity.** This and other studies with similar focus are often limited

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[27] Race and Hispanic ethnicity data was less likely to be missing for rural, Medicare, Minnesota Health Care Programs, and self-pay or uninsured patients.

[28] It is expected that mandatory reporting of data on race, ethnicity, preferred language and country of origin, which begins with a few measures in July 2017, will produce more complete information, offering the opportunity to confirm the outcomes of this research for a broader set of clinics.

by the level at which available data are aggregated. For example, the University was limited to using ZIP code-level deprivation data because the most granular geographic level of the quality measure data to which the deprivation data was linked was the patient ZIP code; however, research documents that ZIP codes may be too large and heterogeneous to convey the effect from specific socio-demographic factors. More detailed geographic data, such as U.S. Census Block Group data and patient Census Block indicators, could add precision.

Results Were Counterintuitive to Technical Panel, and Members Discussed Potential Enhancements to Risk Adjustment and Alternatives

Panel members considered the evidence the University produced on the complex relationship between the socio-demographic factors and quality measures. In particular, panel members contemplated how the socio-demographic factors could add only a small amount of explanatory power to the risk adjustment model despite having significant independent effects on the measure outcomes. Some panel members were surprised that adding race, Hispanic ethnicity, preferred language and country of origin data did not significantly improve the risk adjustment model, since these factors are known to be associated with health disparities.

The University's research team explained that these factors are collinear with patient factors, such as primary payer type, that are already used in the risk adjustment model. They also reminded panel members that the analysis was focused on provider performance on specific quality measures, not health outcomes in general. The research team emphasized that the analysis results only pertain to risk adjustment, and do not reflect whether the tested socio-demographic factors should be used to stratify quality measures, which could show variation in outcomes by different socio-demographic characteristics. In addition, they recommended a qualitative assessment of the empirical findings.

The panel also discussed limitations to the socio-demographic factors and data used in the analysis, recognizing that variation exists within socio-demographic categories like race and primary payer type. Panel members acknowledged that socio-demographic factors are frequently correlated, and concluded that it may be worthwhile to consider whether additional measures or more detailed data could improve the risk adjustment model. Some panel members thought the analysis demonstrated that continuing to use primary payer type to risk adjust quality measures is a credible approach until other, more precise socio-demographic factors are available at the patient-level or smaller levels of geography and can be tested.

Panel members cautioned that poor risk adjustment could lead to unintended consequences of setting incentives for delivering lower care quality. Panel members noted that changes to public reporting techniques could also promote more fair comparisons between clinics. Possible reporting changes include grouping similar clinics and displaying results within these groups, and pairing measure results with more information about the differences between clinics' patient populations and organizational structures.

Finally, there was support for MDH monitoring progress in the area of measurement and method development and caution about ensuring that advancement in risk adjustment be tied to a conceptual model for the relationship between risk factors and provider performance outcomes.

Local and National Stakeholders Are Exploring How to Account for Patient Socio-demographic Factors in Health Care

To effectively implement quality measurement risk adjustment requirements, MDH aims to learn from and align with other related local and national efforts. To that end, MDH explored initiatives that are being undertaken by DHS, safety net providers, MNCM, the State Innovation Model, the U.S. Department of Health and Human Services (HHS), and the National Quality Forum (NQF). (See Appendix F for more information about these projects.) The projects highlighted below are ongoing, and MDH will continue to monitor results, collaborate with local project leaders, and consider the applicability of project outcomes for the Quality Reporting System. For example, some projects may identify socio-demographic factors and data sources, and others may develop quality measure risk adjustment methodologies that MDH could also test for use in the Quality Reporting System.

- **DHS is developing a health care payment enhancement methodology based on socio-economic and other risk factors.**[29] DHS is working to identify the Medical Assistance and MinnesotaCare populations that experience the greatest health disparities at the greatest cost. DHS is also examining the evidence-based interventions most likely to improve the health of two such populations—individuals experiencing homelessness and individuals who have a chemical dependency diagnosis. By the end of 2017, DHS anticipates proposing methods for paying for interventions for these two populations. During the second half of 2017, DHS will identify interventions expected to improve the health of a few other populations with significant health disparities, and anticipates proposing methodologies for paying for these interventions by mid-2018. Although the focus is primarily on adjusting *payment* and not *quality measure outcomes*, there are important conceptual and methodological parallels.

- **A local independent alliance of safety-net providers and other clinics, consumer groups, community organizations, academic and research institutions, and communities that experience health disparities are designing a pilot project to develop better methods to account for the impact of social determinants of health in the health care system**

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[29] DHS is undertaking this work to meet legislative requirements to, “develop a methodology to pay a higher payment rate for health care providers and services that takes into consideration the higher cost, complexity, and resources needed to serve patients and populations who experience the greatest health disparities in order to achieve the same health and quality outcomes that are achieved for other patients and populations.” Minnesota Laws 2015, chapter 71, article 9, section 63.

(Scandrett et al., 2016). A primary objective of the project is to develop measurement and data that more effectively can aid accounting for social determinants of health in quality measurement. The collaboration expects to have pilot results in late 2017. As a key stakeholder, MDH is participating in this project.

- **MNCM convenes a Risk Adjustment and Segmentation Subcommittee of its Measurement and Reporting Committee (MARC) to obtain recommendations on risk adjustment and segmentation of quality measure results for public reporting.** As a member of the MARC, MDH participates on this subcommittee. During 2016, the subcommittee considered using race, Hispanic ethnicity, preferred language, and country of origin to risk adjust quality measures (MNCM, 2016b). The subcommittee decided not to use these variables in risk adjustment because of a perceived lack of a conceptual relationship among the variables and measure results, incomplete data reporting, lack of sufficient granularity of data, and lack of evidence that the relationships between the variables and the measures were not caused by provider behaviors. The subcommittee will continue to investigate the best science to understand the impact of socio-economic factors and the role of geography on measure results.

- **The State Innovation Model Data Analytics Subgroup identified top-priority data analytic elements to motivate and guide greater consistency in data sharing among organizations involved in accountable care organization models to support shared accountability for cost and health outcomes.**[30] Recommended essential data analytic elements include: mental health and substance use (current diagnosis or unmet need); race, ethnicity, and language; access to reliable transportation; social services already being received; housing status or situation; and food insecurity (MDH & DHS, 2016a).[31] The subgroup recommended incorporating these elements into reporting and/or payment structures for future alternative payment and quality measurement arrangements.

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[30] In February 2013 the Center for Medicare and Medicaid Innovation awarded Minnesota a State Innovation Model testing grant of over $45 million to use across a three-year period ending October 2016. As a joint effort between MDH and DHS with support from Governor Mark Dayton's office, Minnesota is using the grant money to test new ways of delivering and paying for health care using the Minnesota Accountable Health Model framework. The goal of this model is to improve health in communities, provide better care, and lower health care costs.

[31] The subgroup identified four other data analytic elements of importance that are not feasible to collect now, but should be considered in the future: social isolation; country of origin or citizenship (to ensure broad inclusion of all members of the community, regardless of documentation status); sexual orientation and gender identity; and adverse childhood experiences for children and/or indications of abuse and neglect for people of any age.

- **Under federal IMPACT legislation,[32] HHS is conducting a set of rigorous studies to assess the relationship between socio-economic status (race, health literacy, limited English proficiency, and Medicare beneficiary activation) and provider performance across the spectrum of current Medicare payment policies, culminating in a set of recommendations about whether and how socio-economic status should be accounted for in these programs.** The Office of the Assistant Secretary for Planning and Evaluation (ASPE) is spearheading the study with a final report due to Congress by October 2019. The National Academies of Sciences, Engineering, and Medicine convened an ad hoc committee to inform ASPE's study and has issued a series of reports that identify social factors and data sources, and specify criteria that could be used as a part of ASPE's ongoing activities.
    - In an initial report, ASPE found that beneficiaries with certain social risk factors had worse outcomes on many quality measures regardless of the providers they saw, and providers that disproportionately served beneficiaries with social risk factors tended to have worse performance on quality measures even after accounting for their beneficiary mix (HHS, 2016).[33] ASPE reported that more research is needed to understand these emerging patterns. As Medicare uses quality measures in two ways—reporting to providers and the public, and determining payment adjustments such as bonuses and penalties—potential solutions may include adjusting the measures for reporting, adjusting the measures for the purpose of determining payments, or directly adjusting the payment methodologies without adjusting the measures themselves.
    - ASPE proposes a three-part strategy: (1) measure and report performance on quality and outcomes specifically for beneficiaries with a range social risk factors; (2) set high fair quality standards for all beneficiaries; and (3) in value-based purchasing programs, provide specific payment adjustments to reward achievement and/or improvement for beneficiaries with certain social risk factors, and, where feasible, provide targeted support for providers who disproportionately serve them.

- **NQF is nearing the end of a two-year trial period during which it explored using socio-demographic factors to risk adjust quality measures.[34]** The trial includes 32 measures—mainly assessing hospital quality—that encompass the areas of cost and resource use, all-cause admissions and readmissions, and cardiovascular care (NQF, 2015a). NQF will report the findings of this trial period, including its implications for whether and how to move

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[32] Improving Medicare Post-Acute Care Transformation Act, H.R. 4994.

[33] The social risk factors that ASPE examined were: dual enrollment in Medicare and Medicaid as a marker for low income, residence in a low-income area, Black race, Hispanic ethnicity, and residence in a rural area. ASPE also examined disability as it is related to many social risk factors, available in claims data, and already used in some Medicare payment calculations.

[34] NQF is a not-for-profit, membership-based organization that leads national collaboration to improve health and health care quality through measurement.

forward with risk adjustment of quality measures to its Board of Directors in 2017. NQF has also established a Disparities Standing Committee to incorporate the reduction and elimination of disparities through quality measurement into NQF's work.

Conclusions

Quality measurement serves multiple purposes, with the ultimate goal of improving the quality of care afforded to patients. Public and private health care purchasers use quality measures to evaluate and reward provider performance, and to consider relative provider performance in network design considerations. Providers use relative performance on quality to identify opportunities for improvement and care redesign. Transparency in provider quality can also be a tool for patients as they choose providers or select health plans with a given provider network, although research suggests that much needs to be done to make public reports understandable, relevant, and used by consumers.

More recently, there has been an interest by the Minnesota Legislature and others to use quality measures to assess inequities in health outcomes, thereby taking more of a population health or public health focus.

While Minnesota has been leading nationally in provider quality measurement and public reporting, particularly in the area of outpatient care, the scope of overall provider quality that is actively assessed remains very narrow and focuses largely on primary care providers. The broader community, locally and nationally, is in the midst of deliberations about the next steps in quality measurement, considering questions of:

- "Measurement fatigue" and prioritization in measures;
- Reach of measurement beyond primary care;
- Patient use of available information; and
- Measurement science.

Setting aside the need for evolution in quality measurement, careful consideration of how existing measures are used and presented—to patients, payers and other providers—is important. This is especially true as the use of quality measurement in advanced payment systems becomes increasingly likely and access to measurement scores becomes more pervasive, aided by new technological capabilities and the motivation for greater transparency and value in health care.

At the same time, concern has been rising, particularly among providers who serve patients who are poor, face housing and food insecurity, are survivors of war or social conflicts, or are more likely to experience disparities in health outcomes, that measurement creates unintended consequences. Of greatest concern to these safety net providers is that by not adequately considering patient complexity, measured through a range of socio-demographic characteristics, the very providers who are caring for the most disadvantaged populations might be financially harmed and become unable to fulfill their mission.

Although our research—largely as a result of lacking empirical evidence and a weak data basis—has not been able to quantify the *precise* impact of patient factors on determining health care quality measure outcomes compared to provider factors, we found a compelling conceptual support for a link between socio-demographic factors and quality measure outcomes. This was borne out of discussions with service providers; exchanges between members of our technical advisory group to the University's empirical analysis; empirical evidence developed by the broader research community; and the powerful evidence of how structural racism and associated factors like persistent poverty and historical trauma affect patients' ability to achieve optimal health.

This does not mean that facility and provider factors—how providers practice, what resources are available to plan and organize care delivery and follow-up, and how well patient care is coordinated across the spectrum of medical care and support services—do not play a decisive role in affecting patient outcomes, but that the social and economic complexities patients bring to treatment also contribute to the relative success of care outcomes.

The empirical analysis conducted by the University underscores the complexity related to understanding and addressing the role of patient factors in affecting health care quality measure outcomes by highlighting that existing socio-demographic variables not yet used in risk adjustment don't add new evidence to risk adjustment, largely because they measure the same impact as other variables.

MDH concludes, based on the empirical research for this study, that improvements are necessary in two key areas:

1. What measures of patient complexity are available for assessing the impact of socio-demographic characteristics and adjusting for them, should there be a conceptual framework on their impact; and
2. The levels of geography at which these data are available.

Existing measures of patient complexity likely fail to capture important patient factors that affect the level of success of providers and patients in reaching optimal health outcomes (e.g., housing and food insecurity). In addition, when patient-level socio-demographic data are not available, research suggests that community variables, unless linkable at the Census Block or Tract level, would fail to capture the impact of diverse populations and fail to improve approaches to risk adjustment (Krieger et al., 2002).

We further conclude, that in the current data environment, there are no immediate opportunities available for meaningfully enhancing MDH's existing risk adjustment. The analysis demonstrated that without a substantially richer set of patient complexity factors, MDH use of primary payer acts as a reasonably effective proxy for patient income in risk adjustment.

- Improvements in model specification or functional form would not substantially affect risk adjusted rates at this time; and
- Given the limited use of MDH's risk adjusted quality measurement rates at this point, refinements to the model would only affect an inconsequential subset of Minnesota's patient population.

Importantly, in order for future improvements in risk adjustment data, methods and evidence to meaningfully affect the fair and equitable use of quality measurement data across the spectrum of health care providers in the state, there would need to be alignment in risk adjustment approaches across health care payers, purchasers, and reporting organizations.

In conclusion, although MDH will maintain its risk adjustment methodology in the Quality Incentive Payment System in the near term, we identified a range of tools and policies that can address in the short term potential unintended consequences resulting from the use of quality measures:

- Identifying and adequately paying for non-medical support services that have been shown to improve patient outcomes for people who face economic and social barriers to good health;
- On a targeted basis financially rewarding improvement in quality performance more strongly than absolute goals;
- Comparing the performance of clinics that have similar features and see similar types of patients; and
- Offering more contextual information on public reporting initiatives about clustering and the unmeasured impact of other patient-complexity factors.

Use of these additional tools and policies would also recognize that risk adjustment, as a technique, will always be limited in accomplishing multiple, finely-targeted policy goals across a range of health care providers and measurement approaches.

Next Steps for the Minnesota Department of Health

As noted throughout the report, the issue of the impact and role of patient complexity factors and socio-demographic characteristics in determining patient outcomes in quality measurement systems is beginning to garner the attention of payers (including federal ones), organizations that work on measurement or improvement, academia and others. We expect the next few years will produce important insights that will have implications for quality measurement use and reporting in Minnesota and nationally that can help better address the questions that motivated this legislative study.

In the course of seeking to bring the strongest method and data to the state's measurement activities, MDH will take the following steps over the next few year to refine its approach:

- Further explore the methods of clinic clustering and grouping similar clinics with available data, and test their application to the Quality Incentive Payment System;
- Collaborate with DHS in identifying effective approaches to quality measurement and risk adjustment.
- Support and advise the Quality Measurement Enhancement Project and assess its implications for Quality Reporting System risk adjustment.
- Continue to participate in and support MNCM's risk adjustment and segmentation activities, including looking for opportunities to align efforts.
- Consider the State Innovation Model Data Analytics Subgroup's recommendations around identifying the highest priority social determinants on which all providers should collect data, and to develop data sources and potential standards for those data elements that providers are not currently collecting.
- Monitor activities underway at HHS and NQF to study the relationship between socio-economic status and performance on quality measures.

Lastly, the health care system in our state has undergone much change and transformation since the Quality Reporting System was first implemented in 2010. MDH is actively evaluating the effectiveness of the Quality Reporting System, measurement goals and priorities, and the roles of the State and stakeholders in evolving our statewide measurement approach. The learnings and issues that emerged from this risk adjustment assessment provide valuable input into exploring and charting the future of the Minnesota Statewide Quality Reporting and Measurement System over the course of this year and in collaboration with communities, providers, payers, and measurement organizations.

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Appendix A. Minnesota Statewide Quality Reporting and Measurement System

Minnesota clinics, hospitals, and health plans have a rich history of health care quality measurement and confidential as well as public reporting through private-public initiatives such as the Minnesota Health Data Institute; collaboratives, such as the Institute for Clinical Systems Improvement; adoption of the National Committee on Quality Assurance's Health Care Effectiveness Data and Information Set (HEDIS); purchasing initiatives such as the Buyers Health Care Action Group (now the Minnesota Health Action Group); and voluntary data submission of Minnesota-grown outpatient measures through MN Community Measurement.

Prior to the passage of state health reform in 2008, Minnesota payers were using a variety of health care quality measures to assess provider performance, resulting in substantial reporting burden and inconsistencies in reporting. To better coordinate measurement activities, establish a common set of metrics, and publicly report results to increase accountability and improve care, the Minnesota Council of Health Plans established the Minnesota Community Measurement Project in 2002.[35] The project issued its first performance report on Optimal Diabetes Care in 2003, and its first report on medical group performance in 2004. In 2005, Minnesota health plans and the Minnesota Medical Association (MMA) partnered to establish MN Community Measurement (MNCM) to better coordinate quality measurement activities including data collection, data validation, and measure development.

Enacted in 2008, Minnesota's Health Reform Law requires the Commissioner of Health to establish a standardized set of quality measures for health care providers across the state.[36] The goal is to create a more uniform approach to quality measurement to enhance market transparency and drive health care quality improvement through an evolving measurement and reporting strategy. While the goal for a standardized quality measure set builds on earlier voluntary efforts, it also explicitly required all providers to participate in data submission efforts, which culminated in the Minnesota Statewide Quality Reporting and Measurement System (Quality Reporting System).[37] Physician clinics and hospitals are required to report quality measures annually.[38] MDH updates the measure set annually, following a process of seeking public comments and recommendations from the community, by issuing an updated

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[35] MN Community Measurement (MNCM), http://mncm.org.

[36] Minnesota Statutes, section 62U.02.

[37] Minnesota Rules, chapter 4654.

[38] Statewide data collection began in 2010 on 2009 dates of service, and 2017 marks the eighth year of statewide data collection.

administrative Rule. The Rule describes specific data elements that providers are required to submit to MDH for each measure. MDH is also required to issue public reports on provider quality. Because MNCM, the Minnesota Hospital Association (MHA), and the Centers for Medicare & Medicaid Services (CMS) have established mechanisms to report quality measure results at the clinic, medical group, and hospital levels, MDH has chosen not to duplicate these efforts and instead, focuses on reporting higher-level trends as part of its market study analyses (MDH, 2016b).

- Payers may use statewide measures for performance-based contracting or pay for performance initiatives, including through the Bridges to Excellence program, the Minnesota Quality Incentive Payment System, and DHS Integrated Health Partnerships program.
- Consumers may use available measure data, including data reported publicly by MNCM, to choose a clinic or engage with their provider on performance differences.
- Providers may use their measure data for quality improvement initiatives and benchmarking.

At this point, more than 1,200 clinics report on 12 quality metrics; similarly, 133 hospitals report on a number of hospital measures (Table B-1).

Table B-1. Quality Reporting System Measures

Provider Type	Measures
Physician Clinic	▪ Optimal Diabetes Care ▪ Optimal Vascular Care ▪ Depression Remission at 6 Months ▪ Adolescent Mental Health and/or Depression ▪ Pediatric Overweight Counseling ▪ Total Knee Replacement ▪ Spinal Surgery: Lumbar Spinal Fusion ▪ Spinal Surgery: Lumbar Discectomy/Laminotomy ▪ Optimal Asthma Control – Adult and Child ▪ Asthma Education and Self-Management – Adult and Child ▪ Colorectal Cancer Screening ▪ Cesarean Section Rate ▪ Patient Experience of Care Survey: Consumer Assessment of Healthcare Providers and Systems Clinician & Group 3.0 Survey – Adult ▪ Healthcare Effectiveness Data and Information Set measures ▪ Health Information Technology Survey
Prospective Payment System Hospital	▪ Hospital Value-Based Purchasing Total Performance Score ▪ Total Hospital Acquired Condition Reduction Program Score ▪ Hospital Readmissions Reduction Program Excess Readmission Score
Critical Access Hospital	▪ Median time from ED Arrival to ED Departure for Admitted ED Patients – Overall Rate (ED-1a) ▪ Admit Decision Time to ED Departure Time for Admitted Patients – Overall Rate (ED-2a) ▪ READM-30 Heart Failure 30-Day Readmission Rate ▪ READM-30 Pneumonia 30-Day Readmission Rate ▪ READM-30 Chronic Obstructive Pulmonary Disease Rate ▪ Influenza Immunization (IMM-2) ▪ Elective Delivery (PC-01) ▪ Healthcare Personnel Influenza Immunization

Provider Type	Measures
	▪ Median Time to Fibrinolysis (OP-1) ▪ Fibrinolytic Therapy Received Within 30 Minutes (OP-2) ▪ Median Time to Transfer to Another Facility for Acute Coronary Intervention – Overall Rate (OP-3a) ▪ Aspirin at Arrival (OP-4) ▪ Median Time to ECG (OP-5) ▪ Median Time from ED Arrival to ED Departure for Discharged ED Patients (OP-18) ▪ Door to Diagnostic Evaluation by a Qualified Medical Professional (OP-20) ▪ ED-patient Left without Being Seen (OP-22) ▪ ED-Median Time to Pain Management for Long Bone Fracture (LBF) (OP-21) ▪ Head CT or MRI Scan Results for Acute Ischemic Stroke or Hemorrhagic Stroke Patients who Received Head CT or MRI Scan Interpretation Within 45 Minutes of Arrival (OP-23) ▪ Safe Surgery Checklist Use (OP-25) ▪ Influenza Vaccination Coverage among Healthcare Personnel (OP-27) ▪ Catheter Associated Urinary Tract Infection ▪ Emergency Department Transfer Communication Composite
Prospective Payment System and Critical Access Hospitals	▪ Patient Experience of Care: Hospital Consumer Assessment of Healthcare Providers and Systems ▪ Emergency Department Stroke Registry Indicators: Door-to-Imaging Initiated Time and Time to Intravenous Thrombolytic Therapy ▪ Mortality for Selected Conditions composite (IQI 91) ▪ Death Rate among Surgical Inpatients with Serious Treatable Complications (PSI 04) ▪ Patient Safety for Selected Indicators Composite (PSI 90) ▪ Health Information Technology Survey

Source: Quality Reporting System, 2017.

To cover essential roles such as data collection, measurement development and maintenance, provider education and making recommendations for changes to the measurement set, MDH contracts with a consortium of vendors that is led by MNCM and includes MHA and Stratis Health.[39] Outside of its role as lead vendor for the Quality Reporting System, MNCM is an independent quality measurement organization that publicly reports a range of quality and cost measures—including measures that are outside of the Quality Reporting System—on Minnesota clinics and hospitals on its MNHealthScores.org website.[40] Any public reporting and risk adjustment on MNHealthScores.org is not bound by methodological decisions made by MDH for the Quality Reporting System. Among other initiatives, MHA collects data from hospitals, including administrative claims data, and uses it in benchmarking and other

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[39] To identify qualified vendors, MDH conducted two competitive procurement processes in 2008 and 2013.

[40] Minnesota HealthScores, http://www.mnhealthscores.org.

analysis.[41] Additionally, MHA maintains a quality reporting website[42] to publicly report Minnesota hospitals' results on quality measures used by the Centers for Medicare & Medicaid Services (CMS) and to meet public reporting statutory requirements.[43] Stratis Health leads a Quality Innovation Network as part of the CMS Quality Improvement Organization Program. It has served Minnesota through this program since it began during the 1970s.[44] Stratis Health helps providers and consumers with the collection and use of data for quality assurance and improvement, and it assists provider organizations to submit data for public reporting.

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[41] Minnesota Hospital Association, http://www.mnhospitals.org.

[42] Minnesota Hospital Quality Report, http://www.mnhospitalquality.org.

[43] Minnesota Statutes, section 62J.82.

[44] Stratis Health, http://www.stratishealth.org.

Appendix B. Department of Health: 2014 Minnesota Laws

Minnesota Laws 2014, Chapter 312, Article 23, Section 10

Quality Transparency.

(a) The commissioner of health shall develop an implementation plan for stratifying measures based on disability, race, ethnicity, language, and other socio-demographic factors that are correlated with health disparities and impact performance on quality measures. The plan must be designed so that quality measures can be stratified beginning January 1, 2017, in order to advance work aimed at identifying and eliminating health disparities. By January 15, 2015, the commissioner shall submit a report to the chairs and ranking minority members of the senate and house of representatives committees and divisions with jurisdiction on health and human services and finance with the plan, including an estimated budget, timeline, and processes to be used for implementation.

(b) The commissioner of health shall assess the risk adjustment methodology established under Minnesota Statutes, section 62U.02, subdivision 3, for the potential for harm and unintended consequences for patient populations who experience health disparities, and the providers who serve them, and identify changes that may be needed to alleviate harm and unintended consequences. By January 15, 2016, the commissioner shall submit a report to the chairs and ranking minority members of the senate and house of representatives committees and divisions with jurisdiction on health and human services and finance with the result of the assessment of the risk-adjustment methodology and any recommended changes.

(c) The commissioner shall develop the plan described in paragraph (a), in consultation with consumer, community and advocacy organizations representing diverse communities; health plan companies; providers; quality measurement organizations; and safety net providers that primarily serve communities and patient populations with health disparities. The commissioner shall use culturally appropriate methods of consultation and engagement with consumer and advocacy organizations led by and representing diverse communities by race, ethnicity, language, and socio-demographic factors.

Appendix C. Quality Reporting System Risk Adjustment Methodology

The Quality Reporting System adjusts for risk in the physician clinic measures using a direct standardization, or “standardized mix” method. This risk adjustment method shows how each clinic or medical group would perform with the same, hypothetical, statewide population. In direct standardization, clinic rates for each patient category are applied to the statewide proportion of patients in that category. This produces a single standardized rate for each clinic based on the individual clinic’s performance with the specific categories, and the statewide proportions of those categories. For example, to risk adjust using payer mix, each clinic’s score for each payer type is multiplied by the statewide average distribution of patients within the corresponding payer type.

The Quality Reporting System risk adjusts outcome quality measures by patient primary payer type with the exception of Depression Remission at Six Months which is risk adjusted by patient severity.[45] Primary payer type serves as a proxy for some patient characteristics, including income, as patients with more resources typically have commercial health insurance. Patients from each clinic are grouped into the following payer categories: Commercial, Medicare, Minnesota Health Care Programs, and uninsured and self-pay. Depression Remission at Six Months is adjusted by severity, because research suggests that high initial severity scores are correlated with a worse response to treatment and lower likelihood of remission. Severity is determined through grouping patient scores on the PHQ-9 test into the following categories: Moderate, initial PHQ-9 score of 10 to 14; moderately severe, initial PHQ-9 score of 15 to 19; and severe, initial PHQ-9 score of 20 to 27.

Table C-1 provides an illustration of direct standardization. Clinic A and Clinic B each have the same quality performance for their patients within each payer category. Each achieves 65 percent Optimal Diabetes Care for commercial patients, 60 percent for Medicare patients, 45 percent for Minnesota Health Care Programs, and 40 percent for uninsured and self-pay patients. However, because Clinic A and Clinic B serve different proportions of patients from each of these payers, their overall quality scores are different without adjustment for payer mix: Clinic A’s unadjusted score is 61 percent, and Clinic B’s unadjusted score is 57 percent.

To adjust these scores by payer type, each clinic’s commercial insurance score is multiplied by 0.432 (the percentage of patients statewide with commercial insurance), the Medicare score is multiplied by 0.383, the Minnesota Health Care Programs is multiplied by 0.153, and the

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[45] Quality Reporting System outcome measures that are risk adjusted using primary payer type include: Optimal Diabetes Care, Optimal Vascular Care, Optimal Asthma Control-Adult, Optimal Asthma Control-Child, Colorectal Cancer Screening, Cesarean Section Rate, Total Knee Replacement, Lumbar Spinal Fusion, and Lumbar Discectomy/Laminotomy.

uninsured and self-pay score is multiplied by 0.032. By applying this adjustment, Clinic A and Clinic B achieve the same overall quality score of 59 percent, which more accurately reflects that they provide the same quality performance for similar populations.

Table C-1. Example of Risk Adjustment Using Payer Mix for Optimal Diabetes Care

	Commercial	Medicare	Minnesota Health Care Programs	Uninsured and Self-pay	Total/Score
Clinic A Number of patients	250	100	35	15	**400**
Clinic A Percent meeting measure (unadjusted score)	65%	60%	45%	40%	**61%**
Clinic B Number of patients	100	200	75	25	**400**
Clinic B Percent meeting measure (unadjusted score)	65%	60%	45%	40%	**57%**
Statewide Average Percent distribution of patients	43.2%	38.3%	15.3%	3.2%	**100%**
Clinic A Rates adjusted to statewide average payer mix (adjusted score)					**59%**
Clinic B Rates adjusted to statewide average payer mix (adjusted score)					**59%**

Total unadjusted scores are calculated by summing the product of the number of patients and the percent meeting a measure for each payer and dividing the results by the total number of patients. For example, for Clinic A the calculation is as follows: [(250 * 0.65) + (100 * 0.6) + (35 * 0.45) + (15 * 0.4)] / (250 + 100 + 35 + 15) = 0.61.

Statewide averages are based on 2014 dates of service for providers that reported data under the Quality Reporting System.

Appendix D. Literature Review

As value-based purchasing and pay-for-performance programs have become increasingly common in health care, researchers are studying the potential unintended consequences of these programs. For providers who see a high volume of patients that experience health disparities, there is interest in using socio-demographic factors to risk adjust quality measures and mitigate some of the negative consequences. To-date, such research has produced mixed results showing some, little, or no effect on provider performance rankings. While the science of risk adjusting quality measures using socio-demographic factors continues to undergo refinements, health care purchasers can use other methods to more equitably assess performance and compensate providers.

Quality Measurement, Social Determinants of Health, and Unintended Consequences

Quality Measurement

There is wide variation in health care quality, access, costs, and outcomes [IOM, 1999; IOM, 2001]. Measuring the quality of care that providers give patients can help improve health care outcomes. Measurement activities help direct the use of health care services and ensure patient safety, identify what does and does not work in health care, drive improvement by holding providers and health plans accountable, measure and address disparities in care delivery and outcomes, and aid consumers in making informed decisions about their care (IOM, 2001; IOM, 2003; MDH, 2014; MDH, 2015; NQF, 2014; DeMeester & Mahadevan, 2014). These activities can provide a comprehensive assessment of care quality including how quality varies by population subgroups (e.g., gender, age, race, ethnicity, income, region of country, size of community) and how quality is changing over time (IOM, 2001; IOM, 2003; MDH, 2015).

Incentivizing Care Quality

Value-based purchasing and pay-for-performance programs have become increasingly common in health care, with the primary goal of paying clinics and hospitals based on the quality of the health care provided to patients rather than the volume of services provided. Research on value-based purchasing and pay-for-performance programs suggests that a substantial financial incentive is needed to create measurable improvements in health care outcomes. For example, incentives may need to be increased up to 10 percent or more to significantly improve provider care patterns, innovation in care systems, and quality and cost outcomes (Cromwell, Trisolini, Pope, Mitchell, & Greenwald, 2011). Studies have shown that pay-for-performance hospitals eligible for larger incentives show the largest improvements in performance. Larger incentives appear to have bigger effects and to be more sustained among those hospitals eligible for a large bonus compared to those eligible for only a small bonus. In one study, 14, 17, and 12 percentage points more of pay-for-performance hospitals eligible for larger incentives achieved a performance score of 90 percent or higher in 2006, 2007 and 2008 respectively compared to nonparticipating hospitals and participants eligible for smaller incentives (Werner, Kolstad, Stuart, & Polsky, 2011). Damberg, Elliott, and Ewing (2015) assert that increasing the size of incentives in pay-for-performance programs may unintentionally further exacerbate disparities in payments among providers based on patient mix, and take resources away from providers that most need them to make improvements.

Public reporting on the measurement of quality of care is a growing tool at both the national and state levels to provide consumers, payers, and health care providers with information on cost, quality, and patient satisfaction (Health Affairs, 2012). This move toward transparency can help consumers make informed decisions when choosing providers, and help motivate improvement of provider performance. In order to be useful, consumers need to have access to public reports that are both understandable and relevant. A 2008 Henry J. Kaiser Family Foundation poll found that 30 percent of Americans said they saw information comparing the quality of different insurance plans, hospitals or doctors, but only 14 percent reported having used such information (Health Affairs, 2012). In 2011, a study examining community collaboratives in the Agency for Healthcare Research and Quality Chartered Value Exchange Program found that some websites comparing hospital performance were used primarily by consumers who were White, college educated, and over age 45 (Health Affairs, 2012). While the effects of current public reporting systems have been mixed, advancements in reporting are increasingly being developed and used across sectors (Fung, Lim, Mattke, Damberg, & Shekelle, 2008; Health Affairs, 2012; Sinaiko, Eastman, & Rosenthal, 2012; Werner & Bradlow, 2010). Important to this advancement is determining the right set of quality measures to use and making sure consumers are educated on what these scores mean and how they can be used to make performance comparisons and informed decisions about care (Health Affairs, 2012; NQF, 2014; Sinaiko, Eastman, & Rosenthal, 2012).

Social Determinants of Health

Socio-demographic factors such as income, education, race, and ethnicity interact with health outcomes in complex ways. Higher levels of income and education are associated with longer lifespans and better health outcomes (NBER, 2003). Financial resource strain, including food and housing insecurity, is connected to poorer health (IOM, 2014). Race and ethnicity are linked with socio-economic status, and racial and ethnic minorities are more likely to experience social disadvantage, discrimination, and poorer health outcomes (IOM, 2014; NASEM, 2016a).

There is little published research on the interactions between patient-level socio-demographic factors and provider- and system-level factors. The impact these interactions may have on quality measure results is not fully understood (Fung et al., 2010; NQF, 2014). Patient-level factors explain the majority of variation in quality measures, but providers and systems are responsible for introducing new therapies and other changes that influence health care quality (Fung et al., 2010). Clinical and social factors can accumulate and interact to complicate care and affect health (Shippee, Shah, May, Mair, & Montori, 2012).

To gain a better understanding of the interactions between patient-level socio-demographic factors and provider- and system-level factors, linking outcomes to socio-demographic or environmental data on the areas in which patients live can complement and enrich health outcome information (IOM, 2014). Tracking health outcomes at a geographical level allows outcome data to be linked to information about the physical and social landscape where the outcome data is located. Useful geographical units for tracking health outcomes include counties, ZIP codes, census tract areas, and individual addresses. Generally, smaller geographical units are desirable because they can provide more detailed and homogenous population information (IOM, 2014; Krieger, Waterman, Chen, Soobader, Subramanian, & Carson, 2002). There is a body of research that suggests ZIP codes are not ideal units for tracking health outcomes because they vary widely in size, change frequently, and are created to optimize mail delivery, not to accurately portray a population (Grubesic & Matisziw, 2006; Krieger et al., 2002).

Unintended Consequences

Value-based purchasing, pay-for-performance, and public reporting initiatives can incentivize improvements in patient quality of care for the services measured, but may bring unintended consequences for populations who experience disparities and the providers who serve them if they do not account for patient social risk factors. These unintended consequences may include but are not limited to: the reduction of payments to physicians serving disadvantaged communities, providers avoiding patients perceived as likely to lower quality scores, reduced access to health care for disadvantaged patients, and financial sustainability challenges for safety net providers (Bernheim, 2014; Joynt & Jha, 2013; Lipstein & Dunagan, 2014; Ryan, 2013). For example, assuming that safety net providers incur financial penalties and the magnitude of the financial penalties increase as the incentive programs continue, the resource reductions from their additive effects on the safety net providers may cause the quality of care to deteriorate among sites caring for more disadvantaged patients (Ryan, 2013).

When providers' patient populations are not taken into account when measuring quality, providers who disproportionally serve patients who experience health disparities may be penalized financially for not achieving performance benchmarks. There is growing evidence that patients who are socially and economically disadvantaged may be unable to achieve health outcomes that are equal to the outcomes of non-disadvantaged patients due to the cumulative effects of deprivation and discrimination (NQF, 2014). The Centers for Medicare & Medicaid Services (CMS) Hospital Readmissions Reduction Program's measures and associated financial penalties have been under examination with calls for performance score adjustments to account for the effects of factors beyond hospital influence at the individual or neighborhood level (Jha & Zaslavsky, 2014).

Studies examining hospital readmission rates show that inpatient quality of care has less influence on hospital readmission rates than do clinical and socio-economic factors, and these studies document socio-economic disparities in readmissions (Barnett, Hsu, & McWilliams, 2015; Berenson & Shih, 2012; Campione, Smith, & Mardon, 2015; Hu, Gonsahn, & Nerenz, 2014; Joynt & Jha, 2013). For example, Joynt and Jha (2013) found that large hospitals, teaching hospitals, and safety net hospitals had higher readmission rates than their smaller, nonteaching, non-safety net peers, and were more likely to receive payment cuts under the Hospital Readmissions Reduction Program. The study noted that prior research suggests that differences between hospitals are likely related to both medical complexity and socio-economic mix of the patient population, with less evidence that readmissions differences are related to hospital quality.

The financial pressure on safety net hospitals coupled with Medicare and Medicaid reduced disproportionate-share hospital payment reductions make the better alignment of incentives a pressing need (Gilman et al., 2014). In 2013, the Medicare Payment Advisory Commission (MedPAC) reported that under CMS's Hospital Readmissions Reduction Program, hospitals' readmission rates and penalties were positively correlated with their low-income patient share—that is, the more low-income patients a hospital had, the larger the readmissions penalties levied by CMS. CMS's readmissions risk adjustment model did not adjust for the effect of socio-economic status on readmissions.

Risk Adjustment

Risk adjusting quality measures to isolate the clinical contribution to outcomes and to remove patient factors can create more equitable comparisons of provider performance for public reporting and incentive-based programs. The National Quality Forum (NQF) recommends risk adjustment decisions consider the distinction between measures designed for population health reporting and measures designed for making payment and reimbursement decisions related to health care quality, and to focus risk adjustment activities on outcome measures as they are influenced by a more complex range of factors (Fiscella, Burnstin, & Nerenz, 2014; NQF, 2014).

Risk Factors

Quality measures can be adjusted using a variety of risk factors as shown in Table D-1. Adjusting for clinical factors can explain much of the variation in quality measure scores, and the variation that remains may or may not be explained using demographic, socio-economic, and other factors (NQF, 2014). Data for some factors, such as clinical factors, are easily attainable while others, such as attitudes and genetics, are more difficult to obtain.

Table D-1. Risk Factors

Factors	Examples
Clinical	Diagnoses, conditions, and severity; physical, mental, and cognitive function
Demographic characteristics	Age, sex, race, ethnicity, primary language

Factors	Examples
Psychosocial, socio-economic, and environmental factors	Income, education, occupation, health insurance and neighborhood
Health-related behavior and activities	Tobacco use, diet, physical activity
Quality of life, attitudes, and perceptions	Health status, cultural beliefs, religious beliefs
Genetics	Predisposition to conditions or health-related behaviors

Source: NQF, 2014.

The National Academies of Science, Engineering, and Medicine (National Academies) analyzed factors that are conceptually likely to affect the health care outcomes of Medicare beneficiaries as an input to the analyses that the U.S. Department of Health and Human Services is conducting through the Office of the Assistant Secretary for Planning and Evaluation under federal IMPACT legislation.[46] The National Academies identified six areas for consideration: socio-economic position; race, ethnicity, and cultural context; gender; social relationships; residential and community context; and health literacy (NASEM, 2016a).

Using Socio-demographic Factors in Risk Adjustment

The increased use of health care quality measures in incentive programs that reward superior performance and penalize poor performance has raised questions about the validity and fairness of these rewards and penalties when the socio-demographic complexity of patients is not considered, and has generated interest in using socio-demographic factors to risk adjust quality measures (NQF, 2014). The NQF cites income, education, homelessness, English language proficiency, and insurance status as socio-demographic factors that should be tested as potential risk adjustment factors, as they can influence a patient’s ability to meet health care benchmarks regardless of the quality of health care patients receive.

The study of using socio-demographic factors to risk adjust quality measures—especially ambulatory measures—is nascent and thus far has produced mixed results showing some, little, or no effect on provider performance rankings (NASEM, 2016a). For example, one study examined whether factoring socio-economic status into a congestive heart failure readmission measure changed hospital readmission rates (Blum et al., 2014). The researchers found that the impact of socio-economic status on readmission was small and did not impact hospital rankings. Another study examined combining census track-level socio-economic data such as poverty rate, educational attainment, and housing vacancy rate with hospital readmissions measures for acute myocardial infarction, heart failure, and pneumonia (Nagasako, Reidhead, Waterman, & Dunagan, 2014). Researchers found that including these socio-demographic variables

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[46] Improving Medicare Post-Acute Care Transformation Act, H.R. 4994.

explained some of the variation in results, although there was little difference in average readmission rates between the adjusted and unadjusted scores.

Challenges

Critics of including socio-demographic factors in quality measurement risk adjustment models argue that the adjustment would mask disparities and make it difficult to hold providers of lower-quality care accountable (Jha & Zaslavsky, 2014; Krumholz & Bernheim, 2014; Iezzoni, 2013; NQF, 2014). For example, while research suggest that including socio-economic factors in readmission measures might increase the usefulness of the measures for hospitals, payers and other stakeholders, there is much concern that the decreased variation decreases the ability to discriminate among hospitals with different performance, and obscure the detection of disparities in care (Nagasako et al., 2014). Bernheim (2014) states that risk adjusting quality measures for patient socio-economic status sets worse outcomes as the expectation and risks diminishing the incentives for improving care for vulnerable patients of low socio-economic status by enshrining and accepting current outcomes disparities. Further, while there is growing evidence as to the unintended consequences of not accounting for the social determinants of health in quality measurement systems, especially for purposes of payment, there is a relative dearth of evidence on how exactly to correct for these shortcomings through risk adjustment specifically. Findings have been mixed on analyses involving the impact of risk adjustment including socio-economic status and other social determinants of health. Some studies show including socio-economic status and other social determinants substantially alter provider quality rankings, some find that including social determinants has little impact on most quality scores, and several found that inclusion of socio-economic status in predictive models improves the model’s predictive ability (NASEM, 2016a).

Alternatives to Risk Adjustment

Other methods and combinations of them can be used to assess and compare provider performance on quality metrics.

Stratification

Stratification can may be particularly useful for uncovering disparities in care and for rewarding health plans and physician groups that reduce such disparities (Fiscella, Franks, Gold, & Clancy, 2000). Analyses that focus on the presence of socio-demographic disparities in health care are well-suited to stratification. Stratification provides clear information about performance across patient categories (NQF, 2014). NQF (2014) recommends that if quality measures are risk adjusted by socio-demographic factors, they should also be stratified to avoid masking disparities. The health system’s data can better equip them to develop, apply and use quality metrics stratified by race, ethnicity, or other socio-demographic factors to improve clinical services, improve population health, and reduce health disparities (IOM, 2009; IOM, 2014). Limitations of stratification include the occurrence of small group sizes in reporting, which decrease the reliability of the rates and could potentially lead to concerns about privacy. To address those issues, the NQF recommends that explanations about limitations or minimum cell sizes should accompany stratified data (NQF, 2014).

Peer Grouping

Peer grouping can be used to better compare providers that see similar populations. In health care quality measurement, peer grouping refers to the creation of peer groups of health care units caring for a similar mix of patients (NQF, 2014). The rationale behind peer grouping is that clinics or hospitals with similar structural and patient characteristics can be more equitably compared to each other (Byrne et al., 2009). Risk adjustment that incorporates patient characteristics does not address differences in community factors or funding, which can influence the performance of hospitals and clinics. Peer grouping can involve grouping units with similar resources (e.g., FQHCs, rural clinics, etc.), and may often also involve grouping units with similar patient populations (e.g., patients in Minnesota Health Care Programs, veterans, etc.). Constructing peer groups for comparison occurs after performance scores are computed. This approach avoids the issue of reducing sample sizes seen with stratification. Risk adjusting a performance score for socio-demographic factors would not always or automatically exclude the possibility of also using peer groups for comparison (NQF, 2014).[47]

A recent MedPAC recommendation regarding hospital readmissions is an example of creating peer groups for comparison as a way to lessen the impact of a performance penalty on safety-net hospitals (MedPAC, 2013). In 2013, to address the issue of readmissions reduction for hospitals with high shares of low-income patients and lessen the impact of a performance penalty on those hospitals, MedPAC recommended that CMS compare hospitals serving a similar share of low-income patients on their readmissions rates. MedPAC advised against adjusting readmissions rates for socio-demographic factors so as to not mask disparities. When computing penalties, MedPAC explained that each hospital’s target readmission rate would be based on the performance of hospitals with similar patient populations. MedPAC’s proposal was essentially to use one method of risk adjustment for public reporting and a second method when assessing financial penalties to correct for the problem of hospitals serving poor patients paying disproportionate penalties. MedPAC suggested that using peer groups to determine penalties and directing resources to providers serving poor communities may help reduce disparities in penalties between hospitals serving poorer and wealthier communities.

Peer groups can potentially mask quality differences. Even within the same categories, providers can still have variation in location, patient populations, and funding sources, making comparisons challenging—this is particularly true for safety net providers (NQF, 2014). While

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[47] In 2010, the NQF Advisory Group recommended the following six conditions for peer grouping: diabetes, coronary artery disease, pneumonia, asthma, congestive heart failure, and total knee replacement. These conditions were chosen because they are common, they impact a variety of patient and payer populations, they vary greatly in cost between providers, and they include either a major hospital component and/or a major specialty physician component.

risk adjustment accounts for the distribution of patient characteristics, peer grouping adjusts for unit characteristics. An above-average performer in a low-performing peer group of units is still low-performing when compared to all units.

Payment Adjustment

In value-based purchasing and pay-for-performance programs, instead of risk adjusting quality measures, payers can adjust the payment mechanism to account for differences in patient populations. Incentive-based programs may address unintended consequences by paying greater amounts per goal to entities that primarily serve disadvantaged patients, pay greater amounts for each disadvantaged patient that meets a goal or benchmark (Damberg, Elliott, & Ewing, 2015), create “post-adjusted” provider payments, or reward improvement on quality metrics in a similar fashion as absolute achievement (Casalino et al., 2007). Payment adjustment can be accomplished by either basing payment on measures that are risk adjusted taking into consideration social factors, or through other methods such as directly funding programs to improve the quality of care for disadvantaged patients (Berenson & Shih, 2012).

Appendix E. University of Minnesota Empirical Analysis

An Assessment of the Use of Socio-demographic Variables for Risk Adjusting Diabetes, Vascular, Asthma, and Colorectal Cancer Screening Measures

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Introduction

The increasing use of public reporting of clinic quality measures to inform consumer choice and incentives has spurred interest in or socio-demographic characteristics to assure that the comparisons between clinics are grounded in a similar patient mix and result in fair comparisons between clinics (National Quality Forum 2014). A goal of quality measurement and reporting is to incent improvement through a variety of pathways, while avoiding unintended consequences such as attributing differences due to social factors--for instance neighborhood effects--to clinics and obfuscating differences in clinic quality, thus holding providers accountable for factors outside their control, and accepting lower quality for disadvantaged populations (Committee on Accounting for Socioeconomic Status in Medicare Payment Programs et al. 2016. While there is a strong desire to adjust for socio-demographic characteristics, there is also a strong desire to avoid unintended consequences.

As part of Minnesota's efforts to measure clinic performance, the Minnesota Department of Health (MDH), through the Minnesota Statewide Quality Reporting and Measurement System (SQRMS), seeks to assess the use of certain socio-demographic data for potentially risk adjusting and stratifying clinic quality measures (Minnesota Department of Health 2015). This report, done by the University of Minnesota under contract to MDH, uses data collected and validated by MN Community Measurement (MNCM) to assess risk adjusting quality measures for race, ethnicity, language, country of origin, insurance type, and other patient socio-demographic indicators for the purpose of performance categorization for diabetes, vascular, and asthma care quality and colorectal cancer screening.

The analysis addresses three major issues in risk adjusting performance:

1. Heterogeneity in patient populations across clinics;
2. The need for a conceptual basis and considering unintended consequences; and
3. The potential for statistical error to affect metrics.

The fact that clinics serve populations with different demographic composition creates challenges for comparability across clinics and risk adjustment through direct standardization (Shahian and Normand 2015). Direct standardization is used to compare clinics as if they were serving the same patient mix; a pivotal requirement is that the clinics being compared all have some representatives within each patient category. If the direct standardization involves insurance type (commercial, Medicare, Minnesota Health Care Programs (MHCP), self-pay/uninsured) and race/ethnicity (Black, Hispanic, Asian, American Indian, Pacific Islander) then each clinic being compared must serve some patients in each cell (e.g., MHCP – American Indian). If this condition is not met direct standardization cannot be employed. A similar point holds for indirect adjustment when clinics populations do not overlap – "In the absence of covariate overlap, there may be patients from one hospital for whom there are no comparable patients in the other hospital (in causal inference parlance, there is no empirical counterfactual, and thus no way to fairly compare performance in all patients cared for by the two hospitals)" (Shahian and Normand 2015). A further issue is imbalance and bias across clinics – "the prevalence of relevant risk factors may be different and this covariate imbalance may bias the interpretation of results and the determination of outliers" (Shahian and Normand 2015). These arguments suggest that the degree to which clinics are comparable in terms of overlap and balance in the components of the risk adjustment calculation, e.g. the groups of patients being served, affects whether direct adjustment can be used and the comparability of clinics when doing indirect adjustment.

The second issue is the selection of risk adjusters. A goal of risk adjustment is to account for patient-population characteristics that may independently affect results of a given measure and are not randomly distributed across all providers (Minnesota Rules, Chapter 4654). A concern with risk adjustment is that there may be unintended consequences for patient populations who experience health disparities and the providers who serve them (The Office of the Revisor of Statues 2014). Methodologically, in performance categorization that assesses whether provider performance is worse or better than average, risk adjustment aims to reduce over-dispersion due to systematic factors that are outside the control of the provider and that can result in errors in identifying providers with worse or better than average performance (Spiegelhalter 2005a; Spiegelhalter 2005b). Commonly used criteria to assess whether a risk adjuster is appropriate to use: (a) it influences an outcome, (b) it is significant between providers, (c) it is outside the control of providers, (d) it has no unintended consequences, and (e) it is feasible to collect (MN Community Measurement and Risk Adjustment Sub-Committee of the Measurement and Reporting Committee 2016). The criteria "influences an outcome" can be interpreted in two ways, depending on what the risk adjustment is being used for. The first is whether the adjuster affects a quality measure. The second is the degree to which risk adjustment for a specific factor affects performance categorization. This report assesses risk adjusters in terms of these criteria and their influence on both types of outcomes.

The third issue is performance categorization, identifying clinics as having worse or better than average performance. Performance categorization is difficult because displays of simple rankings or even rankings with standard errors in caterpillar plots can result in inappropriate inferences and influence the standard errors associated with a clinic due to clinic size differences, since the errors are larger for smaller clinics (Spiegelhalter 2005a).

These three issues result in three questions that guide this evaluation:

1. How comparable are clinics in terms of the patient mix when patients are categorized by socio-demographic characteristics such as insurance type, race/ethnicity/preferred language/country of origin (RELO), and deprivation?
2. What are the effects of risk adjustment on care quality at the patient level and on clinic performance categorization?
3. How does clustering of patients in clinics, and implicitly in neighborhoods, affect performance categorization?

Data and Methods

The research design is an observational, retrospective, multivariate analysis of care quality in Minnesota clinics. The sample consists of patients nested in clinics. The unit of analysis is the patient and the inferential focus is clinic performance. The data include patients served by Medicare, Medicaid and commercial insurance, and uninsured and self-pay patients.

Population and Sample

The population is all Minnesota patients with diabetes, vascular, or asthma conditions or who are eligible for colorectal cancer screening. The sample is patients with these conditions seen in clinics that report quality data to MNCM for the Minnesota Statewide Quality Reporting and Measurement System (SQRMS) (Minnesota Department of Health 2015). The number of medical groups, clinics, and patients for each measure is reported in Table 1 below.

Measures

Quality

Diabetes, vascular, asthma, and colorectal cancer screening measures follow specifications for these measures developed by MNCM in collaboration with the community (MN Community Measurement 2015a, the measurement definitions come from these documents; 2015b, 2015c, 2015d). **Diabetes** performance is measured as the number of diabetes patients who met all of the following targets: (a) The most recent HbA1c in the measurement period has a value less than 8.0; (b) The most recent Blood Pressure in the measurement period has a systolic value of less than 140 and a diastolic value of less than 90 (both values must be less than); (c) Patient is currently a non-tobacco user; and (d) If the patient has a co-morbidity of Ischemic Vascular Disease, the patient is on daily aspirin OR an accepted contraindication. **Vascular** performance is measured as the number of IVD patients who met all of the following targets: (a) The most recent blood pressure in the measurement period has a systolic value of less than 140 and a diastolic value of less than 90 (both values must be less than); (b) Patient is currently a non-tobacco user; and (c) Patient is on daily aspirin OR an accepted contraindication (any date). **Asthma** performance is measured as the number of asthma patients who meet both of the following targets: (a) Asthma well-controlled; and (b) Patient not at elevated risk of exacerbation: The total number of emergency department visits and hospitalizations due to asthma, as reported by the patient, are less than two occurrences. **Colorectal cancer screening** performance is measured as the number of patients who were up-to-date with appropriate colorectal cancer screening exams. Appropriate exams include colonoscopy, sigmoidoscopy, or fecal blood tests. Each performance measure was a binary variable indicating whether all of the performance criteria was met or not.

MDH requires clinics with electronic health records (EHR) operational for the full measurement period to submit data on all patients who meet denominator definitions during the subsequent reporting cycle (MN Community Measurement 2015c). Clinics without an operational EHR for the full period are allowed to submit a random sample of patients. As per MN Community Measurement guidance, clinics with less than 60 patients in a population submit all patients and clinics with 60 or more patients submit at least 60 randomly sampled patients (MN Community Measurement 2015c). The measurement documentation provides extensive descriptions of the denominator definitions and methodology for selecting measures. MNCM certifies data submission and completes comprehensive validation prior to accepting it.

Table 1 shows the quality measures, dates of service (DOS), number of medical groups, number of clinics, and number of patients for all data submitted.

Table 1: Quality Measurement Data

Measures	Medical Groups	Clinics	Patients	Maximum # Patients Reported by a Clinic
Optimal Diabetes Care 01/01/2014 – 12/31/2014 DOS	121	579	211,103	4,290
Optimal Vascular Care 01/01/2014 – 12/31/2014 DOS	119	579	84,624	3,023
Optimal Asthma Control – Adult 07/01/2014 – 06/30/2015 DOS	134	614	58,881	841
Colorectal Cancer Screening 07/01/2014 – 06/30/2015 DOS	133	624	997,223	15,420

The minimum number of patients reported by clinics was 1 for all conditions.

Risk Adjusters / Control Variables

The data elements that identify the patient's **race, ethnicity, preferred language and country of origin (RELO)** are specified by MNCM and reported by MNCM as a component of the quality measure data that MN Community Measurement collects from data submitters (MN Community Measurement 2010, 2014). The socio-demographic data were collected by MNCM using processes they developed. For the cycle of data collection this evaluation is based on, submission of RELO data to MNCM was completely voluntary. RELO data is validated by MNCM to ensure that the data is collected using best practices: "1. Patients were allowed to self-report their race, Hispanic ethnicity, preferred language and country of origin; 2. Patients were allowed to select one or more categories for race (i.e., medical groups/clinics did not collect data using a Multi-Racial category); and 3. Medical groups/clinics are able to capture and report more than one race as selected by the patient"(MN Community Measurement 2016).

Clinics could provide up to four race/ethnicity codes for each patient, with the codes including American Indian, Asian, Black, Hispanic, Pacific Islander, White, Other, and Declined. Patients responding "Unknown" were excluded from the analysis. Because preferred language and country of origin had sparse counts for most languages, Non-English speaking, and Non-US codes were used in models. To account for the Somali and Hmong (Laotian) population in Minnesota, additional models were estimated including indicators for these groups.

Deprivation was constructed using data from American Factfinder (United States Census Bureau 2016) for data through 2014 (see Singh 2003 for a similar methodology). Measures at the ZIP code Tabulation Areas (ZCTA) level were used to construct the deprivation measure (the data was not detailed enough to work at a finer grain): (a) 100 - median household income as percent of maximum median household income; (b) Percent receiving public assistance; (c) Percent receiving SNAP; (d) Percent in poverty; (e) Percent unemployed; and (f) Percent single female with children. The Cronbach Alpha for the standardized measures is = 0.79 and the percent of common variance explained is 0.51. The deprivation measure is a standardized measure with a mean of 0 and a standard deviation of 1. The ZCTA data were integrated with patient level data by cross-walking on patient ZIP codes.

Insurance type at the time for measure reporting was reported for each patient: (a) Commercial; (b) Minnesota Health Care Programs (MHCP, including Medicaid); (c) Medicare; (d) Uninsured; and (e) Self-pay. Patients where insurance types was not reported, 4.6 percent of diabetes, 3.8 percent of vascular, 5.7 percent of asthma, and 3.2 percent of colorectal cancer screening patients, were excluded from the analysis. Indicators for insurance type were included in the models with commercial insurance as the contrast category and with self-pay and uninsured combined.

Age and gender were reported for each patient. The age range was 18 to 75. For analysis purposes, indicators for age categories similar to those used by Minnesota Community Measurement were used (diabetes and vascular: 18 to 25; 25 to 50; 50 to 65; over 65; colorectal cancer screening: Under 65; 65 or over; asthma: Adult only). Age and gender indicators were included in the models.

The patient and clinic ZIP codes were used to calculate the distance between the patient and the clinic's ZIP code centroids. Indicators were constructed for same ZIP code, within 10 miles, 10 to 20 miles, and more than 20 miles. Greater distance indicates either greater difficulty in accessing a clinic or patients with greater severity traveling further to get to a clinic they prefer. The percent of the patients living in the same ZIP code as the clinic were 24 percent for urban, 49 percent for micropolitan, 53 percent for small town, and 45 percent for frontier communities. Of the urban patients who did not live in the same ZIP code as the clinic, 55 percent lived with 10 miles of the clinic. Patients in small town and frontier communities tended to live in either the same ZIP code as the clinic or more than 10 miles away from the clinic.

Indicators for clinic types are critical access hospital (outpatient clinics) and federally qualified health centers. Clinic rurality was coded using rural urban commuting areas into the categories of urban, Micropolitan, small town, and frontier (WWAMI Rural Health Research Center 2006). Urban was the contrast category.

Methods

Missing Data

Missing RELO was assessed using cross-tabulations. The results of the analysis informed the procedures for addressing missing data.

Comparable Groups

Nearest neighbor cluster analysis was used to group clinics into groups that are similar in the types of patients served (see Ketchen and Shook 1996 for a description of the use of clustering methods to identify organizational groups). Clinics are characterized by vector that includes measures of the proportion of their patients who have commercial insurance, Medicare coverage, Minnesota Health Care Program coverage, or self-pay/uninsured; the proportion who are Asian, American Indian/Pacific Islander, Black, Hispanic, or White; and average deprivation. The clustering procedure groups similar clinics into hierarchical agglomerative clusters where similarity is measured by the distance between the clinics calculated using each clinic's vector (SAS procedure CLUSTER, Wards Method, standardized measures). The empirically derived clusters are evaluated by comparing the clusters along dimensions not used in the clustering, such as the proportion of the clinic in the cluster that are federally qualified health centers or critical access hospitals, to assess cluster characteristics. Clustering is based on a combination of factors rather than the presence/absence of a factor alone. For example, clinics in different clusters can each have patients of a particular race but the proportion of the patients in a race will differ. The clustering approach can be described as a pattern recognition/discovery method rather than a hypothesis testing method.

Risk Adjustment

Four methods were used to calculate risk adjusted rates. First, direct standardization to measure each clinic's performance for a standard population was tried (SAS procedure STDRATE). This approach was not feasible because not all clinics had patients in every insurance type, RELO, age, and gender combination. The next three methods were indirect risk adjustment using logistic regression because the outcome measure was binary (did not meet/met all goals). The three regressions varied in the structure of the error term suggesting over-dispersion among clinics (Spiegelhalter 2005b). *Over-dispersion* is the situation "in which the observed variability cannot be attributed to chance and a few divergent institutions. This typically arises when there is insufficient risk adjustment; there are many small institutional factors that contribute to excess variability and these may not be particularly important nor indicate poor quality care. The consequence is that, if one is not careful, the majority of institutions can be labelled as abnormal and this appears a contradiction in terms" (Spiegelhalter 2005b). The first regression treated all patient scores as fully independent and identically distributed, the second regression allowed for residual over-dispersion, and the third regression allowed for residual over-dispersion and included a random intercept for the clinic. The random intercept model was used to assess the ability of risk adjustment to account for the clustering of patients within clinics and to address fully the violation of the independent, identically distributed assumption for significance testing.

All models included only observations where all data in the most fully specified model are not missing. Only clinics with at least 30 non-missing observations are included to increase reliability and to maintain consistency with MN Community Measurement procedures.

The effect of adding risk adjusters into models is evaluated using the area under the receiver operating characteristics curve (estimated using SAS procedure Logistic) (Hajian-Tilaki 2013). Intra-class correlation coefficients for the total clinic effect and the marginal clinic effect net of risk adjusters are also calculated (Ene et al. 2015).

Performance Comparison

Performance was measured using an indirect standardization approach, comparing actual performance to expected performance. The expected number of patients meeting the quality goal in a clinic was calculated as the sum of the predicted probabilities at the patient level for meeting the quality goal by clinic. The residual over-dispersion model was used to categorize performance. The use of the random intercept model for performance categorization is discussed in the conclusions.

Performance categories, in five levels ranging from much worse than average to much better than average, are determined using methods that take into account the differences in reliability of performance measurement due to the number of patients reported by a clinic and that avoid the risk of comparison of rankings without accounting for confidence intervals (Spiegelhalter 2005a; Spiegelhalter 2005b). Since plots of both unadjusted average performance and observed/expected performance showed that the performance measures deviated from distributional expectations, bootstrap methods were used to obtain confidence intervals that reflect the empirical distribution of the unadjusted and adjusted performance measures (Neuburger et al. 2011).[52] An implicit assumption in this bootstrap methodology is that patients are randomly distributed across all clinics, which is an assumption unlikely to be met because patients are clustered within clinics. To address clustering of patients within clinics, the bootstrap methodology was extended, as follows: (a) sample 10,000 clinics with replacement from those reporting at least the number of patients the confidence interval is being calculated for (e.g., 30, 40, 50, ... 1,000, … patients); (b) within each clinic, sample the number of patients the confidence interval is being calculated for, with replacement; and (c) for each clinic

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[52] The results for the bootstrap methodology are consistent with an alternative methodology. We used a random intercept model for risk adjustment and reducing over-dispersion (Spiegelhalter, D. J. 2005b. “Handling over-dispersion of performance indicators.” *Quality and Safety in Health Care* 14(5): 347-351.) combined with the bootstrapping that did not take into account the clustering of patients within clinics and had similar performance categorization results to the over-dispersion only model that used bootstrapping that took into account the clustering of patients in clinics (results not reported).

calculate mean performance. The confidence limits were calculated at the 0.1, 2.5, 97.5 and 99.9 percentiles of the distribution of 10,000 clinics. These confidence limits were used because they approximate the 2 and 3 standard deviations from the mean typically used in quality improvement (Spiegelhalter 2005a).

To assess the effect of patients clustered within clinics, the results compare the average unadjusted proportion of patients meeting the quality goal performance category without accounting for clustering with the average unadjusted proportion of patients meeting the quality goal performance accounting for clustering. To assess the effect of risk adjustment, the results compare the average unadjusted proportion of patients meeting the quality goal performance category accounting for clustering with the residual over-dispersion risk adjusted performance measure (actual / expected) performance category that takes into account clustering of patients in clinics.

Results

Missing RELO Data and Descriptive Statistics

Table 2 shows the analysis of missing race / ethnicity (RE) data because of the focus on RELO in this analysis. The similarity of the RE missing pattern to the missing pattern for language and country of origin is also discussed. Data on age, gender, co-morbidities, and patient ZIP code are very rarely missing.

The analysis of missing data suggests that with few exceptions, medical groups chose to either submit or not submit race / ethnicity data. The proportion of data that was missing due to groups choosing not to submit any race / ethnicity data varied from 16.8 to 18.5 percent across measures. Among the medical groups submitting data, approximately 3 percent of patients were missing race / ethnicity data. This percentage includes some medical groups that had very high levels of missing race / ethnicity data. The pattern of missing country of origin data was similar, while the pattern of missing preferred language data was more similar to age and gender. The latter pattern may be due to preferred language being used in practice situations to identify the need for a translator. Because some medical groups chose not to submit race / ethnicity data we *cannot conclude* that the data is missing at random and care should be taken in generalizing the findings in this study to all clinics reporting quality data.

Analyses showed that for asthma and colorectal cancer screening, RE data was more likely to be missing for urban patients, and for diabetes and vascular data, RE was more likely to be missing for urban and micropolitan patients. Small town and frontier patients were less likely to be missing RE data for all measures. This suggests that the medical groups that chose not to provide RE data were more likely to be in urban areas. For diabetes and asthma, RE data was slightly more likely to be missing for commercial patients. For vascular, RE data was slightly more likely to be missing for commercial and self-pay or uninsured patients. For colorectal cancer screening, RE data was slightly more likely to be missing for MHCP and commercial patients. In sum, the RE data was less likely to be missing for rural (micropolitan, small town, frontier) patients and for Medicare, MHCP, and self-pay or uninsured patients.

Table 2: Missing Values by Medical Groups

	Some RE Data Missing				All RE Data Missing			Total
	# Medical Groups	# Patients	# Missing RE	Percent Missing	# Medical Groups	# Patients	Maximum Number of Missing RE	% Missing RE
Diabetes[1]	95	177,510	5,510	3.10%	26	33,593	11,547	18.5
Vascular[2]	93	71,990	1,592	2.21%	26	12,634	3,790	16.8
Asthma[3]	108	50,531	1,549	3.07%	26	8,350	3,177	16.8
Colorectal[4]	107	846,706	22,836	2.70%	26	150,517	48,512	17.4

1. There were two medical groups with 49% and 83% missing race/ethnicity data.
2. There were two medical groups with 87% and 63% missing race/ethnicity data.
3. There were two medical groups with 50% missing race/ethnicity data.
4. There were two medical groups with 58% and 98% missing race/ethnicity data.

Descriptive statistics

Table 3 shows the descriptive statistics for the performance and the primary risk adjusters. 67 to 80 percent of the patients are seen at urban clinics and 75 percent of the patients are seen within 10 miles of their clinic. The proportion of insurance types varies by condition, with self-pay/uninsured being very low. Average deprivation is below zero, which means that the average patient included in the measures has below average deprivation). In summary, the population predominantly has commercial/Medicare coverage, is White, has low deprivation, and with the exception of asthma, are in their late 50s.

Table 3: Descriptive Statistics for Patients Included in Analysis

	Optimal Diabetes Care		Optimal Vascular Care		Optimal Asthma Care		Colorectal Cancer Screening	
Measure	**Mean**	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**
Prop. Patients Meeting Target	0.53	0.50	0.70	0.46	0.57	0.49	0.73	0.45
RELO*								
American Indian	0.02	0.13	0.01	0.11	0.01	0.11	0.01	0.08
Asian	0.03	0.17	0.01	0.12	0.02	0.15	0.02	0.13
Black	0.08	0.28	0.04	0.19	0.11	0.32	0.04	0.20
Hispanic	0.04	0.20	0.01	0.10	0.03	0.18	0.02	0.12
Pacific Islander	0.00	0.04	0.00	0.03	0.00	0.04	0.00	0.03
White	0.84	0.36	0.93	0.25	0.83	0.37	0.93	0.26
Other	0.00	0.06	0.00	0.04	0.01	0.08	0.00	0.04
Non English Speaking	0.06	0.24	0.02	0.14	0.02	0.15	0.03	0.17
Non US Origin	0.10	0.29	0.04	0.20	0.05	0.22	0.05	0.22

Table 3: Descriptive Statistics for Patients Included in Analysis

	Optimal Diabetes Care		Optimal Vascular Care		Optimal Asthma Care		Colorectal Cancer Screening	
Measure	**Mean**	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**
Deprivation	-0.13	0.90	-0.25	0.81	-0.16	0.96	-0.29	0.77
Demographics								
Age	58.43	11.47	63.91	8.33	35.01	9.69	61.65	6.83
Female	0.47	0.50	0.30	0.46	0.67	0.47	0.56	0.50
Co-Morbidities								
Type 1 Diabetes	0.07	0.25						
Vascular	0.18	0.38						
Type 1 or 2 Diabetes			0.33	0.47				
Depression	0.24	0.43	0.20	0.40	0.26	0.44		
Insurance Type**								
Insurance - Commercial	0.41	0.49	0.33	0.47	0.63	0.48	0.49	0.50
Insurance - Medicare	0.39	0.49	0.55	0.50	0.06	0.24	0.36	0.48
Insurance - MHCP	0.16	0.37	0.10	0.30	0.28	0.45	0.14	0.34
Insurance - Self-Pay/Uninsured	0.02	0.13	0.00	0.05	0.01	0.09	0.01	0.07
Clinic Rurality								
Urban	0.70	0.46	0.73	0.44	0.81	0.39	0.67	0.47
Micropolitan	0.14	0.35	0.14	0.34	0.10	0.30	0.15	0.36
Small Town	0.10	0.31	0.09	0.29	0.07	0.26	0.11	0.31
Frontier	0.06	0.24	0.04	0.20	0.02	0.14	0.07	0.25
Patient Distance to Clinic								
Same ZIP Code	0.31	0.46	0.25	0.43	0.29	0.45	0.33	0.47
Within 10 Miles	0.44	0.50	0.43	0.50	0.49	0.50	0.42	0.49
Between 10 and 20 Miles	0.16	0.37	0.18	0.39	0.15	0.36	0.16	0.37
Over 20 Miles	0.09	0.29	0.13	0.34	0.07	0.26	0.08	0.28
N	126,976		53,431		33,273		612,869	

* RE may sum to greater than 1 because patients could select multiple categories.
** Insurance unknown omitted.

Comparable Groups

Table 4 presents the comparable clinics analysis that was done using cluster analysis. In contrast to approaches that assign clinics to categories, the cluster analysis used the proportion of each clinic's patients in various categories (clustering data) to identify clinics that have similar patient mixes (a cluster). The clusters are interpreted/validated using measures not used in the clustering (validation data). The bold/highlighted cells call attention to variables that help interpret a cluster. Cluster 1 consists of clinics relatively high in White, Medicare patients that are located in rural areas. Cluster 1 includes critical access hospitals, also an indication of rurality. Cluster 2 consists of clinics with relatively wealthy (deprivation is very low) patients with commercial insurance. Clusters 3, 4, and 5 include the federally qualified health clinics. Cluster 3 is a small number of clinics serving predominantly Asian populations with relatively high commercial insurance. Clusters 4 and 5 include a large percentage of MHCP and self-pay / uninsured patients who are Black (cluster 4) or Hispanic (cluster 5).

The cluster analysis suggests that there may be non-comparable groups of clinics serving different patient populations. The very high percentage of White patients in clusters 1 and 2 combined with the low percentage of MHCP or self-pay / uninsured patients is consistent with being unable to do direct risk adjustment and consistent with the observation that not all clinics may be easily comparable between clusters (Shahian and Normand 2015). In the remainder of analysis, clusters 3, 4, and 5 are combined and referenced as safety-net clinics.

Table 4: Comparable Clinics Analysis

	Cluster				
	1	**2**	**3**	**4**	**5**
Clustering Data	N=361	N=130	N=9	N=45	N=9
% Commercial	41%	**65%**	**56%**	23%	17%
% Medicare	**39%**	20%	16%	30%	19%
% MHCP	14%	9%	17%	**40%**	**36%**
% Self-Pay / Uninsured	2%	1%	2%	4%	**25%**
% Asian	1%	3%	**62%**	6%	2%
% Amer. Indian / Pac. Isl.	1%	1%	0%	4%	**11%**
% Black	1%	4%	4%	**34%**	**18%**
% Hispanic	1%	1%	15%	5%	**31%**
% White	**96%**	**91%**	2%	52%	52%
Average Deprivation	-0.34	**-0.51**	-0.23	**0.77**	**0.34**
Validation Data					
% FQHC	2%	0%	**11%**	**16%**	**56%**
% CAH	**10%**	1%	0%	0%	0%
% Urban	51%	98%	100%	93%	89%
% Micropolitan	**11%**	2%	0%	2%	**11%**
% Small Town	**13%**	0%	0%	0%	0%
% Frontier	**25%**	0%	0%	4%	0%

Risk Adjustment Effects

Table 5 shows the effect of various sociodemographic risk adjusters reported as odds ratios. The odds ratio of 0.54 for American Indian patients with diabetes is interpreted as meaning that American Indian patients have 54 percent the chance of optimal diabetes care as a White patient. A one standard deviation increase in deprivation for a patient is associated with a 92 percent chance of optimal diabetes care. The bold/highlight cells call attention to significant effects ($p < .05$). The number and pattern of significant effects shows that the analysis was sufficiently powered to detect effects. Because an indicator for age over 65 was included in all models except asthma, the Medicare effect for those models most likely reflects dual-eligible patients. The RE effects suggest that American Indians and Blacks are consistently less likely than Whites to reach quality goals. While the effects for Pacific Islander are similar to American

Indians and Blacks, the low number of Pacific Islanders may have produced less precise estimates. Interestingly, non-English speakers and non-US origin patients have higher diabetes and vascular outcomes. This effect is difficult to interpret because it is net of RE effects.

Table 5: Risk Adjuster Odds Ratios and 95% Confidence Intervals

	Optimal Diabetes Care			**Optimal Vascular Care**			**Optimal Asthma Care**			**Colorectal Cancer Screening**		
	Odds Ratio	**Lower CL**	**Upper CL**	**Odds Ratio**	**Lower CL**	**Upper CL**	**Odds Ratio**	**Lower CL**	**Upper CL**	**Odds Ratio**	**Lower CL**	**Upper CL**
RE (Contrast=White)												
American Indian	**0.54**	0.49	0.59	**0.76**	0.63	0.90	**0.70**	0.57	0.86	**0.70**	0.65	0.75
Asian	**0.88**	0.80	0.96	1.17	0.96	1.45	0.90	0.76	1.08	1.02	0.97	1.08
Black	**0.69**	0.65	0.72	**0.71**	0.64	**0.79**	**0.65**	0.59	0.71	**0.85**	0.82	0.88
Hispanic	**0.85**	0.78	0.91	1.16	0.95	1.42	0.95	0.82	1.11	**1.10**	1.04	1.17
Pacific Islander	**0.63**	0.48	0.84	0.84	0.46	1.52	0.62	0.36	1.05	**0.70**	0.58	0.85
Other	**0.78**	0.63	0.96	0.84	0.54	1.30	0.93	0.70	1.24	**0.69**	0.61	0.79
Language, Origin, and Deprivation												
Non English Speaking	**1.14**	1.06	1.24	**1.47**	1.22	1.78	0.97	0.79	1.18	**0.77**	0.73	0.80
Non US Origin	**1.49**	1.40	1.60	**1.27**	1.10	1.46	0.97	0.84	1.12	**0.83**	0.80	0.86
Deprivation*	**0.92**	0.90	0.93	**0.91**	0.89	0.93	**0.95**	0.92	0.98	**0.92**	0.91	0.93
Comorbidities												
Type 1 Diabetes (Measured for Diabetes Care)	**0.68**	0.64	0.71									
Depression	**0.82**	0.79	0.84	**0.86**	0.82	0.90	**0.94**	0.89	0.99			
Vascular Disease	**0.81**	0.79	0.84									
Diabetes (Type 1 or 2) (Measured for Vascular Care)				**1.14**	1.09	1.19						
Insurance Type (Contrast=Commercial)												
Medicare (Duals)	**0.83**	0.81	0.86	**0.69**	0.66	0.74	**0.62**	0.56	0.69	**0.90**	0.88	0.91
Minnesota Health Care Plans	**0.61**	0.59	0.63	**0.51**	0.47	0.54	**0.62**	0.59	0.66	**0.59**	0.58	0.60
Self-pay/ Uninsured	**0.65**	0.60	0.69	**0.47**	0.40	0.55	**0.45**	0.39	0.52	**0.31**	0.29	0.32
Clinic Type												
Federally Qualified	**0.62**	0.51	0.74	**0.55**	0.41	0.76	**0.16**	0.06	0.44	**0.32**	0.26	0.41

Table 5: Risk Adjuster Odds Ratios and 95% Confidence Intervals

	Optimal Diabetes Care			**Optimal Vascular Care**			**Optimal Asthma Care**			**Colorectal Cancer Screening**		
	Odds Ratio	**Lower CL**	**Upper CL**	**Odds Ratio**	**Lower CL**	**Upper CL**	**Odds Ratio**	**Lower CL**	**Upper CL**	**Odds Ratio**	**Lower CL**	**Upper CL**
Health Center												
Critical Access Hospital	0.95	0.81	1.12	0.95	0.78	1.15	0.60	0.26	1.39	0.96	0.78	1.17
Rurality (Contrast=Urban)												
Micropolitan	**0.86**	0.75	0.97	**0.86**	0.75	0.98	**0.53**	0.31	0.90	0.97	0.82	1.15
Small Town	**0.84**	0.73	0.96	**0.78**	0.67	0.92	**0.47**	0.25	0.90	**0.83**	0.69	0.99
Frontier	**0.75**	0.67	0.85	**0.83**	0.70	0.99	**0.33**	0.13	0.85	**0.63**	0.55	0.73
Distance to Clinic (Contrast=Same ZIP Code)												
Within 10 Miles	0.98	0.95	1.02	0.97	0.92	1.02	1.00	0.94	1.06	**1.02**	1.01	1.04
10 to 20 Files	0.96	0.93	1.00	1.01	0.95	1.08	1.01	0.93	1.10	1.00	0.99	1.02
More than 20 Miles	**0.89**	0.85	0.93	0.95	0.89	1.02	0.98	0.88	1.08	**0.89**	0.87	0.91

* Effect of a one standard deviation change. Odds ratios in shaded bold are significantly different than 1 ($p < .05$). Age and gender effects not reported.

Table 6 shows the intra-class correlation coefficients (calculated using methods described in Ene et al. 2015) that estimate the proportion of the variation in quality outcomes that is due to unobserved clinic level differences, without and with risk adjusters. It can be interpreted as the degree to which patients within the same clinic receive high-quality care. The variation explained is consistent with other reports (Fung et al. 2010). The high proportion explained for asthma may be due to its more recent adoption as a quality measure and being at an earlier stage of implementation.

Table 6: Intraclass Correlation Coefficients at the Clinic Level

(Proportion of Variance Explained)

Measure	**Without Adjusters**	**With Adjusters**
Diabetes	5.17%	3.58%
Vascular	4.15%	2.67%
Asthma	36.53%	32.96%
Colorectal	11.83%	8.52%

Table 7 shows the performance of the models using a statistical tool known as “the area under the receiver operating characteristics curve” (AUROC) (Bewick, Cheek, and Ball 2004; Hajian-Tilaki 2013). A value of 1 for AUROC means that the model perfectly predicts high quality and a value of .5, which is equivalent to a toss of a fair coin, means that the model does not provide information about high quality (Hanley and McNeil 1982). Values under .70 can be interpreted as a poor fit (Tape 2015). While the risk adjustment models significantly improve the prediction of quality outcomes, their overall effect is low. Adding RELO, deprivation, and insurance type to the other measures results in modest improvements in model fit in the range of 4 to 12 percent. Even with improvement, the final models that include the full adjustment for socio-demographics would still be considered to not add much explanatory power. Consistent with the intra-class correlation analysis the highest percentage gains were with Asthma and Colorectal Cancer screening.

Table 7: Model Performance Assessed With Area Under Receiver Operating Characteristic Curve (AUROC)

					Improvement by Adding Insurance, Race, Ethnicity, Deprivation	
Measure	**Without Insurance, RELO, Deprivation**	**Adding RELO, Deprivation**	**Adding Insurance**	**Adding Insurance, RELO, Deprivation**	**Amount**	**Percentage**
Diabetes	0.608	0.627	0.626	0.636	0.028	4.61%
Vascular	0.586	0.599	0.602	0.609	0.023	3.92%
Asthma	0.572	0.623	0.621	0.639	0.067	11.71%
Colorectal	0.552	0.589	0.596	0.607	0.055	9.96%
Other measures included in all models were age, gender, clinic type, clinic rurality, patient distance to clinic, co-morbidities						

In summary, our risk adjustment model shows that:

1. RELO and deprivation are significant predictors of quality outcomes and they add significant explanatory power to the risk adjustment models including other factors (e.g., age, gender, insurance type).
2. The overall models including RELO and all other measures are modest in their explanatory power.
3. The increase in explanatory power of adding RELO to existing risk adjustment models is attenuated because of collinearity (similarity to existing measures in the model).

Performance Categorization and Change

Table 8 shows the effects of risk adjustment (unadjusted/adjusted) and performance categorization method (not clustering by clinic, clustering by clinic) on the distribution of clinics in each performance category. The most striking effect is due to performance categorization method. Within a type of measure (unadjusted, adjusted), categorizing clinics taking into account the clustering of patients within clinics results in substantially fewer clinics being categorized as different than average performance—the variation in performance is converging towards the mean. Within performance categorization method (not clustered, clustered) risk adjustment results in a slight increase in the number of clinics categorized different from average performance.

The analyses show that taking into account clustering of patients in clinics for performance categorization has larger effects than current risk adjustment or risk adjustment with available SES enhancements. Not taking into account clustering of patients within clinics in performance categorization results in substantial over-dispersion, where more clinics are identified as different from average than would be expected with the given confidence intervals. Taking into account clustering of patients within clinics in performance categorization results in an expected number of clinics being identified as different from average given the confidence intervals used.

Table 8: Performance Categorization by Risk Adjustment and Categorization Method

		Much Worse than Average	Worse than Average	Average	Better than Average	Much Better than Average
Optimal Diabetes Care						
Unadjusted	**Not Clustered**		92	173	20	53
	Clustered		11	332	3	2
Adjusted	**Not Clustered**	54	30	193	30	41
	Clustered		14	327	5	2
Optimal Vascular Care						
Unadjusted	**Not Clustered**		53	185	23	19
	Clustered		7	269	2	2
Adjusted	**Not Clustered**	24	20	204	22	10
	Clustered		6	269	3	2
Optimal Asthma Care						
Unadjusted	**Not Clustered**		74	86	23	65
	Clustered			244	2	2
Adjusted	**Not Clustered**	57	10	95	38	48
	Clustered			237	9	2
Colorectal Screening						
Unadjusted	**Not Clustered**		182	95	24	108
	Clustered		22	383	3	1
Adjusted	**Not Clustered**	137	37	119	28	88
	Clustered		28	369	11	1

Performance Change

Table 9 compares the change in adjusted performance between performance categorization that does not take into account patient clustering and performance categorization that does take into account patient clustering in clinics. The results are consistent for all conditions. Safety net clinics tend to change to a higher performance category compared to other types of clinics, which tend to decrease or increase in their performance category, with some of the clinics decreasing two levels in performance (e.g. from Much Better than Average to Average).

Table 10 shows a similar comparison for geographic location. Rural clinics (micropolitan, small town, and frontier) are more likely to move to a higher performance category while urban clinics are more likely to move to a lower performance category.

In summary, categorizing performance by taking into account the clustering of patients within clinics tends to result in movement to a higher performance category for safety net and rural clinics. For asthma and colorectal cancer screening, categorizing performance by taking into account the clustering of patients within clinics results in slightly more clinics moving to a higher performance category than moving to a lower performance category. The converse holds for diabetes and vascular.

Table 9: Performance Ranking Change By Type of Clinic Cluster

Change	Medicare, Rural	Commercial, Not Deprived	Safety Net	Total
Diabetes				
-2	33	17	0	50
-1	25	5	1	31
0	124	37	16	177
1	49	12	29	90
Total	231	71	46	348
Vascular				
-2	10	2	1	13
-1	21	5	0	26
0	138	41	11	190
1	28	5	18	51
Total	197	53	30	280
Asthma				
-2	31	36	0	67
-1	11	8	0	19
0	47	23	10	80
1	52	8	22	82
Total	141	75	32	248
Colorectal				
-2	61	37	4	102
-1	18	8	1	27
0	75	32	20	127
1	116	12	25	153
Total	270	89	50	409

Compares performance categorization without clustering by clinics and with clustering by clinics; Clusters 3, 4, and 5 are safety net clinics.

Table 10: Performance Ranking Change By Rurality

Change	Urban	Micropolitan	Small Town	Frontier	Total
Diabetes					
-2	44	6	0	0	50
-1	20	3	5	3	31

0	97	17	26	37	177
1	52	11	7	20	90
Total	213	37	38	60	348
Vascular					
-2	13	0	0	0	13
-1	21	5	0	0	26
0	122	18	25	25	190
1	30	9	7	5	51
Total	186	32	32	30	280
Asthma					
-2	63	3	1	0	67
-1	16	1	1	1	19
0	62	11	7	0	80
1	44	10	17	11	82
Total	185	25	26	12	248
Colorectal					
-2	86	13	2	1	102
-1	22	1	1	3	27
0	77	11	21	18	127
1	66	16	17	54	153
Total	251	41	41	76	409
Compares performance categorization without clustering by clinics and with clustering by clinics					

Conclusion

The results show that among the clinics studied (a) socio-demographic risk adjusters have significant effects on quality, but do not result in substantial change in performance categorization; and (b) accounting for the clustering of patients within clinics has a substantial effect in assessing comparative clinic performance. When clustering of patients in clinics is not taken into account, the number of outlier clinics (low or high performance) is substantially greater than what would be expected given the confidence limits.

If the purpose of performance grouping and risk adjustment is to identify clinics with different than average performance while taking into account clinic size and case-mix, our results suggest that choices how clinics are grouped in performance comparisons are as important or more important than the risk adjustment for case-mix. These results imply that the greater the difficulty in adequately separating clinic performance from neighborhood effects, the greater the limitation of risk adjustment.

The results also show that clinics cluster into distinctive types of clinics. This analysis showed that performance grouping can be done methodologically for all clinics by using categories that take into account patient clustering within clinics. Because of the differences between types of clinics, it may be useful to explore further comparisons within types of clinics.

Our analysis shows that risk adjusters affect individual level outcomes and performance categorization, but that these effects were modest, which is consistent with similar analyses (Fung et al. 2010). Because the mix of patients varies across types of clinics, the impact of the risk adjusters varies across clinics.

This analysis cannot determine whether the effect of race/ethnicity or insurance type was completely outside the control of the providers. The models simply estimate the effects of race/ethnicity and insurance type and these effects could be due to either patient characteristics or provider behavior when caring for patients. For example, differences due to race may be associated with patient health beliefs and behaviors or may be associated with providers not adequately addressing those health beliefs and behaviors in their treatment of those patients. In other words, risk adjustment must carefully consider the conceptual relationship between variables and performance outcomes so as not to create further unintended consequences.

With regard to additional unintended effects, the analysis shows that not taking into account the clustering of patients within clinics when categorizing performance could result in clinics that are average performers being categorized as worse or better than average.

While the analysis cannot assess the feasibility of collecting socio-demographic characteristics, the fact that the missing data rate for RE data was relatively low among medical groups that provided data suggests that operational procedures for collecting such data can be implemented.

Discussion

Our findings that there is limited ability to enhance the existing risk adjustment with available measures of patient complexity, but that how clinics are grouped is critical for effective risk adjustments appears to derive from a number of factors presented here in simplified terms: (a) race/ethnicity/deprivation disparities exist; (b) most causes of health outcomes are non-health care delivery factors; (c) patients geographically cluster – patients are influenced by their local context (Kontopantelis, Roland, and Reeves 2010); and (d) clinics tend to serve patients who are located near them. Currently existing variables that attempt to measure patient complexity and socioeconomic effects on health outcomes fail to account for this complexity or do not exist at the level of granularity that could help isolate the effects of local context. In addition, the results suggest that clinic performance is affected, at least in part, by contextual factors outside the control of the clinic. Consistent with this argument, when patient clustering by clinics is taken into account through performance grouping, most clinics are found to be average.

If one of the goals of assessing performance is to avoid the unintended consequence of reducing access to health care (Chassin, Hannan, and DeBuono 1996; Dranove et al. 2003; Narins et al. 2005), then taking into account neighborhood effects by using a performance grouping method that takes into account clustering of patients in clinics, and implicitly in neighborhoods, is valuable when conducting performance assessment and comparison.

One approach to address measurement issues in risk adjustment is to explore other risk factors. While this is a worthwhile undertaking that could help fill gaps in our knowledge of these factors, it is also fraught with complexities that need to be well understood and assessed against other alternatives to address measurement shortcomings:

- First, because new measurement can place significant burden on providers, careful assessment of the usefulness of proposed measures should precede implementation.
- Second, specifying and measuring social norms, “neighborhood ties, social control, mutual trust, institutional resources, disorder, and routine activity patterns” and linking those factors to a specific clinic’s patient population is analytically complex and is associated with substantial data needs.
- Third, not all new measurement results in meaningful increase in the explanatory power of the risk adjustment models (Fung et al. 2010),
- Fourth, the perception of a more robust scientific approach driven by a richer set of variables may create greater perceived legitimacy of the effectiveness of risk adjustment and comparisons than is warranted (Edelman 1967; Edelman 1977).

A related avenue that is sometimes proposed is to stratify risk adjustment analyses by categories, such as race, ethnicity, deprivation or insurance type. While stratification is essential for understanding disparities in experiencing health and reaching optimal outcomes, it is less well suited to refinement of risk adjustment. Stratification in risk adjustment might produce some improvements in statistical model performance, but will not address the sorting and selection process by which individuals and clinics come to be co-located in the same area. Because stratification is not based on the underlying process associated with disparities it is unlikely to adequately resolve the risk adjustment issues associated with clinic quality performance categorization.

A potential alternative measurement strategy is to explore developing a hybrid portfolio of process and outcome measures, which would somewhat represent a return to earlier measurement approaches. Quality measures are often separated into process and outcome measures (Mant 2001; Rubin, Pronovost, and Diette 2001). For diabetes, examples of process measure are performing HbA1C tests or counselling patients about tobacco cessation, with the corresponding outcome measures being controlled blood sugar and non-smoking. Process measures are more likely to be controlled by providers and are an indication of health care organizational quality – implementing the right activities/processes (Campbell, Roland, and Buetow 2000; Wholey et al. 2003). Outcome measures measure patient outcomes that are the consequence of health care organizational quality. The difficulty with outcome measures is they are more likely to be influenced by the neighborhood / spurious effects issues noted above. Developing a portfolio of measures including both types of measures (e.g., Campbell et al. 1998) may allow assessment of health care organization quality through process and outcome measures. It could also support the measurement of disparities in health care organization quality and patient outcomes as well as being used to validate the relationship between health care organizational quality and patient outcomes. This information could be useful in targeting disparities interventions. The finding that there was low variation in health care organization quality and high variation in patient outcomes, for example, suggests that interventions targeting neighborhood effects may be more promising than interventions targeting clinics.

Given the complexities associated with making meaningful near-term improvements to risk adjustment to account for factors associated with patient complexity, there may be value in validating the statistical methodology with independent qualitative observations at clinics that are low performance to assure that errors in data or performance groupings are not inappropriately affecting the analysis. As always, statistical sensitivity of performance groupings are important and they can be achieved through simple means such as assessing the effect of using different confidence intervals, such as 90 percent and 95 percent.

In summary, measurement and reporting of quality is an important tool for improvement because it allows clinics to benchmark their performance relative to comparable clinics and to their prior performance. For improvement to occur, actions need to address leverage points, key causes of quality (McGlynn 2003). For primary care clinics, our analyses suggest that these causes are likely to be influenced by both clinical care and neighborhood components. Our analyses suggest that understanding how clinics and neighborhoods interact to produce high quality care is difficult. While new measures will be needed to understand this relationship better, new conceptualizations of how clinics and neighborhoods interact to produce high quality care is also needed to guide the modeling of the effects of clinics neighborhoods and clinics interacting in neighborhoods on quality. Developing this understanding could be a guide to targeting interventions and incentives for higher quality to clinics, neighborhoods, or clinics working with neighborhoods. This approach could be a foundation for contributing to the understanding of the sources of disparities and effective approaches for reducing disparities.

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Appendix F. Local and National Related Research Efforts

To effectively implement its quality measurement risk adjustment requirements, the Minnesota Department of Health (MDH) seeks opportunities to learn from and align with other related local and national efforts. Accordingly, MDH explored initiatives that are being undertaken by the Minnesota Department of Human Services (DHS), MN Community Measurement (MNCM), safety net providers, the State Innovation Model, the U.S. Department of Health and Human Services (HHS), and the National Quality Forum (NQF).

Minnesota Department of Human Services

In 2015, the Minnesota Legislature directed DHS to "develop a methodology to pay a higher payment rate for health care providers and services that takes into consideration the higher cost, complexity, and resources needed to serve patients and populations who experience the greatest health disparities in order to achieve the same health and quality outcomes that are achieved for other patients and populations".[53] This study is distinct from MDH's legislative requirement in that it focuses on assessing whether socio-demographic variables ought to be considered in the development of fair provider payments, not with regard to calculating, reporting and use of health care quality measures.

DHS is approaching this project in two stages. First, they will identify which populations experience the greatest health disparities, and the interventions that could support the health of these populations. Second, DHS will identify which populations require the greatest investments by providers and payers, and develop a payment methodology that best targets the identified populations and their providers.

To inform the development of this project, DHS contracted with the Oregon Health & Science University to conduct a literature review identifying the populations experiencing disparities in health outcomes. DHS contracted with the Improve Group to conduct community interviews on barriers to health. DHS found that the risk factors of low educational attainment, poverty,

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[53] Minnesota Laws 2015, chapter 71, article 9, section 63.

homelessness, mental illness, chemical dependency, and diminished parental functioning are strongly associated with poor health, and immigrants are associated with good health.

DHS is working with Health Management Associates to use Minnesota Health Care Program[54] data to identify social risk factors associated with worse health, worse health care performance, and higher reimbursements. DHS has identified two Medicaid populations that consistently experience poor outcomes in health care indicators: enrollees experiencing homelessness and enrollees who are chemically dependent. DHS is working with contractors to identify interventions that would support the health of these two populations.

In recent years, DHS received grant funding from CMS to pursue the testing, collection, and reporting of the Initial Core Set of Health Care Quality Measures for Medicaid-eligible Adults and to develop a risk adjustment methodology to enhance core measure usage and enable more accurate comparisons among managed care organizations (The Lewin Group, 2015). DHS contracted with The Lewin Group (Lewin) to evaluate health care risk adjustment methodologies and test usability by the core measure set. Lewin found that actuarial health care risk, or the presence of diagnosed conditions, and age were consistently influential risk factors in quality measurement results. Using these and other factors in risk adjustment caused some managed care organization quality measure rates to increase slightly and others to slightly decrease. Lewin also noted that risk adjustment results that include socio-demographic characteristics should be stratified to help ensure any potential disparities are not masked.

Minnesota Quality Measurement Enhancement Project

A local independent alliance of health care clinics that serve communities that are impacted by health disparities, consumer groups, community organizations, academic and research institutions, and communities that experience health disparities are designing a pilot project to develop better methods to account for the impact of social determinants of health in the health care system (Scandrett et al., 2016). As key stakeholders, MDH and DHS are also participating in this project.

The project participants are concerned that the quality measures used in Minnesota by public and private health care payers and organizations that publicly report quality scores do not adequately account for patient social determinants of health, and that this may negatively impact provider quality scores and impose additional costs on providers that serve patients who experience health disparities. They are also concerned that unless new accountable health models account for patient social determinants of health, these arrangements will create a

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[54] Minnesota Health Care Programs primarily include individuals enrolled in Medical Assistance (Minnesota's Medicaid program), and people with MinnesotaCare coverage.

substantial risk of financially penalizing providers who serve low-income, culturally diverse, and disadvantaged patients who experience health disparities.

A primary objective of the project is to develop a tool that effectively accounts and adjusts for social determinants of health in quality measurement. The collaboration expects to have pilot results in late 2017.

The goals of the project are to:

- Develop a methodology that will:
    - Account for the social determinants of health that impact measure performance when measuring health care quality and setting provider payment rates,
    - Use data that low or no burden for providers to collect and report, and
    - Be adaptable for use in all types of measurement systems—state and federal, and public and private;
- Develop an index based on social determinant of health data that represents the level of deprivation of the patient population in a geographic area;
- Develop a measure of resource intensity that summarizes the level of services needed at the clinic and population levels based on patient characteristics;
- Identify and propose payment mechanisms for clinics that predominantly serve communities impacted by health disparities, informed by both the index that takes into account social determinants of health and the resource intensity measure; and
- Identify additional health care quality measures that better capture the health priorities and needs of patient populations, particularly those experiencing health inequities.

MN Community Measurement

MNCM is an independent quality measurement organization focused on public reporting of quality and cost measures for a variety of applications. MNCM began reporting risk adjusted results on MNHealthScores.org in 2014. MNCM convenes a subcommittee of the Measurement and Reporting Committee—called the Risk Adjustment and Segmentation Subcommittee—which makes recommendations on risk adjustment and segmentation of quality measure results for public reporting. MNCM has established criteria for considering risk factors that align with those of NQF.

MNCM adjusts nine measures using an indirect standardization—or, “actual-to-expected”—methodology and reports results on MNHealthScores.org and in its Health Care Quality Report. This decision to use indirect standardization was motivated by concerns that the simplicity of direct standardization could potentially mask disparities and inaccurately portray clinics or medical groups that served unusual or high-risk patient mixes. MNCM’s risk adjusted results are reported as categorical results that show whether clinics and medical groups performed significantly above, at, or significantly below their expected rate. MNCM uses insurance product type to adjust most measures, and includes other clinical and patient characteristics depending on the measure (MNCM, 2016a).

During 2016, the subcommittee considered using race, Hispanic ethnicity, preferred language, and country of origin to risk adjust quality measures (MNCM, 2016b). The subcommittee decided not to use these variables in risk adjustment because they was a lack of a conceptual relationship among the variables and measure results, an inability to guarantee that the empiric relationship was not a function of the provider contribution, and the socio-demographic variable data was incomplete or insufficiently granular. Moving forward, the subcommittee plans to incorporate an evaluation of risk adjustment variables into MNCM's standard measure development process. It will continue to consider adjustment with socio-demographic factors whenever this is feasible and warranted.

State Innovation Model

The State Innovation Model Data Analytics Subgroup identified top-priority data analytic elements to motivate and guide greater consistency in data sharing among organizations involved in accountable care organization models to support shared accountability for cost and health outcomes and recommended these elements to the Community Advisory and Multi-Payer Alignment Task Forces (MDH & DHS, 2016a).[55] During 2016, this subgroup identified a set of essential data analytic elements related to social determinants of health that are of the highest priority to ensure that all providers across Minnesota—in health care and in community social services—have access to information on social determinants of health to improve individual and population health. The subgroup developed guiding principles for the identification of data analytic elements (MDH & DHS, 2016b) and determined that each element must:

- Have clear value for impacting the Triple Aim;
- Be feasible to extract from an existing, identified data source;
- Be useful for health care or social services providers to take action to improve population health at the community level; and

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[55] In February 2013 the Center for Medicare and Medicaid Innovation awarded Minnesota a State Innovation Model testing grant of over $45 million to use across a three-year period ending October 2016. As a joint effort between MDH and DHS with support from Governor Mark Dayton's office, Minnesota is using the grant money to test new ways of delivering and paying for health care using the Minnesota Accountable Health Model framework. The goal of this model is to improve health in communities, provide better care, and lower health care costs.

- Assume that the data or information should be available to all providers.

Recommended essential data analytic elements include:

- Mental health and substance use (current diagnosis or unmet need)
- Race, ethnicity, and language;
- Access to reliable transportation;
- Social services already being received;
- Housing status or situation; and
- Food insecurity.[56]

The subgroup recommended incorporating these elements into reporting and/or payment structures for future alternative payment and quality measurement arrangements. The task forces concurred with these recommendations.

U.S. Department of Health & Human Services

As a part of federal Medicare health care delivery system reform, providers and plans are increasingly held accountable for quality, outcomes, and costs through value-based and alternative payment models. Accordingly, there is rising concern about the impact of these payment programs on providers and plans that serve populations of low socio-economic status.

Under federal IMPACT legislation[57], the U.S. Department of Health & Human Services (HHS) is conducting a set of studies to assess the relationship between socio-economic status (race, health literacy, limited English proficiency, and Medicare beneficiary activation) and performance across the spectrum of current Medicare payment policies, culminating in a set of recommendations about how (and if) socio-economic status should be accounted for in these programs. The Office of the Assistant Secretary for Planning and Evaluation (ASPE) is executing the study with a final report due to Congress by October 2019.

ASPE’s over-arching research questions are:

- Do low socio-economic status patients have worse performance/outcomes on the measures that comprise each Medicare payment program, and if so, is this primarily due to the hospitals, providers, or plans at which they receive care? Are poor patients more often readmitted? Is this a patient or hospital effect?

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[56] The subgroup identified four other data analytic elements of importance that are not feasible to collect now, but should be considered in the future: social isolation; country of origin or citizenship (to ensure broad inclusion of all members of the community, regardless of documentation status); sexual orientation and gender identity; and adverse childhood experiences for children and/or indications of abuse and neglect for people of any age.

[57] Improving Medicare Post-Acute Care Transformation Act, H.R. 4994.

- Do the Medicare payment programs impact hospitals/providers/plans that serve a high proportion of low socio-economic status patients differently? Does the Hospital Readmissions Reduction Program penalize hospitals that serve the poor?
- How would different policy options change how these hospitals, providers, or plans are impacted by these programs? Would adjusting for poverty in the Hospital Readmissions Reduction Program change its impact on the safety net (Epstein, 2015)?

ASPE has delineated four main components to this work:

- Study the impact of socio-economic status on quality and resource use in Medicare using measures such as poverty and rurality from existing Medicare data;
- Study the impact of socio-economic status on quality and resource use in Medicare using measures (e.g. education and health literacy) from other data sources;
- Conduct qualitative analysis of potential socio-economic status data sources; and
- Develop secretarial recommendations on obtaining accesses to necessary data on socio-economic status and accounting for socio-economic status in determining payment adjustments (Epstein, 2015).

ASPE asked the National Academies of Sciences, Engineering, and Medicine (National Academies) to convene an ad hoc committee to provide definition, identify social factors, and specify criteria that could be used as a part of these ongoing activities. ASPE will use the findings and recommendations from these National Academy reports as it develops its empirical assessment of the relationship between socio-economic status and performance across multiple Medicare payment policies. The committee has issued five reports which:

- Identify social risk factors that are important to Medicare beneficiaries' health outcomes (NASEM, 2016a);
- Identify best practices of high-performing providers and health plans that serve disproportionately higher shares of socio-economically disadvantaged populations (NASEM, 2016b);
- Provide guidance on which social risk factors Medicare could consider, criteria to identify factors, and methods to do so in ways that can improve care and promote greater health equity for socially at-risk patients (NASEM, 2016c);
- Provide guidance on data sources for and strategies to collect data on social risk factors that could be accounted for Medicare quality measurement and payment programs (NASEM, 2016d); and
- Synthesize content from the four reports and offer suggestions for future research to help ASPE and CMS determine the optimal way in which to adjust indicators used in value-based purchasing for social risk factors (NASEM, 2017).

ASPE submitted an initial report to Congress in December 2016 that studied the impact of social risk factors from existing Medicare data on quality and resource use in Medicare (HHS, 2016). ASPE examined the social risk factors of dual enrollment in Medicare and Medicaid as a proxy for low income, residence in a low-income area, Black race, Hispanic ethnicity, and residence in a rural area. ASPE also included disability. ASPE found that beneficiaries with social risk factors had worse outcomes on many quality measures regardless of the providers they saw, and dual enrollment status was the strongest predictor of poor outcomes. Additionally, ASPE found that providers that disproportionately served beneficiaries with social risk factors tended to have worse performance on quality measures even after accounting for their beneficiary mix.

ASPE investigated whether beneficiaries with social risk factors have worse outcomes due to their social risk profile or because of the providers they see, and found that both dual enrollment status is independently associated with worse outcomes, and dually enrolled beneficiaries are more likely to see lower-quality providers. ASPE also examined whether providers that serve beneficiaries with social risk factors perform worse due to the high proportion of beneficiaries with social risk factors or provide lower-quality care overall, and found both that providers serving high proportions of beneficiaries with social risk factors tended to perform worse in part due to the patient population and in part due to poor performance.

Nevertheless, ASPE could not determine why these relationships emerged. Beneficiaries with social risk factors may have poorer outcomes due to myriad factors such as high levels of medical risk, worse living conditions, greater challenges in adherence and lifestyle, and/or bias or discrimination. Some of these factors are outside of provider control, whereas others are within their sphere of influence. Providers serving these beneficiaries may have poorer performance due to multiple factors such as fewer resources, more challenging clinical workloads, lower levels of community support, or worse quality of care, with some of these factors being within and others being outside of provider control. More research is needed to better understand these patterns.

As Medicare uses quality measures in two ways—reporting to providers and the public, and determining payment adjustments such as bonuses and penalties—potential solutions may include adjusting the measures for reporting, adjusting the measures for the purpose of determining payments, or directly adjusting the payment methodologies without adjusting the measures themselves. ASPE proposes a three-part strategy: (1) measure and report performance on quality and outcomes specifically for beneficiaries with social risk factors; (2) set high fair quality standards for all beneficiaries; and (3) in value-based purchasing programs, provide specific payment adjustments to reward achievement and/or improvement for beneficiaries with social risk factors, and, where feasible, provide targeted support for providers who disproportionately serve them.

National Quality Forum

In 2014, the NQF Board of Directors approved a two-year trial period to allow the risk adjustment of quality measures using socio-demographic factors beginning in April 2015. Findings will be reported to the NQF Board of Directors in 2017 after the conclusion of the trial, at which point, NQF will determine whether to make this policy change permanent after assessing emerging evidence of the impact of adjusted measures on patients and providers and monitoring for unintended consequences (NQF, 2015b).

Originally, NQF policy prohibited risk adjusting quality measures using socio-economic status factors due to concerns that doing so may mask care inequalities and result in lower standards of provider performance. In 2014 through a contract with CMS, NQF convened a multi-stakeholder panel of experts in health care performance measurement and disparities to review NQF’s standing risk adjustment policy (NQF, 2014). The panel recommended that NQF allow socio-economic status factors to be used in quality measure risk adjustment when conceptual reasons and empirical evidence demonstrate that doing so is appropriate. The panel established a set of core principles to ground its recommendations related to risk adjusting quality measures for socio-economic status and socio-demographic factors. The panel developed 10 recommendations related to socio-demographic factor adjustment, NQF policy, and broader policy issues, and it developed risk adjustment guidelines for socio-demographic factors. Accordingly, NQF has entered into a trial period to test risk adjusting new and existing quality measures using socio-demographic factors. The trial includes 32 measures—mainly hospital measures—that include the areas of cost and resource use, all-cause admissions and readmissions, and cardiovascular care (NQF, 2015a).

NQF has also established a Disparities Standing Committee to incorporate the reduction and elimination of disparities through quality measurement into NQF’s work. The Committee is expected to review the findings from the risk adjustment trial period and report to the NQF Board in 2017 (NQF, 2015c). Additionally, the committee will assess other studies on the impact of adjusting measures using socio-economic status factors on patients and providers, monitor the unintended consequences of risk adjustment, and develop a high-level roadmap to better measure disparities and consider how measurement can proactively reduce disparities.

Appendix G. Acronym Reference

Table G-1 Acronym Reference

Acronym	Definition
ASPE	Office of the Assistant Secretary for Planning and Evaluation
CMS	Centers for Medicare & Medicaid Services
DHS	Minnesota Department of Human Services
EHR	Electronic Health Record
FQHC	Federally Qualified Health Center
HEDIS	Health Care Effectiveness Data and Information Set
HHS	U.S. Department of Health and Human Services
IMPACT	Improving Medicare Post-Acute Care Transformation Act
IOM	Institute of Medicine
IVD	Ischemic Vascular Disease
MARC	Measurement and Reporting Committee
MCHP	Minnesota Council of Health Plans
MDH	Minnesota Department of Health
MedPAC	Medicare Payment Advisory Commission
MHA	Minnesota Hospital Association
MHCP	Minnesota Health Care Programs
MMA	Minnesota Medical Association
MMB	Minnesota Management and Budget
MN	Minnesota
MNACHC	Minnesota Association of Community Health Centers
MNCM	MN Community Measurement
MNHAG	Minnesota Health Action Group
NASEM	The National Academies of Sciences, Engineering, and Medicine
NBER	National Bureau of Economic Research
NQF	National Quality Forum
RE	Race/Ethnicity
RELO	Race, Ethnicity, Preferred Language, and Country of Origin
SEGIP	State Employee Group Insurance Program
SNAP	Supplemental Nutrition Assistance Program

Acronym	Definition
SQRMS	Minnesota Statewide Quality Reporting and Measurement System
ZCTA	ZIP Code Tabulation Areas