A STUDY OF PREVENTABLE HOSPITAL UTILIZATION AMONG MEDICAID-INSURED PEDIATRIC PATIENTS IN NORTH CAROLINA'S FEDERALLY QUALIFIED HEALTH CENTERS

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A dissertation submitted to the faculty at the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Health Policy & Management in the Gillings School of Global Public Health.

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ABSTRACT

Rebecca Garr Whitaker: A Study of Preventable Hospital Utilization among Medicaid-Insured Pediatric Patients in North Carolina's Federally Qualified Health Centers
(Under the direction of Pam Silberman)

Objective. The goal of this research is to evaluate preventable hospital utilization among Medicaid-insured federally qualified health center (FQHC) patients in North Carolina and to determine organizational factors associated with preventable hospital use.

Methods. Using 2013-2015 Medicaid claims data, we applied instrumental variable analysis using two-stage residual inclusion to account for differential patient selection into FQHCs and estimated the association of FQHC use on preventable hospital utilization. Because there is no "gold standard" in performance classification, we applied three different methodologies to rank FQHC organizations according to their relative rates of preventable hospital use and estimated an overall performance ranking that incorporated the results of the three statistical approaches. Finally, we estimated patient-level regression models with FQHC fixed effects and ran organization-level configurational comparative analyses to identify organizational characteristics associated with preventable hospital utilization.

Results. Across all model specifications in this study sample, we found that FQHC patients had a significantly higher probability of preventable hospital utilization when compared to patients accessing primary care services from non-FQHC providers. We identified variation in the absolute rankings of FQHC organizations across performance classification methodologies, but the organizations comprising the top- and bottom-performance quartiles remained consistent. We demonstrated that the geometric mean could be used to estimate an overall performance ranking across methodologies. Finally, we found that patients utilizing FQHCs with a broader scope of non-medical services and more of certain non-medical services staff were more likely to experience preventable hospital use even after controlling for patient characteristics. However, these results were associated with significant limitations.

Conclusions. The differential effect of FQHC use may be driven by higher emergency department utilization among FQHC patients, as this comprised the majority of hospital use among pediatric asthma patients in this study. Patients using FQHCs with a broader scope of non-medical services and more of certain types of non-medical services staff were more likely to have preventable hospital utilization, but these organization-level factors do not reflect patient-level utilization of services. Children may be accessing non-medical services in FQHCs less frequently than adults, for example. Future research should incorporate FQHCs' electronic health record data and qualitative interviews to best identify organization structures and processes associated with performance. This research also underscores the need for policymakers and payers to incorporate encounter-level data on non-medical services in claims submissions in order to better measure the effect of non-medical services on health care costs, utilization and outcomes across all provider types.

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LIST OF ABBREVIATIONS

2SRI	Two-stage residual inclusion
AHRQ	Agency for Healthcare Research and Quality
BPHC	Bureau of Primary Health Care
CCNC	Community Care of North Carolina
CCI	Chronic Condition Indicator
CCM	Configurational Comparative Method
CCS	Clinical Classification Software
CDC	Centers for Disease Control
CMS	Centers for Medicare & Medicaid Services
CNA	Coincidence analysis
CPT	Current Procedural Terminology
ED	Emergency department
EHR	Electronic health record
FQHC	Federally Qualified Health Center
FTE	Full-time equivalent
GEE	Generalized estimating equation
GLM	Generalized linear model
HGLM	Hierarchical generalized linear model
ICD-9	International Classification of Diseases, 9th Revision, Clinical Modification
ICD-10	International Classification of Diseases, 10th Revision, Clinical Modification
NPPES	National Plan & Provider Enumeration System
NPI	National Provider Identifier
PCMH	Patient-centered medical home

QCA	Qualitative comparative analysis
QIC	Quasi-likelihood under the independence model criterion
UDS	Uniform Data System

CHAPTER ONE: INTRODUCTION

Overview of the Federally Qualified Health Center Program

Federally qualified health centers (FQHCs) represent the largest network of independent primary care practices serving vulnerable populations. Of the roughly 26 million patients served in FQHCs in 2016, more than 90% had incomes below 200% of the federal poverty line, more than 60% were racial/ethnic minorities, and nearly 25% were uninsured.[1] Because they predominately care for low-income and uninsured patients, FQHCs are uniquely positioned to make substantial improvements to the health of these vulnerable groups. Researching successful FQHC models can help improve population health and may have the potential to reduce health care costs and utilization.

FQHCs' focus on vulnerable populations is driven in part by the federal regulations governing the program. The FQHC program is administered by the Bureau of Primary Health Care, part of the Health Resources and Services Administration in the US Department of Health and Human Services. To receive the FQHC designation, facilities must be located in medically underserved areas or serve medically underserved populations.[2] The FQHC designation confers certain financial benefits (e.g., grant money to offset some of the costs of caring for the uninsured) in exchange for complying with a series of program requirements related to governance, services and operations, and financial management.[3] For example, FQHC program requirements stipulate that facilities provide access to comprehensive primary care services including physical and behavioral health services, as well as dental and pharmacy services. FQHCs also have to provide enabling services, which encompass non-clinical services like case management, outreach and transportation meant to address non-medical barriers to good health.[2]

Two other program requirements are key features of the FQHC model: serving all patients regardless of ability to pay and operating under a patient-majority governing board.[4–6] Serving all patients regardless of ability to pay ensures access to primary health care for everyone, and maintaining a patient-majority board is intended to ensure that the FQHCs are guided by and responsive to community needs.[7] Because of these federal requirements, the FQHC primary care delivery model is markedly different from most other primary care providers.

The FQHC primary care model has benefited patients utilizing these clinics. In fact, previous research found that compared to other practice settings, FQHCs attenuated racial/ethnic disparities in clinical outcomes,[8] had equivalent or better ambulatory care quality measures,[9] reduced preventable hospitalizations and ED visits,[10–12] and lowered annual health expenditures[13–16] despite serving more vulnerable patients.[17] Other studies exploring area-level effects of FQHCs found that increased FQHC density (sites per 100 square miles) and increased funding for FQHCs (funding per person living in poverty) were associated with lower ED utilization and greater utilization of office-based care for low-income and uninsured patients in the community.[18,19]

However, little evidence exists identifying the mechanisms by which FQHCs are able to improve patient outcomes and reduce costs and unnecessary utilization in their patient population. Identifying factors associated with successful FQHC care delivery models can provide insight into how to address the Triple Aim of health care for vulnerable groups: better population health, better patient experience and lower health care costs.[20]

Factors Associated with Organization Performance

Previous studies of FQHC characteristics associated with performance have been inconclusive, finding heterogenous effects of across clinical quality performance measures.[8,17] In one study, Shi and colleagues[17] measured FQHC performance using six clinical quality indicators, each of which reflected primary care management processes. The researchers estimated logistic regression models using one year of data to predict membership in the top performance quartile as a function of various organization-level measures. The researchers found no consistent relationships between FQHC organizational characteristics and performance across the various clinical quality measures, indicating a need for additional research. More definitive research findings could promote the replication of successful care models both within the FQHC program and across other providers caring for vulnerable patients.

In a mixed methods study, Gurewich and colleagues[21] identified operational practices associated with high-performing FQHCs. To identify the high performers, Gurewich and colleagues utilized Medicaid claims to estimate organization performance on six quality of care measures and two cost-related measures. The regression models included FQHC fixed effects to account for unobserved organization-level factors affecting performance and controlled for patient demographic and clinical characteristics, as well as months of Medicaid enrollment. Following the quantitative analysis, they interviewed staff from the high-performing FQHCs to identify common operational practices and systems. The interviews identified four program elements characterized by fourteen operational practices. The program elements and examples of the associated operational practices included: facilitating access to care through extended operating hours or wait-time reduction strategies; managing referrals through a centralized system and patient tracking; supporting providers and patients through care teams and decision support tools; and monitoring/initiating performance improvement through organization-level and provider-level quality measures and performance incentives.

Importantly, Gurewich and colleagues noted variation in how services were structured and delivered across FQHCs—there was no “one size fits all” model for FQHCs.[21] Instead, they found that FQHCs’ operational differences “appear to reflect variations in the local conditions in which individual [FQHCs] operate, including the patient population served, resource availability, and provider preferences.”[21(p455)] In other words, the services provided in an FQHC may depend on both the needs of the patient population but also whether other community resources are available to meet those needs. Therefore, organizational characteristics associated with performance could also vary by organizational context. For this reason, methodological approaches are needed to distinguish organizational characteristics associated with performance in different contexts.

An organization's patient mix can also influence performance. Cross and colleages[22] examined private insurance claims to determine how the concentration of high-needs patients (patients with two or more chronic conditions) within a practice influenced health outcomes for high-needs patients across thirteen utilization, spending and quality measures. They found lower spending and utilization but worse quality measures for practices with higher concentrations of high-needs patients. The authors hypothesized that providers caring for significant proportions of high-need patients might develop specialized approaches and expertise to serve their target population. They suggested these practices might be prioritizing keeping patients out of the hospital instead of compliance with evidence-based guidelines, which could explain the worse quality of care measures but lower spending and utilization for practices with high concentrations of high-need patients.[22] Because FQHCs are known to predominately serve low-income, uninsured and underinsured individuals,[1] methodological approaches to estimate performance should consider variation in the concentration of high-needs patients both across FQHCs and in FQHCs relative to other practice settings. For this reason, the Bureau of Primary Health Care uses the percent of patients who are uninsured, racial/ethnic minorities, homeless and migrant/seasonal farmworkers to assess FQHCs' clinical quality rankings relative to other FQHCs with a similar patient mix.[23]

Study Objective and Specific Aims

The objective of this study is to gain a better understanding of what makes FQHCs successful. To that end, this study applies a cross-sectional design to identify organizational characteristics associated with FQHC performance. We use preventable hospital utilization (including emergency department or ED visits, as well as observation and inpatient stays) as a proxy for FQHC performance, as it is a reflection of the downstream effect of primary care management in the health care system.[24–27] We hypothesize that a broader scope of services and more non-medical services staffing (behavioral health, pharmacy and enabling services staff) will be associated with lower preventable hospital utilization rates among FQHC patients. Providing a broader scope of FQHC services and staffing greater numbers of non-medical services FTEs acknowledges a patient population with medical and non-medical barriers to good health and can reduce the likelihood that unmet needs lead to preventable hospital utilization by creating a “one-stop shop” for health services.[28]

Previous research underscores the importance of non-medical services on improving patient outcomes,[29–32] particularly among vulnerable patient populations. For example, Vest and colleauges[32] examined whether utilizing one of five “wraparound services” – behavioral health, social work, dietetics, respiratory therapy and patient navigation services – in a large, urban FQHC reduced high-cost hospital utilization among adult patients. Using electronic health record data, they found a seven-percentage point reduction in hospitalizations ($p<.001$) and a five-percentage point reduction in ED visits ($p<.001$) following receipt of a wraparound service.[32]

FQHCs are required to provide enabling services (e.g., transportation and case management) and access to comprehensive primary care services, including behavioral health and pharmacy services, but requirements do not stipulate how these services are delivered. In fact, the choice of which non-medical, services to provide has been found to vary by organizational characteristics. In one study, Wright found that the scope of enabling services provided in FQHCs varied according to the number of representative consumers on the FQHC’s governing board executive committee.[5] In another study, Wells and colleagues[33] found that patient characteristics influenced both the scope and volume of enabling services provided the following year. For example, higher percentages of migrant/seasonal farmworker, homeless, or uninsured patients were significantly associated with both broader scope of services and greater volume of enabling services provided in the subsequent year. The authors also found that FQHCs with more managed care contracts and more full-time equivalent (FTE) staff in the previous year provided both a broader scope and larger volume of enabling services in the following year. These studies underscore the need for methodological approaches to account for interdependencies among organizational characteristics.

We organize our research according to the following three aims:

Aim 1: Estimate the performance of FQHCs in reducing preventable hospital utilization relative to other primary care providers. *Hypothesis: FQHC patients will have lower preventable hospital utilization relative to patients in other primary care settings.* In this study, we use instrumental variable analysis to account for the endogeneity associated with differential patient selection into FQHCs.

Aim 2: Establish an overall performance ranking for FQHCs based on multiple methodological approaches and model specifications commonly used to classify performance. *Hypothesis: Variation will exist in FQHC rankings across statistical methodologies and model specifications.* We apply three common statistical approaches for estimating performance -- crude rate, hierarchical generalized linear models and fixed effect models – and establish an overall ranking using the geometric mean. The rankings from this analysis will be used for the configurational comparative analysis in Aim 3.

Aim 3: Identify organizational characteristics associated with preventable hospital utilization among FQHC patients. *Hypothesis: A broader scope of services and more non-medical services staffing will be associated with lower hospital utilization rates.* We use both regression-based and configurational comparative methods to test this hypothesis. The patient-level regression models estimate the net effects of FQHC characteristics for the average person in the average FQHC. The organization-level configurational comparative analysis identifies "typologies" of successful FQHCs by identifying complex conditions associated with high performance. In other words, the econometric analysis indicates which FQHC characteristics are significantly associated with the probability a patient experiences a preventable hospital visit, while the configurational comparative analysis uncovers the different combinations of characteristics that high performing organizations have in common.

Conceptual Model

FQHCs are constructed to be responsive to community needs. A consequence of this community-driven health care model is wide variation in FQHC organization design, which is reflected in a common saying in the FQHC community: "if you have seen one FQHC, you have seen one FQHC." Because of the variation across FQHCs, research is needed to identify organizational characteristics associated with high-performing organizations.

The conceptual model for this study (Figure 1) is based on structural contingency theory and is adapted from Hung and colleague's study of the effects of contextual and structural factors on patient safety.[34] Structural contingency theory is a useful conceptual model to explore organizational characteristics associated with FQHC performance because it maintains that there is no optimal organizational design associated with high performance.[35] Instead, structural contingency theory holds that organization performance depends on the organization's adaptation to changing external and internal environments.[36] The external environment encompasses factors that are beyond the control of the organization, while the internal environment includes factors that shape work processes and activities within an organization.[36] Organizations can respond to a changing external context by adapting their internal environment.[37] Organizations can also respond to changes in external and internal environments by modifying internal structures and processes in order to achieve "fit" with the new context, which encourages better performance.[37] Staffing is one example of an internal structure influenced by the organization's external and internal context.

Because they serve predominately vulnerable patients, we expect that FQHCs have shaped their internal environment, structure and processes to better care for these patients. The studies by Gurewich and colleagues[21] and Cross and colleagues[22] support this notion. Applying their reasoning to this research study, FQHCs' organizational characteristics might vary based on the patients and communities served. In particular, we expect that FQHCs tailored their scope of services and non-medical services staffing to reflect their patients' barriers to good health with the goals of addressing patients' unmet needs and helping to improve health outcomes. A broad scope of services translates to providing FQHC patients with access to behavioral health, pharmacy and enabling services staff.

As illustrated in Figure 1, **Aim 1** estimates variation in preventable hospital utilization – including inpatient stays, observations stays, and ED visits – among FQHC and non-FQHC patients. These models adjust for external factors and patient characteristics known to influence preventable hospital utilization. **Aim 2** utilizes the same variables to rank FQHC organizations according to their patients' preventable hospital use. Finally, **Aim 3** estimates the relationship between organization performance and a variety of internal FQHC organizational characteristics. In total, these aims provide insight into how FQHCs reduce preventable hospital use among their patient population. Although this study included patient-level analysis models, an organizational-level conceptual model was appropriate given the intent to make organization-level inferences.

Study Population

The study population is narrowly constructed to include North Carolina Medicaid-insured children with asthma for the following reasons:

1) At the time of this research, North Carolina was one of the few states yet to implement fully capitated Medicaid managed care. (A behavioral health carve-out represents the only form of capitated Medicaid managed care in the state.) The lack of Medicaid

managed care limits variation in benefit design in the Medicaid program because there are no managed care intermediaries to impose their own utilization review or quality management systems.

2) Limited research exists on the effect of FQHC use on pediatric populations, and the studies that do exist are limited by imprecise definitions of FQHC use.[16,19] One study applied area-level measures of FQHC access (sites per 100 square miles and percent of low-income children served in FQHCs),[19] which could capture other area-level changes that might affect health care utilization, such as the availability of non-FQHC providers. Another study measured FQHC use using Medical Expenditure Survey data,[16] but this survey broadly defines "community health centers" as facilities that provide services in areas with limited access to care[38] which could include other non-FQHC organizations. This study also included neighborhood health clinics in the definition of community health center use.[16] Furthermore, the service locations in the Medical Expenditure Panel Survey are based on patient self-report, which could be inaccurate if patients do not know whether their primary care clinic is a FQHC or another type of community provider.[11]

3) Asthma is amenable to primary care intervention: it is one of two pediatric chronic conditions[1] considered ambulatory care-sensitive,[39] and chronic conditions are better reflections of ongoing care management and systems of care than are acute conditions. According to an algorithm developed by Billings and colleagues to classify emergency department (ED) utilization using New York City ED claims, 98% of all emergency department visits for asthma were considered emergent but preventable/avoidable,[40,41] meaning that asthma has high face validity as an ambulatory care-sensitive condition. Additionally, the evidence-based guidelines for asthma care have remained consistent

[1] Short-term complications from diabetes represents the second ambulatory care-sensitive pediatric chronic condition, but hospital utilization rates for this condition are very low.[49]

over recent years, limiting the "noise" present in the measure of asthma-related hospital utilization that could stem from changing practice guidelines.

4) Asthma is a leading cause of preventable hospital utilization in a pediatric population, the cost of which has been estimated to exceed $270 billion in the Medicaid program nationwide.[42] Nearly 18% of North Carolina children have asthma, and 30% of asthmatic children utilized emergency or urgent care because of asthma according to a parent self-report measure.[43] Prevalence and utilization rates are even higher among racial/ethnic minority and low-income children.[44] Therefore, research identifying organizational factors associated with lower asthma-related preventable hospital utilization can have a significant impact on population health and health care costs.

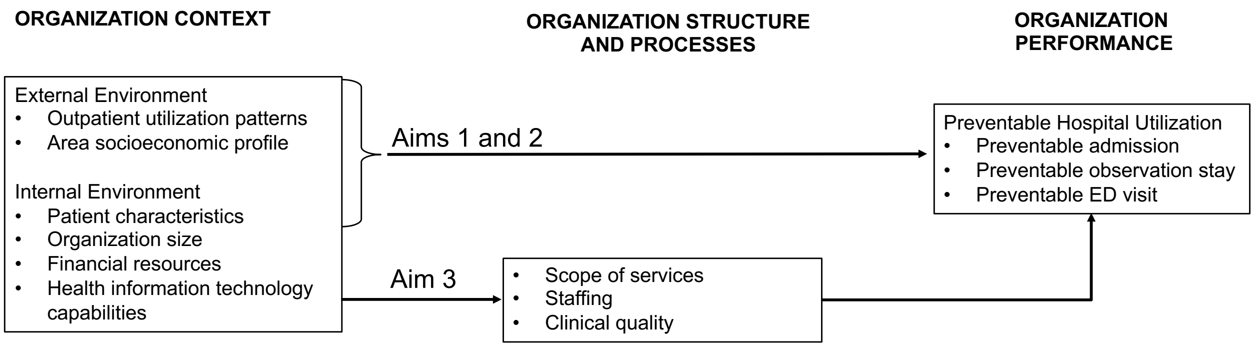
Significance and Policy Implications

This study has important implications for the development of health care delivery models targeting vulnerable patients with asthma. Previous research suggests that low-income and uninsured individuals often have worse health outcomes.[45,46] Therefore, this study presents an opportunity to improve population health and reduce health care costs by identifying successful FQHC practice models that could be implemented across the FQHC program and translated to other practice settings.

Understanding the organizational characteristics associated with lower preventable hospital utilization among FQHCs is both timely and policy-relevant given the growth of the FQHC program[47] and ongoing health care payment and delivery system reforms. Recent discussions to restrict federal funding and eligibility thresholds for federal health insurance programs may cause FQHCs to be an even more significant health care provider for vulnerable groups. Furthermore, this research has the potential to guide both federal grant-making and policy change within the FQHC program, as well as influence the development of new delivery models within the Medicare and Medicaid programs aimed at improving the health of vulnerable groups. For example, North Carolina's efforts to reform Medicaid and support the development of advanced medical homes[48] could be informed by this research.

The remainder of this dissertation is organized as follows: Chapters Two, Three and Four describe each of the three studies that comprise this dissertation. Chapter Five discusses the implications of the study findings and proposes directions for future research.

Figure 1.1 Conceptual Model Illustrating the Influence of Organization Context, Structures and Processes on Organization Performance



REFERENCES

1. Bureau of Primary Health Care. 2016 Health Center Data - National Program Grantee Data. Uniform Data System. https://bphc.hrsa.gov/uds/datacenter.aspx. Published 2017. Accessed October 4, 2017.

2. *Section 330 of the Public Health Service Act*. http://uscode.house.gov/view.xhtml?edition=prelim&req=42+usc+254b&f=treesort&fq=true&num=20&hl=true. Accessed August 9, 2017.

3. Bureau of Primary Health Care. What is a Health Center? https://bphc.hrsa.gov/about/what-is-a-health-center/index.html. Accessed August 9, 2017.

4. Bureau of Primary Health Care. Summary of Program Requirements. https://bphc.hrsa.gov/programrequirements/summary.html. Accessed August 9, 2017.

5. Wright DB. Consumer governance and the provision of enabling services that facilitate access to care at community health centers. *Med Care*. 2012;50(8):668-675. doi:10.1097/MLR.0b013e3182551763.

6. Wright B. Who governs federally qualified health centers? *J Health Polit Policy Law*. 2013;38(1):27-55. doi:10.1215/03616878-1898794.

7. Geiger HJ. The first community health centers: a model of enduring value. *J Ambul Care Manage*. 2005;28(4):313-320. http://www.ncbi.nlm.nih.gov/pubmed/16172560. Accessed September 14, 2017.

8. Lebrun LA, Shi L, Zhu J, et al. Racial/ethnic differences in clinical quality performance among health centers. *J Ambul Care Manage*. 2013;36(1):24-34. doi:10.1097/JAC.0b013e3182473523.

9. Goldman LE, Chu PW, Tran H, Romano MJ, Stafford RS. Federally Qualified Health Centers and Private Practice Performance on Ambulatory Care Measures. *Am J Prev Med*. 2012;43(2):142-149. doi:10.1016/j.amepre.2012.02.033.

10. Falik M, Needleman J, Wells BL, Korb J. Ambulatory care sensitive hospitalizations and emergency visits: experiences of Medicaid patients using federally qualified health centers. *Med Care*. 2001;39(6):551-561. http://www.ncbi.nlm.nih.gov/pubmed/11404640. Accessed August 24, 2016.

11. Laiteerapong N, Kirby J, Gao Y, et al. Health care utilization and receipt of preventive care for patients seen at federally funded health centers compared to other sites of primary care. *Health Serv Res*. 2014;49(5):1498-1518. doi:10.1111/1475-6773.12178.

12. Wright B, Potter AJ, Trivedi A. Federally Qualified Health Center Use Among Dual Eligibles: Rates Of Hospitalizations And Emergency Department Visits. *Health Aff*. 2015;34(7):1147-1155. doi:10.1377/hlthaff.2014.0823.

13. Mukamel DB, White LM, Nocon RS, et al. Comparing the Cost of Caring for Medicare Beneficiaries in Federally Funded Health Centers to Other Care Settings. *Health Serv Res*. 2016;51(2):625-644. doi:10.1111/1475-6773.12339.

14. Richard P, Ku L, Dor A, Tan E, Shin P, Rosenbaum S. Cost savings associated with the use of community health centers. *J Ambul Care Manage*. 2012;35(1):50-59. doi:10.1097/JAC.0b013e31823d27b6.

15. Nocon RS, Lee SM, Sharma R, et al. Health Care Use and Spending for Medicaid Enrollees in Federally Qualified Health Centers Versus Other Primary Care Settings. *Am J Public Health*. 2016;106(11):1981-1989. doi:10.2105/AJPH.2016.303341.

16. Bruen B, Ku L. *Community Health Centers Reduce the Costs of Children's Health Care*.; 2017. http://publichealth.gwu.edu/projects/geiger-gibson-program-community-health-policy. Accessed June 28, 2017.

17. Shi L, Lebrun LA, Zhu J, et al. Clinical quality performance in U.S. health centers. *Health Serv Res*. 2012;47(6):2225-2249. doi:10.1111/j.1475-6773.2012.01418.x.

18. McMorrow S, Zuckerman S. Expanding federal funding to community health centers slows decline in access for low-income adults. *Health Serv Res*. 2014;49(3):992-1010. doi:10.1111/1475-6773.12141.

19. Nath JB, Costigan S, Lin F, Vittinghoff E, Hsia RY. Federally Qualified Health Center Access and Emergency Department Use Among Children. *Pediatrics*. 2016;138(4). doi:10.1542/peds.2016-0479.

20. Berwick DM, Nolan TW, Whittington J. The triple aim: care, health, and cost. *Health Aff*. 2008;27(3):759-769. doi:10.1377/hlthaff.27.3.759.

21. Gurewich D, Capitman J, Sirkin J, Traje D. Achieving excellence in community health centers: implications for health reform. *J Health Care Poor Underserved*. 2012;23(1):446-459. doi:10.1353/hpu.2012.0008.

22. Cross DA, Cohen GR, Lemak CH, Adler-Milstein J. Outcomes For High-Needs Patients: Practices With A Higher Proportion Of These Patients Have An Edge. *Health Aff*. 2017;36(3):476-484. doi:10.1377/hlthaff.2016.1309.

23. Health Resources and Services Administration. Uniform Data System (UDS) Health Center Adjusted Quartile Ranking. https://bphc.hrsa.gov/datareporting/reporting/ranking.html. Accessed April 21, 2017.

24. Starfield B, Shi L, Macinko J. Contribution of Primary Care to Health Systems and Health. *Milbank Q*. 2005;83(3):457-502. doi:10.1111/j.1468-0009.2005.00409.x.

25. Friedman B, Basu J. Health insurance, primary care, and preventable hospitalization of children in a large state. *Am J Manag Care*. 2001;7(5):473-481. http://www.ncbi.nlm.nih.gov/pubmed/11388127. Accessed August 24, 2017.

26. Basu J, Friedman B, Burstin H. Primary care, HMO enrollment, and hospitalization for ambulatory care sensitive conditions: a new approach. *Med Care*. 2002;40(12):1260-1269. doi:10.1097/01.MLR.0000036409.56436.ED.

27. Whittaker W, Anselmi L, Kristensen SR, et al. Associations between Extending Access to Primary Care and Emergency Department Visits: A Difference-In-Differences Analysis. *PLoS Med*. 2016;13(9):e1002113. doi:10.1371/journal.pmed.1002113.

28. Andersen RM. Revisiting the behavioral model and access to medical care: does it matter? *J Health Soc Behav*. 1995;36(1):1-10. http://www.ncbi.nlm.nih.gov/pubmed/7738325. Accessed January 27, 2015.

29. Bradley EH, Elkins BR, Herrin J, Elbel B. Health and social services expenditures: associations with health outcomes. *BMJ Qual Saf*. 2011;20(10):826-831. doi:10.1136/bmjqs.2010.048363.

30. Bradley EH, Canavan M, Rogan E, et al. Variation In Health Outcomes: The Role Of Spending On Social Services, Public Health, And Health Care, 2000-09. *Health Aff*. 2016;35(5):760-768. doi:10.1377/hlthaff.2015.0814.

31. Gottlieb LM, Hessler D, Long D, et al. Effects of Social Needs Screening and In-Person Service Navigation on Child Health. *JAMA Pediatr*. 2016;170(11):e162521. doi:10.1001/jamapediatrics.2016.2521.

32. Vest JR, Harris LE, Haut DP, Halverson PK, Menachemi N. Indianapolis Provider's Use Of Wraparound Services Associated With Reduced Hospitalizations And Emergency Department Visits. *Health Aff*. 2018;37(10):1555-1561. doi:10.1377/hlthaff.2018.0075.

33. Wells R, Punekar RS, Vasey J. Why do some health centers provide more enabling services than others? *J Health Care Poor Underserved*. 2009;20(2):507-523. doi:10.1353/hpu.0.0151.

34. Hung C-C, Hsu S-C, Lee L-L, Huang C-M. The Effects of Contextual and Structural Factors on Patient Safety in Nursing Units. *J Nurs Res*. 2013;21(3):225-233. doi:10.1097/jnr.0b013e3182a0b004.

35. Donaldson L. Strategy and Structural Adjustment to Regain Fit and Performance: In Defense of Contingency Theory. *J Manag Stud*. 1987;24(1):1-24. doi:10.1111/j.1467-6486.1987.tb00444.x.

36. Donaldson L. The Normal Science of Structural Contingency Theory. In: Clegg SR, Hardy C, eds. *Studying Organization: Theory & Method*. 1 Oliver's Yard, 55 City Road, London EC1Y 1SP United Kingdom: SAGE Publications Ltd; 1999:51-70. doi:10.4135/9781446218556.n2.

37. Donaldson L. *The Contingency Theory of Organizations*. Thousand Oaks, California: SAGE Publications, Inc.; 2001.

38. MEPS Household Component Main Study Glossary. Medical Expenditure Panel Survey. https://meps.ahrq.gov/survey_comp/hc_ques_glossary.shtml#C. Published 2010. Accessed August 9, 2017.

39. Agency for Healthcare Research and Quality. Pediatric Quality Indicators Technical Specifications - Version 6.0. https://www.qualityindicators.ahrq.gov/Modules/PDI_TechSpec_ICD09_v60.aspx. Published 2017. Accessed October 3, 2017.

40. Billings J, Parikh N, Mijanovish T. *Emergency Department Use in New York City: A Substitute for Primary Care?*; 2000.

41. Faculty Research. NYU Center for Health and Public Service Research. https://wagner.nyu.edu/faculty/billings/nyued-background. Accessed October 3, 2017.

42. Pearson WS, Goates SA, Harrykissoon SD, Miller SA. State-Based Medicaid Costs for Pediatric Asthma Emergency Department Visits. *Prev Chronic Dis*. 2014;11:140139. doi:10.5888/pcd11.140139.

43. North Carolina State Center for Health Statistics. 2013-2014 CHAMP Topics. http://www.schs.state.nc.us/data/champ/201314/topics.htm#as. Published 2017. Accessed March 15, 2017.

44. Centers for Disease Control. Asthma - Data, Statistics and Surveillance. http://www.cdc.gov/asthma/asthmadata.htm. Published 2016. Accessed October 13, 2016.

45. Hadley J. Sicker and poorer--the consequences of being uninsured: a review of the research on the relationship between health insurance, medical care use, health, work, and income. *Med Care Res Rev*. 2003;60(2 Suppl):3S-75S; discussion 76S-112S. doi:10.1177/1077558703254101.

46. Poulton R, Caspi A, Milne BJ, et al. Association between children's experience of socioeconomic disadvantage and adult health: a life-course study. *Lancet*. 2002;360(9346):1640-1645. doi:10.1016/S0140-6736(02)11602-3.

47. Bureau of Primary Health Care. Health Center Program: Impact and Growth. https://bphc.hrsa.gov/about/healthcenterprogram/index.html. Accessed August 9, 2017.

48. North Carolina Department of Health and Human Services. *North Carolina's Proposed Program Design for Medicaid Managed Care*. Raleigh; 2017.

49. Fingar K, Washington R. *Potentially Preventable Pediatric Hospital Inpatient Stays for Asthma and Diabetes, 2003–2012. HCUP Statistical Brief #192.* Rockville, MD; 2015. https://www.hcup-us.ahrq.gov/reports/statbriefs/sb192-Pediatric-Preventable-Hospitalizations-Asthma-Diabetes.pdf. Accessed December 1, 2016.

CHAPTER TWO: THE EFFECT OF FEDERALLY QUALIFIED HEALTH CENTER USE ON PREVENTABLE HOSPITAL UTILIZATION FOR ASTHMA IN NORTH CAROLINA

Overview

Purpose. To estimate the effect of federally qualified health center (FQHC) use relative to other sources of primary care on preventable hospital utilization in a population of Medicaid-insured children with asthma.

Methods. A cross-sectional analysis utilized North Carolina Medicaid claims from January 1, 2013 through September 30, 2015. Instrumental variable analysis using two-stage residual inclusion estimated distance from the centroid of the patient's zip code to the nearest FQHC medical clinic to account for differential patient selection into FQHCs. Generalized linear models predicted the probability of preventable hospital utilization (inpatient stay, observation stay or emergency department visit) for Medicaid-insured children ages 2-17 years with a diagnosis of asthma. Sensitivity analyses varied outcome definitions and the method of patient attribution to organization/organization types.

Results. FQHC use was associated with a statistically significant increase in average preventable hospital utilization among Medicaid-insured children with asthma across all model specifications. The results from main analyses indicated that, compared to children receiving primary care from non-FQHC providers, FQHC use was associated with an average one percentage point increase in preventable hospital utilization (ED visit, observation stay or inpatient stay) with a primary diagnosis of asthma ($p<.01$) and a nearly three-percentage point increase in preventable hospital utilization for any diagnosis of asthma ($p<.001$).

Conclusion. FQHC use was associated with an average increase in preventable hospital utilization among North Carolina Medicaid-insured children with asthma as compared to children

with asthma who received care in other primary care settings. Future research should examine processes of care within FQHCs and the availability of non-hospital urgent care resources within FQHC service areas to determine why pediatric FQHC patients with asthma are going to the hospital more frequently than similar patients in non-FQHCs in North Carolina.

Background

Federally qualified health centers (FQHCs) represent the largest network of independent primary care practices serving vulnerable populations. Nationwide, FQHCs served 26 million patients in 2016. More than 90% of these patients had incomes below 200% of the federal poverty line, more than 60% were racial/ethnic minorities, and nearly 25% were uninsured.[1] The 2016 patient population in North Carolina FQHCs was even more underrepresented: of the roughly 510,000 patients served, over 40% were uninsured, including 24% of children, and 66% of patients represented racial/ethnic minorities.[2] Because they predominately care for low-income and uninsured patients, FQHCs are uniquely positioned to make substantial improvements to the health of these vulnerable groups.

FQHCs' focus on vulnerable populations is driven in part by the federal regulations governing the program. As part of the Health Center Program overseen by the Bureau of Primary Health Care, FQHCs must serve all patients regardless of ability to pay. They operate under a patient-majority governing board,[3] which is intended to ensure that FQHCs are guided by and responsive to community needs.[4] FQHC program requirements also stipulate that facilities provide access to comprehensive primary care services including physical and behavioral health services, as well as dental and pharmacy services. FQHCs have to provide enabling services, which encompass non-clinical services like case management, outreach and transportation meant to address non-medical barriers to good health.[5] Because of these federal requirements, the FQHC primary care delivery model is markedly different from most other primary care providers.

Previous research indicates the FQHC primary care model has benefited patients utilizing these clinics. FQHCs provide guideline-concordant care at the same rate or more frequently than other primary care practices.[6,7] Medicaid-insured and uninsured individuals utilizing FQHCs are more likely to report having a usual source of care than similar patients in other settings,[8] and greater primary care access is associated with lower hospital utilization.[9,10] In fact, previous studies indicate that FQHC patients have lower rates of inpatient admissions,[11–14] but the evidence for ED utilization is mixed.[7,15,16] Furthermore, Medicaid patients utilizing FQHCs have lower total annual health care expenditures than patients utilizing other primary care practices.[13,17,18] These findings are significant because FQHC patients tend to be sicker, poorer and more socioeconomically disadvantaged than patients in other primary care practices.[6] However, some of these studies comparing FQHCs to other primary care practices fail to account for patient selection into FQHCs,[11,15,19,20] which could bias study findings.

Patients utilizing FQHCs may be different from non-FQHC patients in unobservable ways, and these differences can affect their health care utilization, spending and health outcomes. Previous studies of FQHC performance that incorporated methods to address the endogeneity of patient selection into the FQHC utilized either an instrumental variable approach[18] or propensity score analysis.[7,13,17] Propensity score analysis has been more commonly utilized in the FQHC literature to account for patient selection into the FQHC, but this method can only reduce bias to the extent that unobserved variables do not explain a large portion of the variation in FQHC use. For this reason, instrumental variable analysis represents a more rigorous methodological approach.

Previous research on the effect of FQHC use has focused on adult Medicare and Medicaid populations.[7,13,16,18] Few studies have examined the effect of FQHC use in a pediatric population, and these studies are limited by imprecise definitions of FQHC use.[12,17] One study applied area-level measures of FQHC access,[12] which could capture other area-level changes that might affect health care utilization. Another study measured FQHC use from the Medical

Expenditure Panel Survey data,[17] but this survey broadly defines “community health centers” as facilities that provide services in areas with limited access to care[21] which could include other non-FQHC organizations. Additional research is needed to quantify the effect of FQHCs on pediatric populations’ health care utilization, cost and outcomes.

The objective of this study is to generate a causal estimate of the effect of FQHC use on pediatric patients’ preventable hospital utilization for asthma. As the federal FQHC program continues to expand, understanding the effect of FQHC use on specific population groups is important in order to focus quality improvement efforts.

We chose to focus this study on Medicaid-insured children with asthma in North Carolina. At the time of this writing, North Carolina represented one of the few states without fully capitated Medicaid managed care, which decreased the “noise” in claims data stemming from variation in clinical guidelines and processes across managed care companies. Moreover, asthma is a leading cause of preventable hospital utilization in a pediatric population, the cost of which has been estimated to exceed $270 billion in the Medicaid program nationwide.[22] According to parent self-report, nearly 18% of North Carolina children have asthma, and 30% of this population utilize emergency or urgent care for asthma.[23] Prevalence and utilization rates are even higher among racial/ethnic minority and low-income children.[24] Identifying primary care practices associated with lower pediatric asthma morbidity can help reduce health care spending and improve child health.

Methods

This cross-sectional study estimated the effect of FQHC use on preventable hospital utilization rates among Medicaid-insured children with asthma in North Carolina. Preventable hospital utilization is a useful measure of organization performance because it represents the downstream effect of primary care management of chronic conditions in the health care system.[25–28]

Our analysis focused on children with asthma because asthma represents the most commonly diagnosed chronic condition among children.[29] Moreover, asthma is amenable to primary care intervention: it is one of two pediatric chronic conditions[2] considered ambulatory care-sensitive,[30] and chronic conditions are better reflections of ongoing care management and systems of care than are acute conditions. According to an algorithm developed by Billings and colleagues to classify emergency department utilization, 98% of all emergency department visits for asthma are considered emergent but preventable/avoidable,[31,32] meaning that asthma has high face validity as an ambulatory care-sensitive condition. Additionally, the evidence-based guidelines for asthma care have remained consistent over recent years, limiting the "noise" present in the measure of asthma-related hospital utilization that could stem from changing practice guidelines.

Data Source and Study Sample

This study analyzed North Carolina Medicaid claims submitted by Medicaid providers to receive payment for services delivered from January 1, 2013 through September 30, 2015. Claims dated after September 30, 2015 were excluded from the analysis due to the transition to International Classification of Diseases, 10th Revision, Clinical Modification (ICD-10) coding and unresolved questions regarding the reliability and validity of coding after the transition.[33]

All continuously Medicaid-enrolled pediatric patients ages 2-17 years (inclusive) were included in the analysis sample beginning with the first year (2013-2015) they had a hospital or outpatient clinic claim with an asthma diagnosis. Children remained in the analysis sample regardless of whether they had a visit for asthma in a given analysis year if they demonstrated a pattern of utilization of care for asthma, i.e., if they had two or more visits for asthma across analysis years. (Roughly 33,000 person-years were excluded from the analysis for having only a single visit for asthma over multiple analysis years.)

[2] Short-term complications from diabetes represents the second ambulatory care-sensitive pediatric chronic condition, but hospital utilization rates for this condition are very low.[73]

Asthma diagnoses were identified using International Classification of Diseases, 9th Revision, Clinical Modification (ICD-9) codes 493.0-493.92. Replicating Domino and colleagues' approach, we applied a broad definition of asthma in order to maintain variation in the outcome variables.[34]

Children were excluded from the analysis sample if they were pregnant or had a diagnosis of cystic fibrosis or other respiratory system anomalies consistent with AHRQ's Pediatric Quality Indicator for asthma (n=237,051 claims dropped).[35] After exclusions, approximately 382,000 person-years representing Medicaid-insured children ages 2-17 years with a diagnosis of asthma were eligible for this study. Analyses were conducted using complete case analysis, which dropped approximately 671 (<1%) person-years due to missing county-level data.

Key Variables and Measures

Outcome specifications were developed using AHRQ's Pediatric Quality Indicator for asthma. The primary outcome was a binary variable, any hospital utilization with a principal diagnosis of asthma. Any hospital utilization encompassed emergency department (ED) visits, observation or inpatient stays. Given the increasing frequency of hospital observation stays, we felt it important to include this type of hospital utilization in our outcome measures.[36–38] ED visits represented the majority of hospital utilization, so we modeled a binary indicator for ED visits with a principal diagnosis of asthma as a secondary outcome. Although AHRQ's Pediatric Quality Indicator for asthma is specific to inpatient admissions, previous studies applied the same definition to ED use.[39–41] Secondary model specifications included hospital utilization with any diagnosis of asthma – i.e., if asthma was included in any one of the ten diagnosis claim fields.

To avoid double-counting claims representing a single hospital visit, we prioritized utilization according to how "far" a patient went in the hospital (either the same hospital or a transfer hospital) in decreasing order of severity: inpatient stay (regardless of whether it initiated in the ED), followed by an observation stay, and finally an ED visit that resulted in a discharge. In other words, a visit to the ED counted only if the patient did not also have an observation or inpatient stay during the same visit.

Sensitivity analyses modified the outcome definitions and modeled hospital utilization after a "washout" period. To create a washout period, we excluded patients' hospital utilization if it occurred within 60 days of their first visit to their attributed practice each year. As a consequence, hospitalizations in the first two months of each calendar year were censored, which could bias the results downward.

Key explanatory variable. The key explanatory variable was a binary indicator for FQHC versus non-FQHC patient. Organizations were identified as FQHCs in Medicaid claims using any of the following identifiers: FQHC taxonomy code, taxonomy qualifier code (provider type and specialty code), place of service code, and billing provider National Provider Identifier (NPI) after an organization name-based search using CMS's National Plan & Provider Enumeration System (NPPES). To the extent possible given data constraints, this approach mirrored the recommended approach for identifying rural health clinics in claims data.[42]

Non-FQHC organizations were restricted to primary care practices and were identified using rendering provider (when available) and billing provider taxonomy codes, as well as primary care-specific Current Procedural Terminology codes, an approach applied in previous research.[18] Current Procedural Terminology codes classified as primary or preventive services in the Affordable Care Act or by the American Academy of Pediatrics were used to identify primary care services. A list of these codes can be found in Appendix A.

To be considered a primary care practice, non-FQHC organizations' taxonomy code on claims had to indicate a primary care provider, and they had to bill at least one primary care service code. Organizations enrolled in Community Care of North Carolina (CCNC), North Carolina's primary care case management and medical home program, that billed at least one primary care service code were also considered to be primary care practices.

Patients were attributed to either a FQHC or non-FQHC organization based on where they received the plurality of their primary care each year (determined by billing provider NPI). Attributing patients to practices based on where they received the plurality of primary care services has been utilized in previous research[19,42] and by the Centers for Medicare & Medicaid Services for Accountable Care Organizations.[44] If patients had the same number of primary care visits to more than one primary care organization, patients were attributed to the organization with the latest visit chronologically in that calendar year.[44] Patients without a primary care visit during the calendar year were assigned to the organization where they received the plurality of primary care services the previous year. (No observations were dropped because of a lack of a primary care visit in the current or prior year.) Attributing patients to a specific organization reflects the value of having a regular source of care for patients with chronic conditions;[45,46] the place where patients receive most of their primary care should have the greatest influence on their outcomes.

FQHC Look-Alikes, a sub-category of FQHCs, were not eligible organizations for patient attribution because these organizations are sufficiently different from both federally-funded FQHCs and non-FQHC practices. Unlike grant-funded FQHCs, FQHC Look-Alikes do not receive federal grant dollars to support care for the uninsured and often serve a greater proportion of publicly- or privately-insured patients. They are sufficiently different from non-FQHC private practices because they receive additional resources and technical support from state Primary Care Associations. Only two FQHC Look-Alikes existed in North Carolina during the study period.

Sensitivity analyses varied the method of patient attribution. In one analysis, patients were attributed to a practice based on their Community Care of North Carolina (CCNC) medical home assignment – a policy-relevant attribution method for North Carolina. Among attributed patients who also had a CCNC medical home (about 98% of the sample), roughly 22% had a CCNC medical home assignment that did not align with where these patients received the plurality of primary care services. Covariates that depended on practice attribution (e.g., continuity of care, number of Medicaid-insured children with asthma served) were recalibrated using the CCNC medical home practice.

An additional sensitivity analysis attributed patients to a practice type – FQHC or non-FQHC – instead of a specific practice. The attribution was based on whether the patients ever used an FQHC for primary care in the analysis year, the weakest definition for being an FQHC patient. A final sensitivity analysis utilized a lagged attribution in which hospital utilization was estimated using the prior year's attribution to a FQHC or non-FQHC organization; this method excludes the first year of claims data (2013). We also applied a lag to the instrumental and organization-level variables for this analysis. This lagged analysis was based on the assumption that the prior year's source of care might better explain the current year's hospital utilization.

For each of the four sensitivity analyses modifying the outcome definition and method of patient attribution, we compared the 95% confidence intervals around the estimated average differential effect of FQHC use to determine whether there were meaningful differences across the various model specifications.

Patient selection into the FQHC is likely endogenous – unobserved variables affect both whether a patient utilizes an FQHC and preventable hospital utilization rates. We applied an instrumental variable, distance from the centroid of a patient's zip code to the nearest FQHC medical care delivery site (based on mailing address), to account for patient selection into an FQHC practice. Distance from patient zip code to the nearest FQHC has been used successfully as an instrument in previous research.[18]

Other model covariates. All models adjusted for the following covariates based on prior research indicating an association with preventable hospital utilization or FQHC selection: patient age, race/ethnicity, sex, number of months in calendar year enrolled in Medicaid, rural residence (Rural-Urban Commuting Area code >=4), an indicator for whether the patient utilized specialty care for asthma (relevant taxonomy codes included in Appendix A), an interaction between rural residence and specialty provider utilization, total number of primary care visits to any provider, the number of comorbidities identified using the Agency for Healthcare Research and Quality's Chronic Condition Indicator (CCI)[47], and continuity of care as defined by Breslau and Reeb's Usual Provider of Care measure.[48]

We include a binary indicator for whether the patient utilized specialty care for asthma in a calendar year because FQHC patients are known to have limited access to specialty care.[49] The CCI defines chronic conditions as lasting 12 months or more and associated with either limitations to self-care or ongoing interventions with medical devices.[47] Breslau and Reeb's Usual Provider of Care measure was developed for a pediatric research study and is defined as the proportion of primary care visits with the attributed organization in a calendar year.

Sensitivity analyses varied both the measure of patient acuity and the continuity of care definition. Measuring patient acuity in a pediatric population is complicated by relatively low morbidity and mortality rates, utilization of non-traditional health care sites like school-based health clinics, and different application of diagnoses, drugs and procedures in pediatric populations than adult populations.[50] Therefore, it was important to test for the robustness of results under different measures of patient acuity. As an alternative specification for patient acuity, Clinical Classification Software (CCS) diagnosis groups associated with the following asthma comorbidities were included in regression models as individual dummy variables: obesity (CCS 3 - Endocrine; Nutritional; and Metabolic Diseases And Immunity Disorders), mental illness (CCS 5 – Mental Illness), and atopic dermatitis (CCS 12 – Skin and Subcutaneous Tissue Infections).[47,51] Including the CCS category inclusive of allergic reactions (CCS 17 - Symptoms; signs; and ill-defined conditions and factors influencing health status), another co-occurring condition complicating asthma management,[52] created problems with model convergence.

To test an alternative definition of continuity of care, we constructed a modified Wolinsky Continuity[53] measure. Using two years of data (current year and prior year), we determined whether patients had at least one primary care visit every six months to their current-year attributed provider to align with the American Academy of Pediatrics' recommendation for visit frequency for children with controlled asthma.[54] The first visit served as the index visit. The models applying this modified Wolinsky Continuity measure also included a variable measuring the number of months enrolled in Medicaid over a two-year period.

We also ran models without the utilization covariates – any specialty provider utilization for asthma in the calendar year and total number of primary care visits in the calendar year – and found qualitatively similar results to the main model specification in effect size, direction and significance.

Using the patient's modal county of residence – where the patient lived for most of the calendar year – we included several county-level measures to account for area-level influences on health: the percent of population living below the federal poverty line, median household income and air quality measured as fine particulate matter concentration (annual PM2.5 level). Poverty and income data were from the U.S. Census Bureau's Small Area Income and Poverty Estimates, and air quality data were from the CDC's National Environmental Public Health Tracking Network. The percent of the population living below the federal poverty line has been found to be a valid proxy for area-level socioeconomic deprivation.[55,56] The county-level air pollution measure adjusted for area-level environmental factors affecting hospital utilization. Maps from the NC Rural Health Research Program suggested area-level variation in ambulatory sensitive hospital admissions for asthma.[57] Hereafter, these covariates are referred to under the larger umbrella of patient-level characteristics.

Regression models also adjusted for the number of Medicaid-insured children with asthma served in each attributed organization, as every additional Medicaid-insured pediatric patient served may generate greater provider and organization expertise in caring for this patient population. (An additional robustness check included a quartile ranking representing the number of Medicaid patients with asthma served by the practice relative to other organizations in a given year.) Models also included year fixed effects to account for secular time trends.

Analytic Approach

Unadjusted differences between FQHC and non-FQHC patients were examined using chi-square tests for categorical and binary variables and t-tests for continuous variables. We estimated multivariate regression models using generalized linear models (GLM) with a binomial family and a logit link given the distribution of the outcome variables. We explored using generalized estimating equations to account for the correlation of observations for the same patient across analysis years (n<=3); however, an independent correlation structure was associated with the lowest quasi-likelihood under the independence model criterion (QIC) and thus the best-fitting model. Because an independent correlation structure is equivalent to a pooled model, we applied GLMs. Differences in average marginal effects between GLM and GEE models ranged between 0.02- 0.4 percentage points, which translated to an average hospital utilization rate of 8.18-8.20% with a principal diagnosis of asthma and an average hospital utilization rate of 22.8%-23.2% with any diagnosis of asthma.

We assessed model specification by adding one additional quadratic term at a time to the models and examining the z-statistic on the quadratic term to determine statistical significance. These tests indicated the following quadratic terms were significant (p<.05) and therefore should be included in the models: quadratic terms for age, continuity of care, percent of county living in poverty and county median household income.

Instrumental variable analysis with two-stage residual inclusion (2SRI) was used to model non-random patient selection into the FQHC. Relative to 2SRI, bivariate probit models are associated with lower bias in average treatment effect estimates in samples with similar treatment and outcome rates.[58] However, model convergence was not achieved with bivariate probit, so we opted to apply 2SRI.

Using 2SRI, the endogenous FQHC indicator was regressed on the instrumental variable – distance from the centroid of the patient's zip code to the nearest FQHC – and the other covariates. This first-stage regression is specified below:

$$\Pr\,(FQHC_{ipt} = 1) = \alpha + \beta_1 Distance_{it} + \beta_2 Patient_{it} + \beta_3 Organization_{pt} + \beta_4 Year_t + \varepsilon_{ipt}$$

where *Distance* represents the instrumental variable, *Patient* represents the series of patient-level covariates, *Organization* represents organization-level covariates, and *Year* represents year fixed effects. We estimated Pearson residuals after this first-stage model and included the residuals (*Stage1residuals*) in the second-stage outcome estimation model to control for the endogeneity of patient selection into the FQHC. After bivariate probit, 2SRI with Pearson residuals has the lowest bias in average treatment effect estimates in samples with similar treatment and outcome rates.[58] The second-stage regression model is specified below:

$$\Pr\,(Y_{ipt} = 1) = \alpha + \beta_1 FQHC_{it} + \beta_2 Stage1residuals_{ipt} + \beta_3 Patient_{it} + \beta_4 Organization_{pt} + \beta_5 Year_t + \varepsilon_{ipt}$$

where Y_{ipt} is the patient-level outcome variable (person-year hospital or ED utilization) and $FQHC_{it}$ indicated whether the patient received the majority of primary care services in an FQHC.

Instrumental variable tests for endogeneity and strength passed accepted thresholds: Durbin-Wu-Hausman tests for endogeneity[59] using a linear model specification rejected exogeneity of the FQHC variable in all models (p<.001 for models predicting any hospital utilization and ED utilization with a principal diagnosis of asthma; p<.05 for any hospital utilization with any diagnosis of asthma and ED utilization with any diagnosis of asthma.) After a logistic regression, distance to the nearest FQHC was associated with a Wald statistic of over 5700 (p<.001); the strength of the instrument far exceeded the recommended statistic of 10.[60]

Average marginal effects were estimated for model covariates, and bootstrapped standard errors (500 replications) accounted for the additional estimation of a two-stage model.

Bootstrapped standard errors were clustered at the patient-level to account for repeated observations across analysis years. All analyses were performed using Stata version 13.0.

Results

Table 2.1 highlights descriptive statistics for the final analysis sample. Roughly 6% of the total sample population were attributed to an FQHC organization using the plurality of primary care services rule. Bivariate comparisons revealed marked differences between FQHC and non-FQHC patients (Table 2.1). FQHC patients were more likely to go to the hospital for asthma, more likely to represent racial/ethnicity minorities and were less likely to utilize specialty providers for asthma. FQHC patients had fewer primary care visits than non-FQHC patients, fewer chronic conditions, and lived in communities with higher poverty rates and lower median household income. Bivariate comparisons indicated slightly better continuity of care for FQHC patients compared to non-FQHC patients ($p<.001$).

Average marginal effects with bootstrapped standard errors are presented in Table 2.2 for the main model specification. Sensitivity analysis results are reported in Appendix B. Across all outcome definitions and model specifications, FQHC patients were more likely to utilize the hospital for asthma even after controlling for selection bias. Figure 2.1 highlights the differential effect estimates and 95% confidence intervals for each of the model specifications.

In the primary model specification—plurality of primary care services-based attribution and hospital utilization with a principal diagnosis of asthma—FQHC use was associated with a 1.21 percentage point ($p<.01$) increase in the probability of any hospital utilization (ED visit, observation or inpatient stay) and a 1.25 percentage point ($p<.01$) increase in the probability of ED use with a principal diagnosis of asthma as compared to children with asthma attributed to non-FQHC primary care providers. This amounted to a hospital utilization rate of 9.4% relative to the baseline rate of 8.2%, and an ED utilization rate of 8.4% relative to the baseline rate of 7.1%.

The effect size was greater for the models predicting hospital utilization with any diagnosis of asthma: FQHC patients were 2.86 percentage points more likely to go to the hospital for any reason (p<.001) and 3.11 percentage points more likely to utilize the ED (p<.001). These increases translate to a hospital utilization rate of 26.1% relative to the baseline rate of 23.2% and an ED utilization rate of 24.1% relative to the baseline rate of 21.0%. It is worth noting that ED use comprised the majority of hospital utilization in this analysis sample, which is evident in the qualitatively similar average differential effects of FQHC use across the models estimating any hospital use and ED use (Model 1 compared to Model 2 and Model 3 compared to Model 4).

Even after applying a 60-day washout period to hospital utilization, the differential effect of being an FQHC patient was still associated with a higher predicted probability of hospital utilization, though the difference between FQHC and non-FQHC patients was smaller relative to the main models predicting hospital utilization with any diagnosis of asthma. (The differential effects were virtually the same in the models predicting hospital use with a principal diagnosis of asthma.) These results are presented in Table B.2 in Appendix B.

On average, Black race increased the predicted probability of any hospital utilization by 5.45 percentage points (p<.001) and increased the predicted probability of utilizing the ED by 4.98 percentage points (p<.001). Specialty provider utilization and greater continuity of care were associated with large and statistically significant increases in the predicted probability of hospital utilization with a principal diagnosis of asthma. However, the direction of the effects changed in the models predicting hospital utilization with any diagnosis of asthma, and these variables were associated with lower hospital utilization. Rural residence and a greater number of chronic conditions were associated with an increase in the predicted probability of hospital utilization with a principal diagnosis of asthma. The magnitude of these effects increased in secondary models predicting hospital utilization with any diagnosis of asthma.

Patient attribution robustness checks. To determine whether the results were robust to different methods of patient attribution, we ran models in which attribution was based on CCNC medical home payment – the practice receiving the per member per month payment to manage the care of the patient – as well as models where patients were attributed to FQHCs if they ever visited an FQHC for primary care in the analysis year. These models produced results similar to the primary analyses in direction and significance, though the effect size associated with FQHC use was larger in the CCNC-based attribution models and variable according to principal versus any diagnosis of asthma in the ever-FQHC attribution models. The results are presented in Tables B.3 and B.4 in Appendix B.

In the models for which preventable hospital utilization was estimated as a function of the prior year's FQHC/non-FQHC attribution, the differential effect of being an FQHC patient on hospital use was 0.2-1.4 percentage points higher in the lagged models than the un-lagged models run on the same analysis sample with 2013 excluded (Tables B.5 and B.6 in Appendix B). A summary table (Table B.1) containing the differential effect of being an FQHC patient from all model specifications is included in Appendix B.

Other sensitivity analyses. The results were robust to different specifications for the number of Medicaid-insured children with asthma served in each attributed provider organization, as well as for different measures of continuity of care and patient acuity. Applying a quartile ranking for the number of Medicaid-insured children with asthma served in each practice was associated with slightly higher preventable hospital utilization rates for FQHC patients, but the differences did not exceed 0.3 percentage points and were not clinically meaningful. Models estimating a longitudinal measure of continuity of care, the modified Wolinsky Continuity[53] measure, and models utilizing the alternative specification for patient acuity demonstrated qualitatively similar results to the main model specification in direction, magnitude and significance of the average differential effect of FQHC use (differences of 0.2 percentage points or less).

Discussion

Across all outcome definitions and model specifications, FQHC patients in North Carolina were more likely to utilize the hospital for asthma even after controlling for patient selection into FQHCs and other patient characteristics. Differences across model specifications were not meaningful; Figure 2.1 highlights the average differential effect estimates and overlapping 95% confidence intervals for each of these model specifications. These results suggest that there may be unmeasured patient-, organization- or community-level factors increasing the probability that FQHC patients use the hospital compared to patients accessing primary care from non-FQHC organizations.

This study's findings are in contrast to previous research that found FQHC patients had lower overall hospital utilization relative to patients utilizing other primary care practices.[7,16,43] Few of these earlier studies examined hospital utilization among Medicaid-insured children, however, which could explain the divergent findings. In particular, the magnitude of the FQHC effect is largely driven by ED utilization, as children rarely have inpatient stays associated with asthma. Furthermore, North Carolina's Community Care of North Carolina (CCNC) primary care case management and medical home model may contribute to better performance among non-FQHC providers in the state, reducing the magnitude of the effect of FQHCs in this patient population. CCNC deploys local case management and care coordination strategies for select patient populations and has reduced hospital utilization, lowered costs and improved health outcomes.[61] Relative to Medicaid managed care enrollees in other states, more CCNC enrollees had better process and outcome measures for chronic disease management for diabetes, hypertension, asthma and cardiovascular disease.[62] Pediatric asthma has been a targeted condition for intervention through CCNC,[63,64] which may have helped improve quality of care among all providers and reduced the effect of FQHCs documented in other states.

At the same time, this study's results align with previous research finding higher ED utilization among FQHC patients.[15,16,65] In three studies examining ambulatory care sensitive hospital utilization among dual-eligible patients, FQHC use was associated with decreases in any inpatient hospitalization but increases in ED utilization.[15,16,65] Although their study focused on spending, Bruen and colleagues[17] applied inverse propensity weights and found that children utilizing FQHCs had significantly lower overall health care spending than similar children utilizing other primary care providers except for ED spending; ED spending for children utilizing FQHCs was no different than the spending for similar children utilizing other primary care practices.

Greater ED utilization among FQHC patients may be driven by appointment availability, clinic accessibility[66] or availability of other non-hospital-based urgent care resources in the community. A study of FQHC access in California found increased geographic density of FQHCs was associated with significant decreases in ED utilization among Medicaid-insured and uninsured children.[12] Non-hospital-based urgent care centers are more prevalent in higher-income communities[67] where FQHCs are less likely to be located, which could limit access to non-hospital urgent care for patients in FQHC service areas.

It is important to note that FQHCs' quality of care may have declined during the analysis years because 2013-2015 also represented a period of tremendous growth and organizational change in the FQHC program: With funding allocated in the Patient Protection & Affordable Care Act of 2010,[68] six new FQHC organizations ("new start" organizations) were established and 23 new clinic sites were added to existing FQHC organizations in North Carolina from 2013-2015.[69,70] Interestingly, the year fixed effects suggest that the likelihood of preventable hospital use declined in 2014 and 2015 relative to 2013 for the entire sample.

Limitations

There are several limitations to this study. First, study results may not be generalizable beyond Medicaid enrollees in North Carolina given the potential that CCNC influenced patient utilization and health outcomes in ways not replicable in other states. Moreover, CCNC might have differentially affected hospital utilization in either FQHC or non-FQHC organizations.

Second, the study included only nine months of data for analysis year 2015 given the transition to ICD-10 coding; however, analyses adjusted for total months of Medicaid enrollment in a calendar year under the assumption that outcomes are linear in the number of months on Medicaid (e.g., outcomes for those in Medicaid for 12 months would be twice as high as for those in Medicaid for six months).

Third, FQHCs, because they are reimbursed on a per-visit rather than a per-procedure basis, may include fewer diagnosis codes in their claims, underestimating claims-based patient acuity.[13,19] However, our analysis somewhat mitigated this bias by utilizing both outpatient and hospital-based claims for measuring patient acuity.

Finally, applying a plurality rule for patient attribution ignores the contribution of other sources of primary care. However, the place where patients receive most of their primary care should have the greatest influence on their outcomes. Roughly 90% of the analysis sample utilized their attributed provider for >50% of their primary care visits, so these patients have arguably established a regular source of care.

Conclusion

FQHC attribution was associated with higher preventable hospital utilization among North Carolina Medicaid-insured children with asthma than attribution to a non-FQHC primary care practice. This study adjusts for patient acuity, continuity of care and specialty provider utilization -- all factors known to be associated with FQHC use or hospital utilization.[6,71,72] Sensitivity analyses that varied the measure of patient acuity and continuity of care suggest that these results are robust to different measure specifications. Furthermore, this study's application of instrumental variable analysis accounts for other unobserved patient characteristics associated with FQHC use and hospital utilization. As a result, the findings suggest future research should examine processes of care within FQHCs and the availability of non-hospital urgent care resources within FQHC service areas to determine why FQHC patients are going to the hospital more frequently than non-FQHC patients in North Carolina.

Table 2.1. Bivariate Statistics for Analytic Sample: 2013-2015 Medicaid Children with Asthma

	Total patients	Non-FQHC patients	FQHC patients	p-value
N (person-years)	381,723	357,724	23,999	
Unique individuals	178,490	166,706	11,784	
Outcomes				
Any hospital utilization (ED, observation or inpatient) with principal diagnosis of asthma, mean %	8.2%	8.1%	9.5%	<.001
ED visit with principal diagnosis of asthma, mean %	7.1%	7.1%	8.6%	<.001
Any hospital utilization (ED, observation or inpatient) with any diagnosis of asthma, mean %	23.2%	23.1%	25.4%	<.001
ED visit with any diagnosis of asthma, mean %	21.0%	20.8%	23.8%	<.001
Patient characteristics				
Age, mean (sd)	9.2 (4.42)	9.2 (4.42)	9.3 (4.43)	<.001
Female enrollee, mean %	42.6%	42.6%	43.3%	0.021
Race/Ethnicity, mean %				<.001
White, not Hispanic	34.1%	35.3%	16.2%	
Black, not Hispanic	41.7%	41.2%	49.3%	
Hispanic	16.2%	15.5%	27.0%	
Multiple/Other, not Hispanic	3.9%	3.9%	3.3%	
Unknown	4.0%	4.0%	4.2%	
Months of Medicaid coverage in calendar year, mean (sd)	10.4 (2.17)	10.4 (2.17)	10.4	0.011
Rural residence, mean %	29.0%	29.0%	28.5%	0.096
Specialty provider utilization in calendar year, mean %	12.5%	12.9%	6.8%	<.001
Number of primary care visits in calendar year, mean (sd)	5.14 (4.42)	5.22 (4.45)	4.07 (3.63)	<.001
Number of chronic conditions, mean (sd)	1.73 (1.22)	1.73 (1.23)	1.63 (1.10)	<.001

Continuity of care (% of primary care visits with attributed organization in calendar year), mean (sd)	0.819 (0.236)	0.818 (0.236)	0.838 (0.224)	<.001
County-level measures				
Percent living under poverty, mean (sd)	18.2 (4.93)	18.1 (4.93)	18.9 (4.98)	<.001
Median household income (in $10,000), mean (sd)	4.65 (0.971)	4.65 (0.972)	4.55 (0.946)	<.001
Annual concentration of air particulate matter, mean (sd)	9.9 (0.952)	9.9 (0.955)	9.8 (0.903)	<.001
Attributed provider characteristics				
CCNC-enrolled practice, mean %	95.0%	95.0%	95.6%	<.001
Number of Medicaid patients with asthma served by attributed provider organization in calendar year (in 10,000), mean (sd)	15.0 (8.42)	14.9 (8.38)	16.2 (8.77)	<.001
Year, mean %				<.001
2013	27.6%	27.5%	29.3%	
2014	36.0%	36.0%	35.9%	
2015	36.4%	36.5%	34.7%	

*p-value based on chi-square for categorical variables or t-test for continuous variables

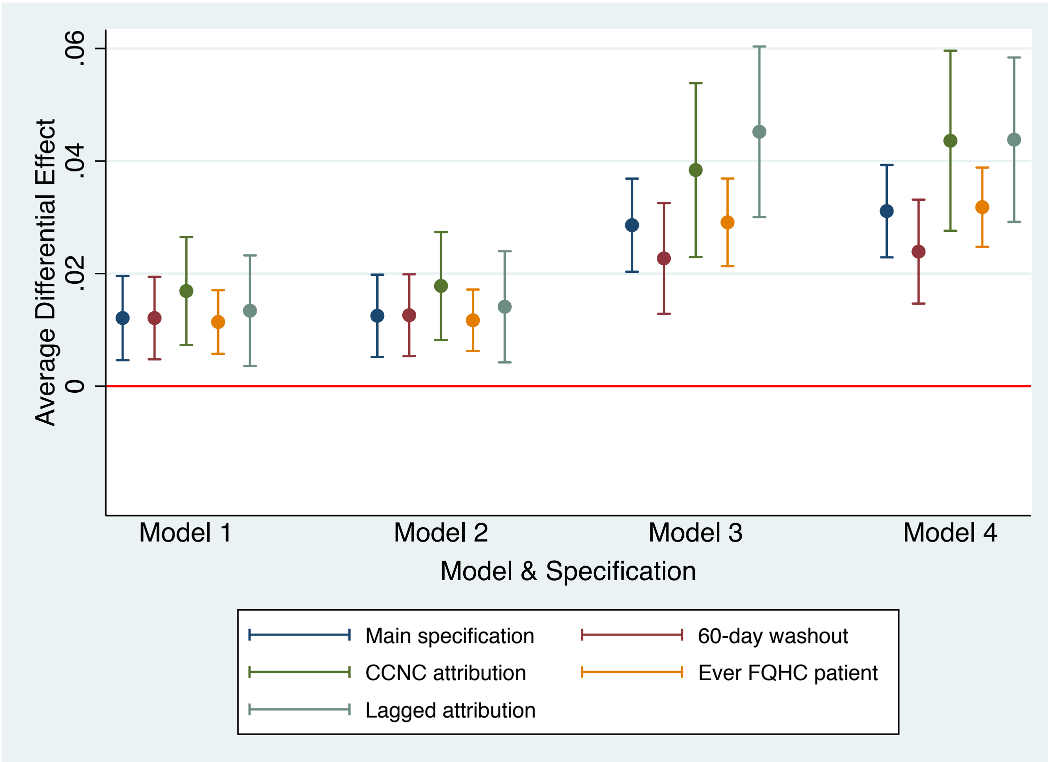
Table 2.2. Average Marginal Effects of Model Covariates on Preventable Hospital Utilization (Main Model Specification)

	Model 1 **Any hospital utilization (ED, observation or inpatient stay) with a principal diagnosis of asthma**	**Model 2** **ED visit with principal diagnosis of asthma**	**Model 3** **Any hospital utilization (ED, observation or inpatient stay) with any diagnosis of asthma**	**Model 4** **ED visit with any diagnosis of asthma**
FQHC patient	0.0121**	0.0125***	0.0286***	0.0311***
	(0.00382)	(0.00373)	(0.00422)	(0.00419)
Age	-0.00501***	-0.00354***	-0.00563***	-0.00393***
	(0.000148)	(0.000132)	(0.000204)	(0.000190)
<u>Race/Ethnicity (*ref. White. not Hispanic*)</u>				
Black, not Hispanic	0.0545***	0.0498***	0.0683***	0.0656***
	(0.00119)	(0.00109)	(0.00178)	(0.00173)
Hispanic	0.00449**	0.00324**	-0.0416***	-0.0414***
	(0.00139)	(0.00125)	(0.00229)	(0.00219)
Multiple/Other, not Hispanic	0.0105***	0.00794***	-0.0116**	-0.0144***
	(0.00255)	(0.00236)	(0.00418)	(0.00402)
Unknown	0.0111***	0.00982***	-0.00469	-0.00766
	(0.00242)	(0.00225)	(0.00403)	(0.00400)
Female sex (*ref. male*)	-0.00701***	-0.00606***	-0.00157	-0.000556
	(0.00102)	(0.00096)	(0.00147)	(0.00145)
Months of Medicaid coverage in calendar year	-0.000413	6.23E-05	0.000669	0.00174***
	(0.000242)	(0.000233)	(0.000376)	(0.000372)
Rural residence (*ref. non-rural*)	0.00569***	0.00671***	0.0265***	0.0285***
	(0.00139)	(0.00129)	(0.00215)	(0.00208)
Utilized specialty care for asthma	0.0291***	0.0192***	-0.0194***	-0.0217***
	(0.00183)	(0.00168)	(0.00219)	(0.00215)
Total primary care visits	0.000812***	0.000599***	0.00110***	0.000109

	(0.000123)	(0.000119)	(0.000196)	(0.000189)
Number of chronic conditions	0.00619***	0.00493***	0.0473***	0.0348***
	(0.000393)	(0.000373)	(0.000679)	(0.000645)
Continuity of care in calendar year	0.0191***	0.0151***	-0.0255***	-0.0307***
	(0.00324)	(0.00308)	(0.00465)	(0.00466)
<u>County-level covariates</u>				
Percent of population living below federal poverty line	0.00236***	0.00192***	0.00044	-0.000341
	(0.000254)	(0.000236)	(0.000397)	(0.000376)
Median household income (in $10,000)	0.00844***	0.00532***	-0.00177	-0.00641**
	(0.00140)	(0.00131)	(0.00209)	(0.00201)
Annual concentration of air particulate matter	-8.44E-05	-0.000837	0.00404**	0.00382**
	(0.000838)	(0.000776)	(0.00127)	(0.00126)
Number of Medicaid patients with asthma served by attributed provider organization in calendar year (in 10,000)	0.000210***	0.000160**	0.000521***	0.000434***
	(0.0000599)	(0.0000551)	(0.0000896)	(0.0000857)
<u>Year (*ref. 2013*)</u>				
2014	-0.0193***	-0.0177***	-0.0428***	-0.0443***
	(0.00186)	(0.00174)	(0.00266)	(0.00261)
2015	-0.0522***	-0.0452***	-0.0982***	-0.0939***
	(0.00176)	(0.00162)	(0.00278)	(0.00268)
Pearson residual	-0.000355	-0.000286	-0.000208	-0.000141
	(0.000782)	(0.000754)	(0.000692)	(0.000679)
Observations	381,723	381,723	381,723	381,723

Bootstrapped standard errors in parentheses.
*** p<0.001, ** p<0.01, * p<0.05

Figure 2.1. Differential Effect of FQHC Use across Sensitivity Analyses and Model Specifications



Note: Models 1 and 2 represent any hospital utilization and ED utilization with a principal diagnosis of asthma. Models 3 and 4 represent any hospital utilization and ED utilization with any diagnosis of asthma.

REFERENCES

1. Bureau of Primary Health Care. 2016 Health Center Data - National Program Grantee Data. Uniform Data System. https://bphc.hrsa.gov/uds/datacenter.aspx. Published 2017. Accessed October 4, 2017.

2. Bureau of Primary Health Care. 2017 Health Center Grantee Data - North Carolina Program Grantee Data. Uniform Data System. https://bphc.hrsa.gov/uds/datacenter.aspx?year=2017&state=NC. Published 2018.

3. Bureau of Primary Health Care. Summary of Program Requirements. https://bphc.hrsa.gov/programrequirements/summary.html. Accessed August 9, 2017.

4. Geiger HJ. The first community health centers: a model of enduring value. *J Ambul Care Manage*. 2005;28(4):313-320. http://www.ncbi.nlm.nih.gov/pubmed/16172560. Accessed September 14, 2017.

5. *Section 330 of the Public Health Service Act*. http://uscode.house.gov/view.xhtml?edition=prelim&req=42+usc+254b&f=treesort&fq=true&num=20&hl=true. Accessed August 9, 2017.

6. Goldman LE, Chu PW, Tran H, Romano MJ, Stafford RS. Federally Qualified Health Centers and Private Practice Performance on Ambulatory Care Measures. *Am J Prev Med*. 2012;43(2):142-149. doi:10.1016/j.amepre.2012.02.033.

7. Laiteerapong N, Kirby J, Gao Y, et al. Health care utilization and receipt of preventive care for patients seen at federally funded health centers compared to other sites of primary care. *Health Serv Res*. 2014;49(5):1498-1518. doi:10.1111/1475-6773.12178.

8. Shi L, Stevens GD, Politzer RM. Access to care for U.S. health center patients and patients nationally: how do the most vulnerable populations fare? *Med Care*. 2007;45(3):206-213. doi:10.1097/01.mlr.0000252160.21428.24.

9. Tom JO, Tseng C-W, Davis J, Solomon C, Zhou C, Mangione-Smith R. Missed well-child care visits, low continuity of care, and risk of ambulatory care-sensitive hospitalizations in young children. *Arch Pediatr Adolesc Med*. 2010;164(11):1052-1058. doi:10.1001/archpediatrics.2010.201.

10. Fishman J, McLafferty S, Galanter W. Does Spatial Access to Primary Care Affect Emergency Department Utilization for Nonemergent Conditions? *Health Serv Res*. November 2016. doi:10.1111/1475-6773.12617.

11. Falik M, Needleman J, Herbert R, Wells B, Politzer R, Benedict MB. Comparative effectiveness of health centers as regular source of care: Application of sentinel ACSC events as performance measures. *J Ambul Care Manage*. 2006;29(1):24-35. http://www.ncbi.nlm.nih.gov/pubmed/16340617. Accessed June 23, 2016.

12. Nath JB, Costigan S, Lin F, Vittinghoff E, Hsia RY. Federally Qualified Health Center Access and Emergency Department Use Among Children. *Pediatrics*. 2016;138(4). doi:10.1542/peds.2016-0479.

13. Nocon RS, Lee SM, Sharma R, et al. Health Care Use and Spending for Medicaid Enrollees in Federally Qualified Health Centers Versus Other Primary Care Settings. *Am J Public Health*. 2016;106(11):1981-1989. doi:10.2105/AJPH.2016.303341.

14. Rothkopf J, Brookler K, Wadhwa S, Sajovetz M. Medicaid patients seen at federally qualified health centers use hospital services less than those seen by private providers. *Health Aff*. 2011;30(7):1335-1342. doi:10.1377/hlthaff.2011.0066.

15. Potter AJ, Trivedi AN, Wright B. Younger Dual-Eligibles Who Use Federally Qualified Health Centers Have More Preventable Emergency Department Visits, but Some Have Fewer Hospitalizations. *J Prim Care Community Health*. 2017;8(1):3–8. doi:10.1177/2150131916657081.

16. Wright B, Potter AJ, Trivedi A. Federally Qualified Health Center Use Among Dual Eligibles: Rates Of Hospitalizations And Emergency Department Visits. *Health Aff*. 2015;34(7):1147-1155. doi:10.1377/hlthaff.2014.0823.

17. Bruen B, Ku L. *Community Health Centers Reduce the Costs of Children's Health Care.*; 2017. http://publichealth.gwu.edu/projects/geiger-gibson-program-community-health-policy. Accessed June 28, 2017.

18. Mukamel DB, White LM, Nocon RS, et al. Comparing the Cost of Caring for Medicare Beneficiaries in Federally Funded Health Centers to Other Care Settings. *Health Serv Res*. 2016;51(2):625-644. doi:10.1111/1475-6773.12339.

19. Gurewich D, Tyo KR, Zhu J, Shepard DS. Comparative Performance of Community Health Centers and Other Usual Sources of Primary Care. *J Ambul Care Manage*. 2011;34(4):380-390. doi:10.1097/JAC.0b013e31822cbc59.

20. Richard P, Ku L, Dor A, Tan E, Shin P, Rosenbaum S. Cost savings associated with the use of community health centers. *J Ambul Care Manage*. 2012;35(1):50-59. doi:10.1097/JAC.0b013e31823d27b6.

21. MEPS Household Component Main Study Glossary. Medical Expenditure Panel Survey. https://meps.ahrq.gov/survey_comp/hc_ques_glossary.shtml#C. Published 2010. Accessed August 9, 2017.

22. Pearson WS, Goates SA, Harrykissoon SD, Miller SA. State-Based Medicaid Costs for Pediatric Asthma Emergency Department Visits. *Prev Chronic Dis*. 2014;11:140139. doi:10.5888/pcd11.140139.

23. North Carolina State Center for Health Statistics. 2013-2014 CHAMP Topics. http://www.schs.state.nc.us/data/champ/201314/topics.htm#as. Published 2017. Accessed March 15, 2017.

24. Centers for Disease Control. Asthma - Data, Statistics and Surveillance. http://www.cdc.gov/asthma/asthmadata.htm. Published 2016. Accessed October 13, 2016.

25. Starfield B, Shi L, Macinko J. Contribution of Primary Care to Health Systems and Health. *Milbank Q*. 2005;83(3):457-502. doi:10.1111/j.1468-0009.2005.00409.x.

26. Friedman B, Basu J. Health insurance, primary care, and preventable hospitalization of children in a large state. *Am J Manag Care*. 2001;7(5):473-481. http://www.ncbi.nlm.nih.gov/pubmed/11388127. Accessed August 24, 2017.

27. Basu J, Friedman B, Burstin H. Primary care, HMO enrollment, and hospitalization for ambulatory care sensitive conditions: a new approach. *Med Care*. 2002;40(12):1260-1269. doi:10.1097/01.MLR.0000036409.56436.ED.

28. Whittaker W, Anselmi L, Kristensen SR, et al. Associations between Extending Access to Primary Care and Emergency Department Visits: A Difference-In-Differences Analysis. *PLoS Med*. 2016;13(9):e1002113. doi:10.1371/journal.pmed.1002113.

29. Pardue Jones B, Fleming GM, Otillio JK, Asokan I, Arnold DH. Pediatric acute asthma exacerbations: Evaluation and management from emergency department to intensive care unit. *J Asthma*. 2016;53(6):607-617. doi:10.3109/02770903.2015.1067323.

30. Agency for Healthcare Research and Quality. Pediatric Quality Indicators Technical Specifications - Version 6.0. https://www.qualityindicators.ahrq.gov/Modules/PDI_TechSpec_ICD09_v60.aspx. Published 2017. Accessed October 3, 2017.

31. Billings J, Parikh N, Mijanovish T. *Emergency Department Use in New York City: A Substitute for Primary Care?*; 2000.

32. Faculty Research. NYU Center for Health and Public Service Research. https://wagner.nyu.edu/faculty/billings/nyued-background. Accessed October 3, 2017.

33. Elixhauser A, Heslin K, PL O. *Healthcare Cost and Utilization Project (HCUP) Recommendations for Reporting Trends Using ICD-9-CM and ICD-10-CM/PCS Data*.; 2017. www.hcup - us.ahrq.gov/datainnovations/icd10_resources.jsp.

34. Domino ME, Humble C, Lawrence WW, Wegner S. Enhancing the Medical Homes Model for Children With Asthma. *Med Care*. 2009;47(11):1113-1120. doi:10.1097/MLR.0b013e3181adcc65.

35. Barrett ML, Wier LM, Washington R. *Trends in Pediatric and Adult Hospital Stays for Asthma, 2000–2010. HCUP Statistical Brief #169*. Rockville, MD; 2014. http://www.hcup-us.ahrq.gov/reports/statbriefs/sb169-Asthma-Trends-Hospital-Stays.pdf. Accessed November 23, 2016.

36. Macy ML, Hall M, Shah SS, et al. Pediatric observation status: Are we overlooking a growing population in children's hospitals? *J Hosp Med*. 2012;7(7):530-536. doi:10.1002/jhm.1923.

37. Conners GP, Melzer SM, Committee on Hospital Care COH, et al. Pediatric observation units. *Pediatrics*. 2012;130(1):172-179. doi:10.1542/peds.2012-1358.

38. Sabbatini AK, Wright B. Excluding Observation Stays from Readmission Rates — What Quality Measures Are Missing. *N Engl J Med*. 2018;378(22):2062-2065. doi:10.1056/NEJMp1800732.

39. Nath JB, Hsia RY. Children's emergency department use for asthma, 2001-2010. *Acad Pediatr*. 2015;15(2):225-230. doi:10.1016/j.acap.2014.10.011.

40. Tang N, Stein J, Hsia RY, Maselli JH, Gonzales R. Trends and Characteristics of US Emergency Department Visits, 1997-2007. *JAMA*. 2010;304(6):664. doi:10.1001/jama.2010.1112.

41. Johnson PJ, Ghildayal N, Ward AC, Westgard BC, Boland LL, Hokanson JS. Disparities in Potentially Avoidable Emergency Department (ED) Care. *Med Care*. 2012;50(12):1020-1028. doi:10.1097/MLR.0b013e318270bad4.

42. Domino M, Tyree S, Rutledge R, Holmes M. *Findings Brief: Identifying Rural Health Clinics in Medicaid Data*.; 2016. https://www.ruralhealthresearch.org/publications/1036.

43. Falik M, Needleman J, Wells BL, Korb J. Ambulatory care sensitive hospitalizations and emergency visits: experiences of Medicaid patients using federally qualified health centers. *Med Care*. 2001;39(6):551-561. http://www.ncbi.nlm.nih.gov/pubmed/11404640. Accessed August 24, 2016.

44. *Medicare Shared Savings Program: Shared Savings and Losses and Assignment Methodology Specifications*. Baltimore; 2015. https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/sharedsavingsprogram/Downloads/Shared-Savings-Losses-Assignment-Spec-V4.pdf. Accessed April 18, 2017.

45. Raphael JL, Cooley WC, Vega A, et al. Outcomes for Children with Chronic Conditions Associated with Parent- and Provider-reported Measures of the Medical Home. *J Health Care Poor Underserved*. 2015;26(2):358-376. doi:10.1353/hpu.2015.0051.

46. Spatz ES, Ross JS, Desai MM, Canavan ME, Krumholz HM. Beyond insurance coverage: Usual source of care in the treatment of hypertension and hypercholesterolemia. Data from the 2003-2006 National Health and Nutrition Examination Survey. *Am Heart J*. 2010;160(1):115-121. doi:10.1016/j.ahj.2010.04.013.

47. Agency for Healthcare Research and Quality. HCUP Chronic Condition Indicator. Healthcare Cost and Utilization Project (HCUP). https://www.hcup-us.ahrq.gov/toolssoftware/chronic/chronic.jsp. Accessed April 21, 2017.

48. Breslau N, Reeb KG. Continuity of care in a university-based practice. *J Med Educ*. 1975;50(10):965-969. http://www.ncbi.nlm.nih.gov/pubmed/1159765. Accessed April 22, 2017.

49. Zuckerman KE, Perrin JM, Hobrecker K, Donelan K. Barriers to specialty care and specialty referral completion in the community health center setting. *J Pediatr*. 2013;162(2):409-14.e1. doi:10.1016/j.jpeds.2012.07.022.

50. Kuhlthau K, Ferris TGG, Iezzoni LI. Risk Adjustment for Pediatric Quality Indicators. *Pediatrics*. 2004;113(1):210-216. http://pediatrics.aappublications.org/content/pediatrics/113/Supplement_1/210.full.pdf. Accessed October 11, 2016.

51. Cazzola M, Segreti A, Calzetta L, Rogliani P. Comorbidities of asthma. *Curr Opin Pulm Med*. 2013;19(1):36-41. doi:10.1097/MCP.0b013e32835b113a.

52. Tan RA, Corren J. The relationship of rhinitis and asthma, sinusitis, food allergy, and eczema. *Immunol Allergy Clin North Am*. 2011;31(3):481-491. doi:10.1016/j.iac.2011.05.010.

53. Wolinsky FD, Miller TR, Geweke JF, et al. An interpersonal continuity of care measure for Medicare Part B claims analyses. *Journals Gerontol Ser B Psychol Sci Soc Sci*. 2007;62(3):S160-8. http://www.ncbi.nlm.nih.gov/pubmed/17507591. Accessed November 8, 2018.

54. American Academy of Pediatrics. Key Points for Asthma Guideline Implementation. https://www.aap.org/en-us/Documents/medicalhome_resources_keypointsforasthma.pdf. Published 2013.

55. Krieger N, Chen JT, Waterman PD, Soobader M-J, Subramanian S V, Carson R. Choosing area based socioeconomic measures to monitor social inequalities in low birth weight and childhood lead poisoning: The Public Health Disparities Geocoding Project (US). *J Epidemiol Community Health*. 2003;57(3):186-199. doi:10.1136/jech.57.3.186.

56. Diez-Roux A V, Kiefe CI, Jacobs DR, et al. Area characteristics and individual-level socioeconomic position indicators in three population-based epidemiologic studies. *Ann Epidemiol*. 2001;11(6):395-405. http://www.ncbi.nlm.nih.gov/pubmed/11454499. Accessed September 15, 2017.

57. *Ambulatory Care Sensitive Condition Hospital Admissions (2004) for Asthma*. http://www.shepscenter.unc.edu/rural/maps/ACS2004_18underNC.pdf.

58. Basu A, Coe NB, Chapman CG. 2SLS versus 2SRI: Appropriate methods for rare outcomes and/or rare exposures. *Health Econ*. 2018;27(6):937-955. doi:10.1002/hec.3647.

59. Hausman JA. Specification Tests in Econometrics. *Econometrica*. 1978;46(6):1251. doi:10.2307/1913827.

60. Stock J, Yogo M. *Testing for Weak Instruments in Linear IV Regression*.; 2002. doi:10.3386/t0284.

61. Jackson CT, Trygstad TK, DeWalt DA, DuBard CA. Transitional Care Cut Hospital Readmissions For North Carolina Medicaid Patients With Complex Chronic Conditions. *Health Aff*. 2013;32(8):1407-1415. doi:10.1377/hlthaff.2013.0047.

62. DuBard AC. Improving the Quality of Care for Medicaid Patients with Chronic Diseases: Community Care of North Carolina. *N C Med J*. 2013;74(2):142-147.

63. Steiner BD, Denham AC, Ashkin E, et al. Community care of North Carolina: improving care through community health networks. *Ann Fam Med*. 2008;6(4):361-367. doi:10.1370/afm.866.

64. Tilson EC. Community Care of North Carolina's Approach to Asthma Management. *NC Med J*. 2013;74(5):393-400. http://classic.ncmedicaljournal.com/wp-content/uploads/2013/09/74505.pdf. Accessed August 1, 2017.

65. Wright B, Potter AJ, Trivedi AN. Use of Federally Qualified Health Centers and Potentially Preventable Hospital Utilization Among Older Medicare-Medicaid Enrollees. *J Ambul Care Manage*. 2017;40(2):139-149. doi:10.1097/JAC.0000000000000158.

66. Kangovi S, Barg FK, Carter T, Long JA, Shannon R, Grande D. Understanding Why Patients Of Low Socioeconomic Status Prefer Hospitals Over Ambulatory Care. *Health Aff*. 2013;32(7):1196-1203. doi:10.1377/hlthaff.2012.0825.

67. Le ST, Hsia RY. Community characteristics associated with where urgent care centers are located: a cross-sectional analysis. *BMJ Open*. 2016;6(4):e010663. doi:10.1136/bmjopen-2015-010663.

68. *Medicaid and Community Health Centers: The Relationship Between Coverage for Adults and Primary Care Capacity in Medically Underserved Communities*.; 2012. https://www.kff.org/health-reform/issue-brief/medicaid-and-community-health-centers-the-relationship/. Accessed August 21, 2018.

69. Bureau of Primary Health Care. 2015 Health Center Data - North Carolina Program Grantee Data. Uniform Data System. http://bphc.hrsa.gov/uds/datacenter.aspx?year=2015&state=NC. Published 2015. Accessed October 13, 2016.

70. Bureau of Primary Health Care. 2013 Health Center Data - National Program Grantee Data. http://bphc.hrsa.gov/uds/datacenter.aspx?year=2013. Accessed February 17, 2015.

71. J. R, P. R. How strong is the primary care safety net? Assessing the ability of federally qualified health centers to serve as patient-centered medical homes. *J Gen Intern Med*. 2015;30(September).

72. Christakis DA, Mell L, Koepsell TD, Zimmerman FJ, Connell FA. Association of Lower Continuity of Care With Greater Risk of Emergency Department Use and Hospitalization in Children. *Pediatrics*. 2001;107(3):524-529. http://pediatrics.aappublications.org/content/107/3/524.short. Accessed October 6, 2016.

73. Fingar K, Washington R. *Potentially Preventable Pediatric Hospital Inpatient Stays for Asthma and Diabetes, 2003–2012. HCUP Statistical Brief #192.* Rockville, MD; 2015. https://www.hcup-us.ahrq.gov/reports/statbriefs/sb192-Pediatric-Preventable-Hospitalizations-Asthma-Diabetes.pdf. Accessed December 1, 2016.

CHAPTER THREE: USING MULTIPLE STATISTICAL METHODS TO GENERATE AN OVERALL PERFORMANCE RANKING FOR PREVENTABLE HOSPITAL USE AMONG FEDERALLY QUALIFIED HEALTH CENTERS

Overview

Performance profiling is used to assess health care organizations' ability to meet utilization, spending, or quality performance benchmarks. Accurately evaluating health care organizations' performance can promote better patient outcomes or help lower costs. Two of the most commonly applied statistical methods for estimating performance are hierarchical generalized linear models (HGLMs) and fixed effect models. However, previous studies found variation in performance classification according to the statistical methodology applied and the choice of risk adjusters. No "gold standard" in performance classification exists, so we sought to incorporate performance classification results across multiple statistical methods and model specifications to generate a more robust performance classification. Data included 2013-2015 Medicaid claims and data from federally qualified health centers' (FQHCs) Uniform Data System. We applied three different methodologies (unadjusted crude rate, HGLMs and fixed effect models) to two model specifications to rank FQHCs according to preventable hospital utilization rates for asthma. We then assigned an overall performance ranking using the geometric mean of the rankings across the four risk-adjusted models. Our results corroborated previous research, finding variation in absolute rankings across methods and model specifications. However, the top and bottom quartiles were largely consistent across models; over half of the organizations identified as the overall, geometric mean-based top-/bottom-performers were in the top/bottom performance quartile across all four risk-adjusted methods. Therefore, variation in absolute rankings across methods was minimal. Health care organization profiling with research or policy applications should examine the influence of methodology and risk adjusters on performance and determine whether results are robust to both methodological approach and model specification. Establishing an overall ranking using the geometric mean represents one way to incorporate performance classification results across different methods and model specifications.

Background

Health care organizations are frequently evaluated according to their ability to meet certain utilization, spending, or quality performance benchmarks in an effort to reward/penalize good/poor performance and to identify opportunities for quality improvement. In particular, performance profiling for federally qualified health centers (FQHCs), primary care providers serving predominately low-income and uninsured patients, could help identify opportunities for quality improvement given the wide variation in care delivery models across FQHC organizations.[1–3] The goal of this study was to compare the relative performance ranking of North Carolina FQHCs.

A variety of statistical methods exist with which to profile health care organizations, and the performance classification results can vary according to the method applied (e.g., one method may fail to identify a poor performer, while another method may misclassify an organization as a poor performer).[4–6] Two commonly utilized statistical methods to estimate health care organization performance include hierarchical generalized linear models (HGLMs), or mixed effect models, and fixed effect models.[4,5,7,8]

Hierarchical models help account for the clustering of patients within organizations and the resulting within-organization correlation in outcomes.[7–9] HGLMs also incorporate a shrinkage estimator, or an empirical Bayes estimator, to help increase the precision of individual organization estimates. Shrinkage estimators borrow strength from the distribution of all organizations in order to generate an organization-level random effect weighted according to the organization's sample size (patient volume); organizations with smaller volumes are weighted more toward the group mean, while organizations with larger volumes borrow less information from the group distribution.[10–12] HGLMs are therefore advantageous when variation in organization sample size exists and when performance is not assumed to be correlated with organization size.[12] However, HGLMs can produce biased estimates when the organization-level random effects are correlated with the covariates included in the model (e.g., when the random effects are not independent of organizations' patient mix).

Despite this limitation, the Centers for Medicare and Medicaid Services uses HGLMs for measuring hospital performance.[13] In their view, because HGLMs account for the within-organization correlation of outcomes and avoid penalizing low-volume hospitals for outcomes that may be due to chance, HGLMs better isolate the true, underlying hospital effects.[10,13]

Organization-specific fixed effects represent another commonly utilized method for classifying organization performance.[5,14] Unlike the HGLMs, fixed effect models are not subject to the same requirement that the fixed effects be uncorrelated with other model covariates. However, fixed effect estimates for organizations with fewer patients (smaller sample sizes) may be less precise and may risk misclassifying the performance of these organizations whose outcomes may be due to chance.[5] CMS uses fixed effect models to classify performance among dialysis facilities, likely because these organizations have sufficient patient volume to obviate the need for HGLM and shrinkage estimators.[13] Fixed effect models are superior to the other regression-based method commonly cited in performance classification literature, patient-level regression to estimate the observed/expected rate, given the lack of control for unobserved, time-invariant factors in the latter model.

Previous research indicates that the choice of both performance measurement methodology and model risk adjusters influence performance classification results. For example, Huang and colleagues[15] examined patient satisfaction with asthma care to profile performance among physician group practices. The authors tested different combinations of patient-level risk adjusters (including various sociodemographic, clinical and self-reported health status measures) with three regression-based approaches for modeling performance (ratio of observed-to-expected, fixed effects and random effects, or HGLM). The authors then used two methods to compare rankings across the various model specifications: 1) Spearman rank tests to examine the correlation of an organization's absolute rankings across the various regression models, and 2) weighted kappa statistics to estimate "agreement" in an organization's quintile ranking across the various regression models. The results indicated that choice of patient-level risk adjusters was more influential changing in performance classification than choice of methodological approach.

Whether to also adjust health care performance for organization-level socioeconomic characteristics has been debated in research and policy circles. Including these organization-level characteristics may adjust away differences related to the quality of the organization but can help reduce confounding between organization case mix and outcomes.[13,16] Opponents of including organization-level socioeconomic risk-adjusters argue that the models could indirectly justify worse-quality care for certain socioeconomic groups.[16] Therefore, it is important for researchers, policymakers and payers to examine the choice of both model covariates and analytical approach in health care performance profiling.

Using the same three regression-based methods as Huang et al. – the ratio of observed-to-expected, fixed effects and HGLM – Ding and colleagues[6] used simulated data to compare the predictive accuracy of the three regression approaches to identify providers exceeding a performance threshold. They varied values for patient volume, size of practice, patient case-mix and between-provider variability and calculated the sensitivity, specificity and root mean squared error of the different statistical approaches. Overall, they found the HGLM approach slightly outperformed the other methods, but the accuracy of the classification methods depended largely on between-provider variability in performance. Thus, the choice of the "optimal" analytical approach can also depend on variation in key variables in the model.

Austin, Alter and Tu[5] used Monte Carlo simulations to test whether fixed effect or random effect (HGLM) regression models were more accurate in identifying outlier hospitals for risk-adjusted mortality rates. They estimated sensitivity, specificity and positive predictive value to assess the accuracy of the two classification measures. The authors found that the HGLMs had greater specificity (ability to identify true negatives) and positive predictive value relative to the fixed effect models when they assumed a normal distribution for the outcome. Fixed effect models, however, exhibited higher sensitivity (ability to identify true positives) than HGLMs. They attribute the low sensitivity of HGLMs to the shrinkage estimator that pulls estimates for smaller organizations toward the mean. A study of New York hospital performance by Racz and Sedransk[4] corroborates the finding that random effects models are more conservative and identify fewer outliers, especially among low-volume organizations.

Decisions around which ranking methodology to utilize may depend on variation in key variables in the analysis model,[6] the underlying purpose for the performance ranking, and the risk associated with mis-identifying health care organizations as either high-performing or low-performing organizations.[5,14]

Given the limitations associated with HGLMs and fixed effect models and the risk associated with mis-classifying organization performance, we did not want to use a single performance classification methodology. Additionally, we were concerned about variation in results stemming differences in covariate selection. For these reasons, we generated an overall performance ranking that would incorporate the results from different performance classification methodologies and risk adjusters. This analysis did not seek to conduct hypothesis tests on the results or to identify statistical outliers in performance. Rather, we aimed to rank organizations relative to one another. For this reason, we did not report uncertainty estimates for the respective methods. Even so, this approach may be useful to policymakers, researchers and payers interested in identifying best practices in top-ranked organizations and pitfalls in the lowest-ranked organizations. Moreover, an overall performance ranking may engender greater confidence in the results of individual performance classification methods.

Methods

This cross-sectional study applied three different methodologies to rank North Carolina FQHCs according to preventable hospital utilization rates for Medicaid-insured children with asthma. Preventable hospital utilization, including emergency department (ED) visits, observation stays and inpatient stays, is a useful measure of organization performance because it represents the downstream effect of primary care management of chronic conditions in the health care system.[17–20]

Our analysis focused on children with asthma because asthma represents the most commonly diagnosed chronic condition among children.[21] Moreover, asthma is amenable to primary care intervention: it is one of two pediatric chronic conditions[3] considered ambulatory care-sensitive,[22] and chronic conditions are better reflections of ongoing care management and systems of care than are acute conditions. Asthma is also a leading cause of preventable hospital utilization in a pediatric population, the cost of which has been estimated to exceed $270 billion in the Medicaid program nationwide.[23]

Furthermore, asthma prevalence and hospital utilization rates are higher among racial/ethnic minority and low-income children.[24] Because FQHCs predominately serve low-income, racial/ethnic minority, uninsured and underinsured communities,[25] FQHCs are an ideal setting in which to study quality of asthma care management.

Federally-funded FQHCs receive grant dollars to help offset the cost of caring for uninsured patients and, in exchange, agree to comply with a series of program requirements. For example, FQHCs must serve all patients regardless of ability to pay and provide access to

[3] Short-term complications from diabetes represents the second ambulatory care-sensitive pediatric chronic condition, but hospital utilization rates for this condition are very low.[47]

comprehensive primary care, including medical, dental, behavioral health, pharmacy and non-clinical support services, also known as enabling services (e.g., interpretation, transportation and outreach). Identifying primary care practices associated with a reduction in pediatric asthma morbidity can help lower health care spending and improve child health.

Analytic Approach

We estimated five models across three different statistical methods to assess differences in FQHC performance rankings. The three methods included: 1) the crude utilization rate (observed utilization/eligible population), 2) HGLMs, and 3) generalized linear models (GLMs) with FQHC fixed effects. FQHC performance was determined using the ratio of observed utilization/eligibility population in the crude model, the predicted rate of utilization/expected rate of utilization in HGLMs, and the estimated individual FQHC fixed effects in the GLMs. The purpose of estimating the five models using three different methodologies outlined in Table 1 was to assess the robustness of FQHC rankings across statistical methods and risk adjusters and to generate an overall performance ranking that incorporated the results of the various approaches.

Method 1: Crude rate. Although this unadjusted method is not commonly used for performance profiling in research or practice, we included it as a basis for comparison for the adjusted methods. The following formula was used to calculate the crude or unadjusted FQHC-specific utilization rate:

$$\frac{Total\ number\ of\ hospital\ visits\ (ED, observation\ or\ inpatient)\ with\ a\ principal\ diagnosis\ of\ asthma}{Total\ number\ of\ Medicaid-enrolled\ children\ with\ asthma}$$

The numerator and denominator were limited to the patients attributed to each FQHC organization.

Method 2: Hierarchical generalized linear models. We ran HGLMs using mixed-effects logistic regression with an unstructured covariance structure for the FQHC random effects to allow for distinct variances and covariances. Models utilizing an exchangeable covariance structure generated nearly identical estimates to the unstructured covariance models.

The hierarchical (multi-level) model with FQHC random effects estimated patient-level hospital utilization according to the following equation:

$$Pr\ (Y_{ipt} = 1) \ = \alpha + \beta_1 X_i + \beta_2 Uninsured_p + \beta_3 Year_t + \beta_4 FQHC_p + \ \varepsilon_{ip}$$

where Y_{ipt} represented patient-level ED, observation stay or inpatient utilization with a principal diagnosis of asthma. X_i represented a variety of patient-level characteristics associated with preventable hospital use in previous studies. A second model also incorporated the percent of patients without health insurance at the patient's attributed FQHC, represented by *Uninsured* in the equation above, to account for organization-level differences in case mix that could affect performance. *FQHC* represented the FQHC-specific random effect, and likelihood ratio tests confirmed the presence of a FQHC-specific effect—that the random effects were not equal to zero.

Following the HGLM estimation, postestimation commands calculated each patient's predicted and expected hospital utilization rate. The *predicted* hospital utilization rate incorporated patient- and FQHC-specific effects (both the deterministic portion, $X\beta$, and the predicted random effect from the hierarchical model). The *expected* hospital utilization rate for each patient incorporated only the deterministic portion of the model, the patient-level covariates and year fixed effects, and represented the patient-specific utilization rate if the patient were treated in the average FQHC. For the second model including the percent uninsured patients at each FQHC, we replaced the percent uninsured with the mean percent for the analysis sample before generating the expected prediction. These individual estimates were then averaged for each FQHC and combined in order to calculate the predicted/expected rate of preventable hospital utilization. The two equations for calculating predicted and expected utilization are outlined below:

Predicted: $\frac{\sum_{i=1}^{n_p} E\left(Y_{ipt} \mid \beta_4 FQHC_p; \beta_1 X_i, \beta_2 Uninsured_p, \alpha, \varepsilon_{ip}\right)}{n_p}$

Expected: $\frac{\sum_{i=1}^{n_p} E\left(Y_{ipt} \mid \beta_1 X_i, \beta_2 \overline{Uninsured}, \alpha, \varepsilon_{ip}\right)}{n_p}$

where Y_{ipt} represented the patient-level ED visit, observation or inpatient stay with a principal diagnosis of asthma, and β_4 represented the predicted FQHC-specific random effects. X_i represented a variety of patient-level characteristics, and n_p represented the number of patients attributed to a given FQHC, *p*. The ratio of predicted-to-expected utilization illustrated how FQHCs performed given their patient mix and FQHC-specific effect relative to the average FQHC treating the same patient mix. The decision to use the predicted/expected rate to measure FQHCs' performance reflected current practice applied by the Centers for Medicare and Medicaid Services for hospital performance classification.[13]

Method 3: Fixed effect models. Here, we estimated patient-level GLMs with a binomial family and logit link given the distribution of the outcome variable. (Generalized estimating equations did not converge due to small cell sizes of some of the FQHC fixed effect indicators.) The following formula describes the approach used to estimate FQHC-level fixed effects:

$$Pr\ (Y_{ipt} = 1)\ =\ (\alpha + \beta_0 FQHC_p) +\ \beta_1 X_i + \beta_2 Uninsured_p +\ Year_t + \varepsilon_{ip}$$

where Y_{ipt} represented the patient-level ED visit, observation or inpatient stay, and β_0 represented the FQHC-specific fixed effect. X_i represented a variety of patient-level characteristics. A second model also incorporated the percent of patients without health insurance at the patient's attributed FQHC, represented by *Uninsured* in the equation above, again to account for organization-level differences in case mix that could affect performance.

Using the individual FQHC fixed effect estimates from the Method 3 regression model, FQHCs were ranked relative to the referent FQHC (fixed effect estimate = 0), which was chosen to be the FQHC with the largest patient population (Organization 1). Nine FQHCs had negative and statistically significant fixed effect estimates ($p<.05$), representing lower hospital utilization among their attributed patients compared to the referent FQHC.

Identifying high- and low-performers. Organizations were ranked relative to the performance measure for each statistical methodology—observed/eligible for the crude rate, predicted/expected for the HGLMs, and individual fixed effect estimates for the FQHC fixed effect models. Assigning a ranking based on model outputs standardized units across the three ranking methodologies to allow for cross-model comparisons. Z-scores represent another method for standardizing units across models,[11] but we elected not to utilize z-scores because we were not interested in the relative difference in rankings, the primary advantage of using z-scores over rankings.

We utilized the 25th and 75th percentile of the various model outputs to identify the highest and lowest performing FQHCs for each of the five models. Top-performing FQHCs had the lowest rates of preventable hospital utilization (<25th percentile), while the lowest performing FQHCs had the highest rates of preventable hospital utilization (>75th percentile).

The geometric mean, because it is indifferent to the various methods used to generate the rankings, was used to assign an overall performance ranking for each FQHC based on the rankings from the four risk-adjusted models. We excluded crude rate rankings from the geometric mean calculation since these rankings represented unadjusted rates, and substantial variation in patient mix across FQHCs likely influenced hospital utilization rates.

We examined alternative approaches for calculating an overall performance ranking, including an all-or-nothing approach[11,26] where organizations had to be in the top/bottom quartile across all four risk-adjusted methods in order to be considered an overall top-/bottom-performer. However, the all-or-nothing approach could discount specific ranking methodologies if, for example, the organization was a high performer in all but the HGLMs. Even so, the all-or-nothing approach could provide a more conservative definition of top-/bottom-performing organizations.

We also generated an overall ranking based on the sum of quintile ranks[27] but found this approach resulted in a loss of information relative to the organizations' absolute ranking, particularly if organizations were at the high/low end of a quintile. For example, organizations could have the same sum of quintile ranks but very different rankings across the methods. For these reasons, we felt the geometric mean of the four risk-adjusted rankings represented the best approach given that it incorporated all data points but was not as susceptible to outlier rankings across methodologies as could occur with the arithmetic mean.

Data Source and Inclusion Criteria

Data included North Carolina Medicaid claims from January 1, 2013 through September 30, 2015 merged with 2013-2015 data from the Uniform Data System, an FQHC-specific dataset that is updated annually and includes data on FQHC patient characteristics, staffing and utilization, clinical indicators, and financial measures. UDS data are reported at the organization level and not the individual clinic site- or individual patient-level. Medicaid claims dated after September 30, 2015 were excluded from the analysis due to the transition to ICD-10 coding and unresolved questions regarding the reliability and validity of coding after the transition.[28]

The analysis sample included continuously enrolled pediatric asthma patients aged 2-17 years (inclusive) who utilized FQHCs for the plurality of their primary care services. Children with asthma were identified using International Classification of Diseases, 9th Revision, Clinical Modification (ICD-9) codes 493.0-493.92. Replicating Domino and colleagues' approach, we applied a broad definition of asthma in order to maintain variation in the outcome variables.[29]

Qualifying children were included in the analysis sample beginning the first year (2013-2015) they had a hospital or outpatient clinic claim with an asthma diagnosis. Children remained in the analysis sample regardless of whether they had a visit for asthma in a given analysis year if they demonstrated a pattern of utilization of care for asthma and if they remained an FQHC patient. Roughly 1,400 person-years were excluded because they had only a single visit for asthma across three analysis years (5.21% of the sample). Another approximately 1,000 person-years were excluded for having a single asthma visit in the two analysis years those individuals appeared in the dataset (3.92% of the sample).

Diagnosis exclusions included pregnancy, cystic fibrosis or other respiratory system anomalies consistent with AHRQ's Pediatric Quality Indicator for asthma.[30] After exclusions, the analysis sample included approximately 24,000 patient-years representing roughly 13,300 FQHC Medicaid-insured children aged 2-17 years with a diagnosis of asthma who were eligible for this study. Analyses were run using complete case analysis; only twenty-seven observations were excluded as a result of missing county indicators.

Key Variables and Measures

The outcome of interest was a binary variable, any hospital utilization with a principal diagnosis of asthma. Any hospital utilization encompassed emergency department (ED) visits, observation or inpatient stays. Given the increasing frequency of hospital observation stays, we felt it important to include this type of hospital utilization in our outcome measures.[31–33] Refer to Appendix A for more information on the codes and fields used to identify ED visits and observation and inpatient stays.

To avoid double-counting claims representing a single hospital visit, we prioritized utilization according to how "far" a patient went in the hospital (same hospital or transfer hospital) in decreasing order of severity: inpatient stay, followed by an observation stay, and finally an ED visit. In other words, a visit to the ED counted only if the patient did not also have an observation or inpatient stay during the same visit.

Identifying FQHCs. Organizations were identified as FQHCs in Medicaid claims using the following methods: FQHC taxonomy code, taxonomy qualifier code (provider type and specialty code), place of service code, and billing provider National Provider Identifier (NPI) after an organization name-based search using CMS's National Plan & Provider Enumeration System. To the extent possible given data constraints, this approach mirrored the recommended approach for identifying rural health clinics in claims data.[34] FQHC Look-Alikes, a sub-category of FQHCs, were excluded from the analysis because these organizations are sufficiently different from federally-funded FQHCs.

Attribution to FQHC organization. Patients were attributed to the FQHC organization (billing provider NPI) where they received the plurality of their primary care in a given year. Attributing patients to a specific organization reflects the value of having a regular source of care for patients with chronic conditions;[35,36] the place where patients receive most of their primary care should have the greatest influence on their outcomes.

Attributing patients to organizations based on where they received the plurality of primary care services has been utilized in previous research[19,42] and by the Centers for Medicare & Medicaid Services for Accountable Care Organizations.[39] Current Procedural Terminology codes defined as primary or preventive services in the Affordable Care Act or by the American Academy of Pediatrics were used to identify primary care services. A list of these codes can be found in Appendix A. As with the Centers for Medicare and Medicaid Services' Accountable Care Organization attribution methodology, patients who had the same number of primary care visits to more than one primary care organization were attributed to the most recent organization.[39] Patients without a primary care visit during the calendar year were assigned to the organization from which they received the plurality of primary care services the previous year. After applying other exclusion criteria, no observations were dropped as a result of having no primary care services across two years.

Patient-level covariates. We adjusted for the following patient characteristics in all multivariate analyses: patient age, race/ethnicity, sex, number of months in calendar year enrolled in Medicaid, rural residence (Rural-Urban Commuting Area code >=4), an indicator for whether the patient utilized specialty care for asthma (relevant taxonomy codes included in Appendix A), an interaction between rural residence and specialty provider utilization, total number of primary care visits to any provider, the number of comorbidities identified using the

Agency for Healthcare Research and Quality's Chronic Condition Indicator (CCI)[40], and continuity of care as defined by Breslau and Reeb's Usual Provider of Care measure.[41]

Area-level covariates. Using the patient's modal county of residence – where the patient lived for most of the calendar year – we included several county-level measures: percent of population living below the federal poverty line, median household income (in $10,000) and air quality measured as fine particulate matter concentration (annual PM2.5 level). Poverty and income data were from the U.S. Census Bureau's Small Area Income and Poverty Estimates, and air quality data were from the CDC's National Environmental Public Health Tracking Network. The percent of the population living below the federal poverty line has been found to be a valid proxy for area-level socioeconomic deprivation.[42,43] The county-level air pollution measure adjusted for area-level environmental factors affecting hospital utilization. Maps from the North Carolina Rural Health Research Program suggested area-level variation in ambulatory sensitive hospital admissions for asthma.[44] Hereafter, these covariates are referred to under the larger umbrella of patient-level characteristics. We included quadratic terms for the number of chronic conditions and the percent of the county population living below the federal poverty line because the z-statistics on the quadratic terms indicated improved model fit ($p<.05$).

Organization-level covariates. We explored FQHC rankings with and without adjustment for the percent of patients without health insurance, a reflection of FQHC resources. The Bureau of Primary Health Care, the government agency overseeing the FQHC program, risk-adjusts FQHC quality metrics using the percent of patients without health insurance, as well as the percent of patients who are racial/ethnic minorities, homeless, or migrant/seasonal farmworkers.[45] They also risk-adjust for whether the FQHC utilizes an electronic health record system for reporting via the Uniform Data System versus whether the FQHC conducts manual reviews of 70 patient charts for reporting.[45] We elected not to mirror BPHC's organization-level risk-adjustment because we did not want to adjust for differences in organizational quality as a result of distinct patient groups, and we felt the electronic health record measure might be a mediator of organization quality.

Results

Thirty-five FQHC organizations were ranked according to their patients' preventable hospital utilization. One FQHC was excluded from the analysis because it represented only a single patient. Two organizations had outlier fixed effect estimates given small sample sizes and no hospital utilization among their attributed patients.

Table 3.2 lists the number of pediatric asthma patients attributed to each FQHC and the FQHC-specific unadjusted rate of hospital utilization. The mean unadjusted hospital utilization rate across all FQHCs was 10.2% with a range of 0-25.3%.

Figure 3.1 illustrates the individual FQHC organization rankings by model and methodology. The yellow boxes outline performance rankings within a methodology – HGLMs and FQHC fixed effect models. Organizations marked with an asterisk indicate the overall top-/bottom-performers as defined by the geometric mean.

As depicted in the chart, FQHC rankings within the HGLM estimation method were identical; there were no changes in organization rank across the two HGLMs. Relatedly, the regression coefficient on percent of patients without health insurance was not statistically significant in the HGLM. In contrast, the rankings based on FQHC fixed effects were more sensitive to the adjustment for percent of patients without health insurance. Even so, there were minimal changes among the top- and bottom-performers across the HGLM and FQHC fixed effect methods. FQHCs with smaller patient populations experienced larger fluctuations in ranking position across the FQHC fixed effect and HGLM methods (e.g., Organizations 33 and 35).

Table 3.3 identifies the highest- and lowest-performing FQHCs according to the ranking model and method. Green-highlighted cells indicate the top-performing 25% of FQHCs, while the red-highlighted cells indicate the lowest-performing 25% of FQHCs according to each ranking methodology specification. Of the 18 organizations in the top and bottom quartile based on the crude rate, 14 (80%) of these organizations were also in the top/bottom quartiles for the overall, geometric mean-based rank. Just over half (10 of 18) of the overall top-/bottom-performing organizations were consistently ranked in the top/bottom quartile across all four regression-based models (representing the all-or-nothing performance classification).

Figure 3.2 displays four graphs of ranking agreement relative to the overall, geometric mean-based performance ranking. In order, these graphs represent: (1) ranking agreement within the HGLMs, (2) within the FQHC fixed effect models, (3) within the models that adjusted for patient characteristics only, and (4) within the models that adjusted for the concentration of uninsured patients in a FQHC. Ranking agreement was highest for the two HGLMs relative to the other methods, but there appears to be potential misclassification of organizations; some organizations classified as overall top-performers were actually more middle-of-the-pack in the HGLM models. In the two FQHC fixed effect models, ranking agreement was most consistent among the overall top-performing organizations. The HGLM and FQHC fixed effects model with only patient-level adjusters also demonstrated reasonable agreement, though the rankings were more dispersed among the overall top-performing organizations. Rankings between the HGLM and FQHC fixed effect model that included an organization-level adjustment for the concertation of uninsured patients were the most inconsistent across models.

Discussion

The goal of this study was to generate relative performance rankings for North Carolina FQHCs according to preventable hospital utilization rates for asthma. However, no “gold standard” in performance classification exists; the choice of performance classification methodology can depend on the type of organization or outcome being profiled (i.e., whether low volumes have the potential to skew results) and the goal of the performance classification (i.e., whether the intent is to estimate individual performance, generate relative rankings among organizations or estimate the distribution of performance across organizations).[14] We incorporated rankings across three statistical methods and five model specifications to generate a more robust performance classification. A similar approach may be useful for payers, policymakers and researchers who are interested in ranking organizations according to performance but who are concerned about the limitations associated with the HGLM and fixed effect models.

Comparisons of ranking agreement across the various methods with the overall geometric mean corroborated the results of previous studies:[4,5] HGLMs were more conservative[5] and classified some overall top-performing organizations as falling in the middle 50%. The FQHC fixed effect models exhibited stronger ranking agreement among the top-ranked organizations. Relative to the model specification with only patient-level risk adjusters, the inclusion of FQHCs' percentage of patients without insurance did not change rankings in the HGLM but did affect rankings in the FQHC fixed effect model.

While variation in FQHC rankings existed across models, the top- and bottom-performing organizations were largely consistent across each of the five models tested. In fact, over half of the overall top-/bottom-performing organizations were ranked in the top/bottom quartile across all four regression-based models. We utilized the geometric mean to identify overall top-/bottom-performers because it is indifferent to the various methods used to generate the rankings. We examined other approaches for classifying overall performance based on various models – an all-or-nothing approach and the sum of quintile ranks – but preferred the geometric mean for two reasons: 1) it allowed for consideration of all data points in assigning an overall rank, and 2) it was not overly sensitive to outlier rankings across methods for an organization.

Limitations

There are several limitations to this study. First, preventable hospital use is arguably a crude indicator of health care quality and may be better conceptualized as a “screening tool” to flag potential health care quality issues warranting additional research.[46] Second, six new FQHC organizations were established during the study period, and these new organizations may have had smaller patient populations or higher hospital utilization rates. Claims billed by these organizations in their first year as an FQHC represented roughly 8% of the total analysis sample (n=1,970 patient-years). While the HGLM methodological approach adjusts for the smaller patient population through the empirical Bayes estimator, the FQHC fixed effect estimates for low-volume organizations may be imprecise given limited data on these organizations. Two organizations had outlier fixed effect estimates due to small sample sizes. Both of these organizations were ultimately identified as top-performers based on the geometric mean, but their ranking might have been skewed by the small sample size within each organization. Third, utilizing rankings to standardize performance measures across methodologies disregards the relative difference between rankings in a category.[11] However, this limitation was less important because we aimed to rank organizations relative to one another and identify overall top- and bottom-performing organizations; we were not interested in relative differences in performance. Finally, the study included only nine months of data for analysis year 2015 given the transition to ICD-10 coding; however, analyses adjusted for total months of Medicaid enrollment in a calendar year so the results should not be biased downward.

Conclusion

The purpose of this analysis was to identify the group of top- and bottom-performing FQHC organizations across multiple performance classification methods, so small changes in ranking order across methodologies and models did not affect interpretation of the results. Similar to prior research, this study highlighted the degree to which methodology and choice of risk adjusters can influence an individual organization's performance classification. For this reason, health care organization profiling with research or policy applications should consider the influence of methodology and risk adjusters on performance classification and determine whether results are robust to the methodological approach and model specification. Decisions regarding which methodological approach to apply should weigh both the goal of the performance classification and whether estimates will be skewed by low-volume organizations or outcomes. Establishing an overall ranking using the geometric mean represents one way to incorporate performance classification results across different methods and model specifications. Future research could utilize an overall ranking to identify characteristics associated with top-performing organizations to help disseminate successful models of care to other practices.

Table 3.1. Summary of FQHC Ranking Methodologies

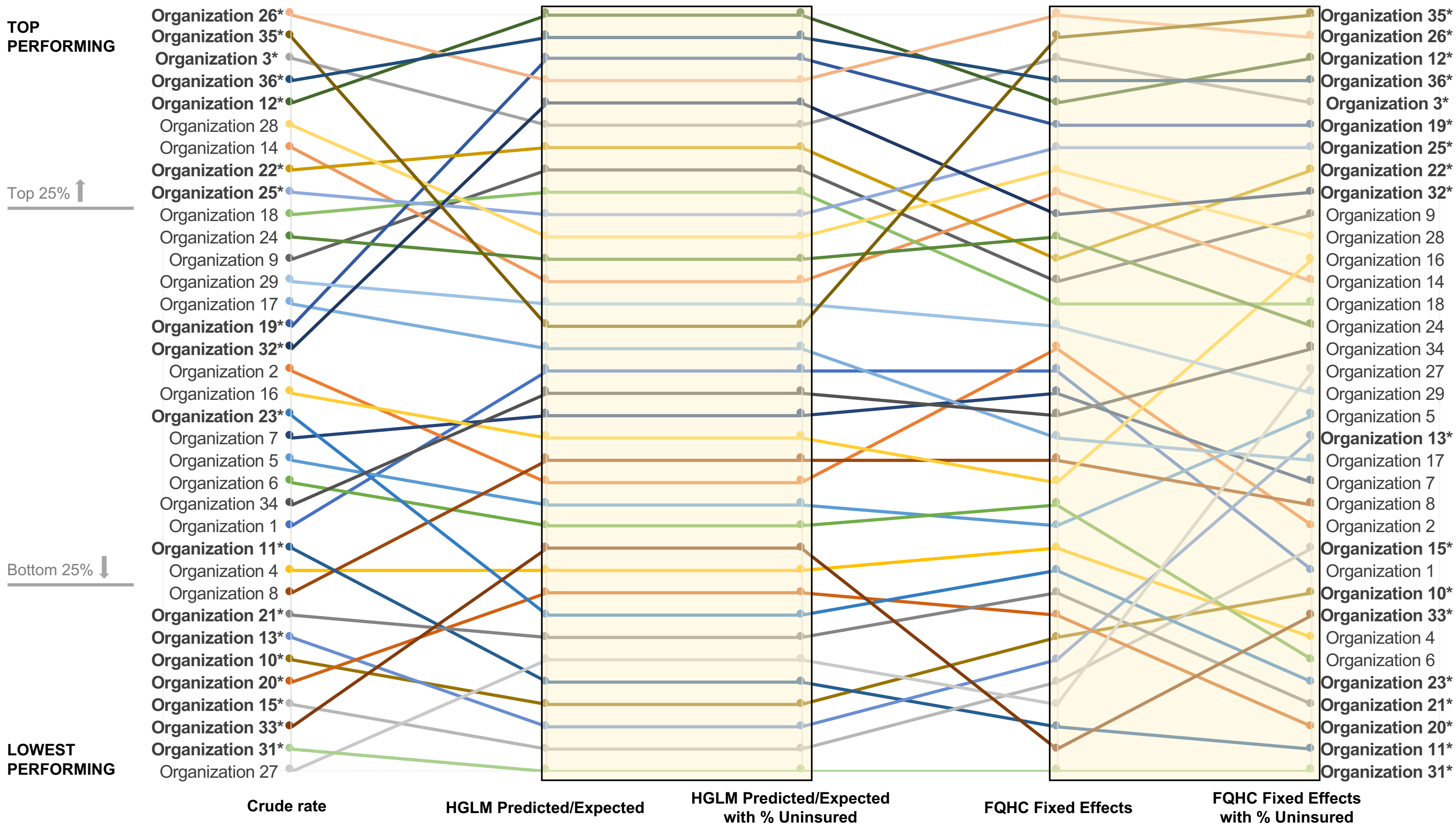
	Model	Adjust for Patient Characteristics?	Adjust for FQHC Characteristics?	Adjust for FQHC Intercepts?	Performance Classification Measure
1	Crude Rate	No	No	No	Observed/Eligible Population
2	HGLM Logit	Yes	No	Yes, random	Predicted/Expected
3	HGLM Logit	Yes	Yes	Yes, random	Predicted/Expected
4	GLM Logit with FQHC Fixed Effects	Yes	No	Yes, fixed	FQHC-specific FE
5	GLM Logit with FQHC Fixed Effects	Yes	Yes	Yes, fixed	FQHC-specific FE

Table 3.2. Hospital Utilization by FQHC Organization, 2013-2015

FQHC ID	Total # of attributed patients with asthma	Mean rate of hospital utilization with a principal diagnosis of asthma
Organization 1	5,202	11.5%
Organization 2	88	9.1%
Organization 3*	38	2.6%
Organization 4	90	13.3%
Organization 5	75	10.7%
Organization 6	222	10.8%
Organization 7	1,054	10.2%
Organization 8	1,892	14.2%
Organization 9	2,835	8.0%
Organization 10*	269	15.6%
Organization 11*	43	11.6%
Organization 12*	1,617	3.5%
Organization 13*	302	15.2%
Organization 14	142	4.9%
Organization 15*	367	16.9%
Organization 16	118	9.3%
Organization 17	1,715	9.0%
Organization 18	1,296	6.6%
Organization 19*	310	9.0%
Organization 20*	49	16.3%
Organization 21*	245	14.7%
Organization 22*	435	5.7%
Organization 23*	258	10.1%
Organization 24	88	6.8%
Organization 25*	100	6.0%
Organization 26*	42	0.0%
Organization 27	198	25.3%
Organization 28	114	4.4%
Organization 29	1,799	8.4%
Organization 31*	101	22.8%
Organization 32*	1,860	9.0%
Organization 33*	10	20.0%
Organization 34	27	11.1%
Organization 35*	6	0.0%
Organization 36*	849	2.7%

[1]Organizations marked with an asterisk indicate an overall top-/bottom-performing organization based on the geometric mean. FQHCs ranked 1-9 were considered in the top quartile, and those ranked 27-35 were listed in the bottom quartile.

Figure 3.1. Variation in FQHC Ranking by Method and Model[1]



[1]Organizations marked with an asterisk indicate an overall top-/bottom-performing organization based on the geometric mean. FQHCs ranked 1-9 were considered in the top quartile, and those ranked 27-35 were listed in the bottom quartile.

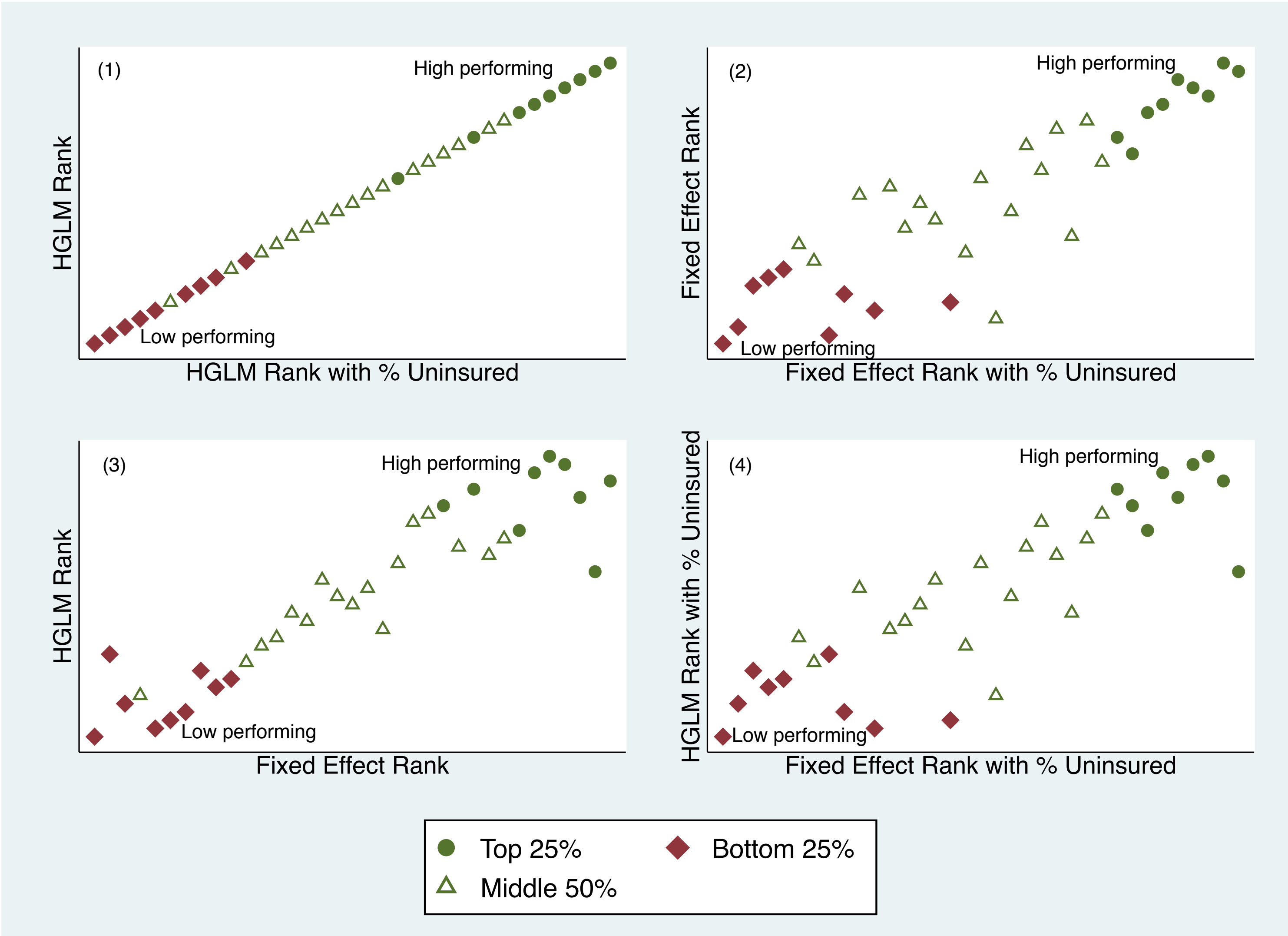
Table 3.3. FQHC Rankings (1-35, Best to Worst) for Preventable Hospital Utilization Rates according to Five Models[1]

FQHC ID[2]	Model 1: Crude rate	Model 2: HGLM Predicted/Expected	Model 3: HGLM Predicted/Expected with % uninsured	Model 4: FQHC Fixed Effects	Model 5: FQHC Fixed Effects with % uninsured	Geometric mean
Organization 1	24	17	17	17	26	19
Organization 2	17	22	22	16	24	21
Organization 3*	3	6	6	3	5	6
Organization 4	26	26	26	25	29	25
Organization 5	21	23	23	24	19	23
Organization 6	22	24	24	23	30	24
Organization 7	20	19	19	18	22	18
Organization 8	27	21	21	21	23	22
Organization 9	12	8	8	13	10	10
Organization 10*	30	32	32	29	27	32
Organization 11*	25	31	31	33	34	34
Organization 12*	5	1	1	5	3	1
Organization 13*	29	33	33	30	20	30
Organization 14	7	13	13	9	13	13
Organization 15*	32	34	34	31	25	33
Organization 16	18	20	20	22	12	20
Organization 17	14	16	16	20	21	16
Organization 18	10	9	9	14	14	12
Organization 19*	15	3	3	6	6	4
Organization 20*	31	27	27	28	33	29
Organization 21*	28	29	29	27	32	31
Organization 22*	8	7	7	12	8	8
Organization 23*	19	28	28	26	31	27
Organization 24	11	12	12	11	15	15

Organization 25*	9	10	10	7	7	9
Organization 26*	1	4	4	1	2	2
Organization 27	35	30	30	32	17	26
Organization 28	6	11	11	8	11	11
Organization 29	13	14	14	15	18	14
Organization 31*	34	35	35	35	35	35
Organization 32*	16	5	5	10	9	7
Organization 33*	33	25	25	34	28	28
Organization 34	23	18	18	19	16	17
Organization 35*	2	15	15	2	1	5
Organization 36*	4	2	2	4	4	3

[1]Green cells indicate the top-performing 25% of FQHCs, and red cells indicate bottom-performing 25% of FQHCs within a methodology.
[2]Organizations marked with an asterisk indicate a top-/bottom-performing organization based on the geometric mean. FQHCs ranked 1-9 were considered in the top quartile, and those ranked 27-35 were listed in the bottom quartile.

Figure 3.2. Ranking Agreement across Four Regression-Based Methods Relative to Overall Performance Ranking



Each graphic represents the ranking agreement across the two methods relative to the overall, geometric mean-based performance ranking. Blue circles indicate organizations in the top quartile based on the geometric mean; red diamonds indicate organizations in the bottom quartile based on the geometric mean; and green triangles represent the middle-performing organizations based on the geometric mean.

REFERENCES

1. Gurewich D, Capitman J, Sirkin J, Traje D. Achieving excellence in community health centers: implications for health reform. *J Health Care Poor Underserved*. 2012;23(1):446-459. doi:10.1353/hpu.2012.0008.

2. Wright DB. Consumer governance and the provision of enabling services that facilitate access to care at community health centers. *Med Care*. 2012;50(8):668-675. doi:10.1097/MLR.0b013e3182551763.

3. Wells R, Punekar RS, Vasey J. Why do some health centers provide more enabling services than others? *J Health Care Poor Underserved*. 2009;20(2):507-523. doi:10.1353/hpu.0.0151.

4. Racz MJ, Sedransk J. Bayesian and Frequentist Methods for Provider Profiling Using Risk-Adjusted Assessments of Medical Outcomes. *J Am Stat Assoc*. 2010;105(489):48-58. doi:10.1198/jasa.2010.ap07175.

5. Austin PC, Alter DA, Tu J V. The Use of Fixed-and Random-Effects Models for Classifying Hospitals as Mortality Outliers: A Monte Carlo Assessment. *Med Decis Mak*. 2003;23(6):526-539. doi:10.1177/0272989X03258443.

6. Ding VY, Hubbard RA, Rutter CM, Simon GE. Assessing the accuracy of profiling methods for identifying top providers: performance of mental health care providers. *Heal Serv Outcomes Res Methodol*. 2013;13(1):1-17. doi:10.1007/s10742-012-0099-5.

7. Normand S-LT, Glickman ME, Gatsonis CA. Statistical Methods for Profiling Providers of Medical Care: Issues and Applications. *J Am Stat Assoc*. 1997;92(439):803. doi:10.2307/2965545.

8. Krumholz HM, Wang Y, Mattera JA, et al. An Administrative Claims Model Suitable for Profiling Hospital Performance Based on 30-Day Mortality Rates Among Patients With Heart Failure. *Circulation*. 2006;113(13):1693-1701. http://circ.ahajournals.org/content/113/13/1693.short. Accessed April 21, 2017.

9. Bradley EH, Herrin J, Elbel B, et al. Hospital Quality for Acute Myocardial Infarction. *JAMA*. 2006;296(1):72. doi:10.1001/jama.296.1.72.

10. Bardach NS, Vittinghoff E, Asteria-Peñaloza R, et al. Measuring Hospital Quality Using Pediatric Readmission and Revisit Rates. *Pediatrics*. 2013;132(3):429-436. http://pediatrics.aappublications.org/content/early/2013/08/20/peds.2012-3527. Accessed April 28, 2017.

11. Shwartz M, Restuccia JD, Rosen AK. Composite Measures of Health Care Provider Performance: A Description of Approaches. *Milbank Q*. 2015;93(4):788-825. doi:10.1111/1468-0009.12165.

12. Mukamel DB, Glance LG, Dick AW, Osler TM. Measuring quality for public reporting of health provider quality: making it meaningful to patients. *Am J Public Health*. 2010;100(2):264-269. doi:10.2105/AJPH.2008.153759.

13. Ash AS, Fienberg SE, Louis TA, Normand S-LT, Stukel TA, Utts J. *Statistical Issues in Assessing Hospital Performance*.; 2012. https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/HospitalQualityInits/Downloads/Statistical-Issues-in-Assessing-Hospital-Performance.pdf. Accessed August 3, 2017.

14. Hubbard RA, Benjamin-Johnson R, Onega T, Smith-Bindman R, Zhu W, Fenton JJ. Classification accuracy of claims-based methods for identifying providers failing to meet performance targets. *Stat Med*. 2015;34(1):93-105. doi:10.1002/sim.6318.

15. Huang I-C, Dominici F, Frangakis C, Diette GB, Damberg CL, Wu AW. Is Risk-Adjustor Selection More Important Than Statistical Approach for Provider Profiling? Asthma as an Example. *Med Decis Mak*. 2005;25(1):20-34. doi:10.1177/0272989X04273138.

16. Gu Q, Koenig L, Faerberg J, Steinberg CR, Vaz C, Wheatley MP. The Medicare Hospital Readmissions Reduction Program: Potential unintended consequences for hospitals serving vulnerable populations. *Health Serv Res*. 2014;49(3):818-837. doi:10.1111/1475-6773.12150.

17. Starfield B, Shi L, Macinko J. Contribution of Primary Care to Health Systems and Health. *Milbank Q*. 2005;83(3):457-502. doi:10.1111/j.1468-0009.2005.00409.x.

18. Friedman B, Basu J. Health insurance, primary care, and preventable hospitalization of children in a large state. *Am J Manag Care*. 2001;7(5):473-481. http://www.ncbi.nlm.nih.gov/pubmed/11388127. Accessed August 24, 2017.

19. Basu J, Friedman B, Burstin H. Primary care, HMO enrollment, and hospitalization for ambulatory care sensitive conditions: a new approach. *Med Care*. 2002;40(12):1260-1269. doi:10.1097/01.MLR.0000036409.56436.ED.

20. Whittaker W, Anselmi L, Kristensen SR, et al. Associations between Extending Access to Primary Care and Emergency Department Visits: A Difference-In-Differences Analysis. *PLoS Med*. 2016;13(9):e1002113. doi:10.1371/journal.pmed.1002113.

21. Pardue Jones B, Fleming GM, Otillio JK, Asokan I, Arnold DH. Pediatric acute asthma exacerbations: Evaluation and management from emergency department to intensive care unit. *J Asthma*. 2016;53(6):607-617. doi:10.3109/02770903.2015.1067323.

22. Agency for Healthcare Research and Quality. Pediatric Quality Indicators Technical Specifications - Version 6.0. https://www.qualityindicators.ahrq.gov/Modules/PDI_TechSpec_ICD09_v60.aspx. Published 2017. Accessed October 3, 2017.

23. Pearson WS, Goates SA, Harrykissoon SD, Miller SA. State-Based Medicaid Costs for Pediatric Asthma Emergency Department Visits. *Prev Chronic Dis*. 2014;11:140139. doi:10.5888/pcd11.140139.

24. Centers for Disease Control. Asthma - Data, Statistics and Surveillance. http://www.cdc.gov/asthma/asthmadata.htm. Published 2016. Accessed October 13, 2016.

25. Bureau of Primary Health Care. 2016 Health Center Data - National Program Grantee Data. Uniform Data System. https://bphc.hrsa.gov/uds/datacenter.aspx. Published 2017. Accessed October 4, 2017.

26. Nolan T, Berwick DM. All-or-None Measurement Raises the Bar on Performance. *JAMA*. 2006;295(10):1168. doi:10.1001/jama.295.10.1168.

27. Shwartz M, Cohen AB, Restuccia JD, et al. How Well Can We Identify the High-Performing Hospital? *Med Care Res Rev*. 2011;68(3):290-310. doi:10.1177/1077558710386115.

28. Elixhauser A, Heslin K, PL O. *Healthcare Cost and Utilization Project (HCUP) Recommendations for Reporting Trends Using ICD-9-CM and ICD-10-CM/PCS Data*.; 2017. www.hcup - us.ahrq.gov/datainnovations/icd10_resources.jsp.

29. Domino ME, Humble C, Lawrence WW, Wegner S. Enhancing the Medical Homes Model for Children With Asthma. *Med Care*. 2009;47(11):1113-1120. doi:10.1097/MLR.0b013e3181adcc65.

30. Barrett ML, Wier LM, Washington R. *Trends in Pediatric and Adult Hospital Stays for Asthma, 2000–2010. HCUP Statistical Brief #169*. Rockville, MD; 2014. http://www.hcup-us.ahrq.gov/reports/statbriefs/sb169-Asthma-Trends-Hospital-Stays.pdf. Accessed November 23, 2016.

31. Macy ML, Hall M, Shah SS, et al. Pediatric observation status: Are we overlooking a growing population in children's hospitals? *J Hosp Med*. 2012;7(7):530-536. doi:10.1002/jhm.1923.

32. Conners GP, Melzer SM, Committee on Hospital Care COH, et al. Pediatric observation units. *Pediatrics*. 2012;130(1):172-179. doi:10.1542/peds.2012-1358.

33. Sabbatini AK, Wright B. Excluding Observation Stays from Readmission Rates — What Quality Measures Are Missing. *N Engl J Med*. 2018;378(22):2062-2065. doi:10.1056/NEJMp1800732.

34. Domino M, Tyree S, Rutledge R, Holmes M. *Findings Brief: Identifying Rural Health Clinics in Medicaid Data*.; 2016. https://www.ruralhealthresearch.org/publications/1036.

35. Raphael JL, Cooley WC, Vega A, et al. Outcomes for Children with Chronic Conditions Associated with Parent- and Provider-reported Measures of the Medical Home. *J Health Care Poor Underserved*. 2015;26(2):358-376. doi:10.1353/hpu.2015.0051.

36. Spatz ES, Ross JS, Desai MM, Canavan ME, Krumholz HM. Beyond insurance coverage: Usual source of care in the treatment of hypertension and hypercholesterolemia. Data from the 2003-2006 National Health and Nutrition Examination Survey. *Am Heart J*. 2010;160(1):115-121. doi:10.1016/j.ahj.2010.04.013.

37. Gurewich D, Tyo KR, Zhu J, Shepard DS. Comparative Performance of Community Health Centers and Other Usual Sources of Primary Care. *J Ambul Care Manage*. 2011;34(4):380-390. doi:10.1097/JAC.0b013e31822cbc59.

38. Falik M, Needleman J, Wells BL, Korb J. Ambulatory care sensitive hospitalizations and emergency visits: experiences of Medicaid patients using federally qualified health centers. *Med Care*. 2001;39(6):551-561. http://www.ncbi.nlm.nih.gov/pubmed/11404640. Accessed August 24, 2016.

39. *Medicare Shared Savings Program: Shared Savings and Losses and Assignment Methodology Specifications*. Baltimore; 2015. https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/sharedsavingsprogram/Downloads/Shared-Savings-Losses-Assignment-Spec-V4.pdf. Accessed April 18, 2017.

40. Agency for Healthcare Research and Quality. HCUP Chronic Condition Indicator. Healthcare Cost and Utilization Project (HCUP). https://www.hcup-us.ahrq.gov/toolssoftware/chronic/chronic.jsp. Accessed April 21, 2017.

41. Breslau N, Reeb KG. Continuity of care in a university-based practice. *J Med Educ*. 1975;50(10):965-969. http://www.ncbi.nlm.nih.gov/pubmed/1159765. Accessed April 22, 2017.

42. Krieger N, Chen JT, Waterman PD, Soobader M-J, Subramanian S V, Carson R. Choosing area based socioeconomic measures to monitor social inequalities in low birth weight and childhood lead poisoning: The Public Health Disparities Geocoding Project (US). *J Epidemiol Community Health*. 2003;57(3):186-199. doi:10.1136/jech.57.3.186.

43. Diez-Roux A V, Kiefe CI, Jacobs DR, et al. Area characteristics and individual-level socioeconomic position indicators in three population-based epidemiologic studies. *Ann Epidemiol*. 2001;11(6):395-405. http://www.ncbi.nlm.nih.gov/pubmed/11454499. Accessed September 15, 2017.

44. *Ambulatory Care Sensitive Condition Hospital Admissions (2004) for Asthma*. http://www.shepscenter.unc.edu/rural/maps/ACS2004_18underNC.pdf.

45. Health Resources and Services Administration. Uniform Data System (UDS) Health Center Adjusted Quartile Ranking. https://bphc.hrsa.gov/datareporting/reporting/ranking.html. Accessed April 21, 2017.

46. Agency for Healthcare Research and Quality. Prevention Quality Indicators Overview. AHRQ Quality Indicators. https://www.qualityindicators.ahrq.gov/modules/pqi_overview.aspx. Accessed April 7, 2019.

47. Fingar K, Washington R. *Potentially Preventable Pediatric Hospital Inpatient Stays for Asthma and Diabetes, 2003–2012. HCUP Statistical Brief #192.* Rockville, MD; 2015. https://www.hcup-us.ahrq.gov/reports/statbriefs/sb192-Pediatric-Preventable-Hospitalizations-Asthma-Diabetes.pdf. Accessed December 1, 2016.

CHAPTER FOUR: ORGANIZATIONAL CHARACTERISTICS ASSOCIATED WITH PREVENTABLE HOSPITAL UTILIZATION AMONG FEDERALLY QUALIFIED HEALTH CENTERS

<u>Overview</u>

Objective. To examine federally qualified health center (FQHC) characteristics associated with preventable hospital utilization.

Data sources/study setting. North Carolina (NC) Medicaid claims data from 01/01/2013-09/30/2015 for patients attributed to FQHCs merged with 2013-2015 Uniform Data System (UDS) data, an FQHC-specific dataset that includes patient characteristics, clinical quality indicators, and staffing, utilization and financial measures.

Study design. This cross-sectional study estimated patient-level generalized linear models (GLMs) with FQHC fixed effects. Coincidence analysis (CNA) – a cross-case comparative analysis – used organization-level, three-year averages of preventable hospital utilization and organizational characteristics to identify complex combinations of characteristics associated with high performance.

Data collection/extraction methods. NC Medicaid claims data were merged with 2013-2015 UDS data on billing provider (organization) National Provider Identifier.

Principal findings. Patient-level regression models indicated that a broader scope of services and more behavioral health, pharmacy and outreach staff were associated with a higher likelihood of preventable hospital utilization with any diagnosis of asthma even after adjusting for patient-level characteristics. Organization-level CNA results indicated that having more clinic sites and low ratios of outreach/patient and community educator and interpretation staff to medical patients was associated with high performance.

Conclusions. Both regression and CNA results found certain non-medical services were associated with higher preventable hospital utilization and lower organization performance. Future studies should include patient-level encounter data from electronic health records to better measure the effect of non-medical services on preventable hospital utilization. Additionally, future studies should incorporate qualitative interviews to better identify organizational structures and processes guiding clinical care and access to non-medical services in FQHCs.

Background

Federally qualified health centers (FQHCs) represent a vital part of the primary care safety net, providing comprehensive primary care services to predominately low-income, uninsured and underinsured individuals living in medically underserved areas.[1] FQHCs are public or private non-profit primary care organizations that meet certain criteria under the Medicare and Medicaid programs and receive federal grant funding through the Health Center Program as administered by the Bureau of Primary Health Care.

The first FQHCs were established during the 1960s as part of the Johnson Administration's War on Poverty.[2] The FQHC model of care was based on community-oriented primary care where community members accessed and shaped the services provided by the FQHC.[2] As a result, the first FQHCs provided access to primary medical services, but they also developed programs and services meant to address the poverty, unemployment, malnutrition, and environmental health issues in the communities where they were located. This model of community-oriented primary care still guides how FQHCs deliver services today.

In fact, there are several unique elements to FQHCs that distinguish their model of care from most other primary care practices. First, according to federal regulations, FQHCs must serve all patients regardless of ability to pay and maintain a patient-majority governing board.[3] Serving all patients regardless of ability to pay ensures access to primary health care for everyone. Maintaining a patient-majority board is intended to ensure that the FQHCs are guided by and responsive to community needs.[2,4] Federal requirements also stipulate that FQHCs provide access to comprehensive primary care services including physical and behavioral health services, as well as dental and pharmacy services. Additionally, FQHCs have to provide enabling services like case management, outreach and transportation meant to address non-medical barriers to good health.[5]

The FQHC model has been found to benefit patients utilizing these clinics. Compared to other primary care settings, FQHCs have reduced racial/ethnic disparities in clinical outcomes,[6] achieved equivalent or better ambulatory care quality measures,[7] reduced preventable hospitalizations and ED visits,[8–10] and lowered annual health expenditures[11–14] despite serving more vulnerable patients.[15] However, little evidence exists elucidating how FQHCs have facilitated these improvements in their patient population. Identifying factors associated with successful FQHC delivery models can provide insight into how to improve the health of vulnerable groups.

Previous studies of FQHC organizational characteristics and organization performance have been inconclusive, finding heterogenous effects of FQHC characteristics across performance outcomes.[6,15] For example, Shi and colleagues[15] modeled FQHC performance as a function of various organization-level characteristics using six clinical quality indicators, each of which reflected primary care management processes. They found that the FQHC organizational characteristics associated with performance varied across the clinical quality measures, indicating a need for additional research. Furthermore, the study's limitations suggest directions for future research: the authors used a single year of data and thus could not account for unobserved, time-invariant FQHC factors influencing performance. Their outcomes focused on clinical process measures, but downstream measures of primary care management could be better reflections of performance. More definitive research findings could promote the replication of successful care models both within the FQHC program and across other providers caring for vulnerable patients.

Organization performance has also been found to vary by patient mix. Cross and colleagues[16] examined private insurance claims to determine how the concentration of high-needs patients (patients with two or more chronic conditions) affected utilization, spending and quality indicators for this patient population. They found lower spending and utilization but worse quality measures for practices with higher concentrations of high-needs patients. However, their study included few organization-level factors that could influence performance for high-needs patients.

Using mixed methods to identify operational practices associated with high-performing FQHCs, Gurewich and colleagues[17] found variation in how services were structured and delivered across FQHCs. They hypothesized that the variation stemmed from FQHCs tailoring services to address patient and community needs. For example, an FQHC's services may reflect both the needs of the patient population but also whether other community resources exist to address those needs. This hypothesis is corroborated by other FQHC-based research.[18,19] Wells and colleagues found that the scope and volume of non-medical services provided in FQHCs varied by organizational characteristics.[18] For example, their analysis indicated that higher percentages of migrant/seasonal farmworker, homeless, or uninsured patients were significantly associated with both broader scope of services and greater volume of enabling services provided in the subsequent year. The authors also found that FQHCs with more managed care contracts and more full-time equivalent (FTE) staff in the previous year provided both a broader scope and larger volume of enabling services in the following year. In another study, Wright found variation in the scope of enabling services provided in FQHCs according to the number of representative consumers – the number of patient representatives who resembled the FQHC's patient population – on the FQHC's governing board executive committee.[19] As these studies suggest, organizational characteristics associated with performance can also vary across contexts. Therefore, methodological approaches are needed that can identify organizational factors or combinations of factors associated with an outcome across an array of contexts.

The purpose of this study was to examine FQHC characteristics associated with preventable hospital utilization. We hypothesized that having a broader scope of services and more non-medical FTEs would be associated with lower preventable hospital utilization. According to structural contingency theory,[20] FQHCs will have responded to their internal context (serving more vulnerable patients) by modifying their services, structures and processes to best meet the needs of their patients. Vulnerable patients are more likely to face social, economic and resource barriers to good health, and providing access to non-medical services and staff is intended to help address or alleviate some of these barriers.[21]

We examined this research question using both regression-based and configurational comparative methods (CCMs), mathematical cross-case comparative methods that use Boolean algebra to systematically identify logical combinations of conditions that contribute to an outcome in a set of data. Applying both regression-based and configurational comparative methods helped improve upon previous studies of FQHC organizational characteristics associated with performance. For instance, our patient-level regression models incorporated multiple years of data and used an outcome reflecting the downstream effect of primary care management, preventable hospital utilization. We also incorporated FQHC fixed effects to account for unobserved, time-invariant FQHC factors associated with the outcome. While previous studies were limited in the number of organization- or patient-level factors included,[15,17] our models estimated a variety of organizational characteristics associated with hospital use after adjusting for patient-level factors. We used an organizational-level CCM to model complex combinations of conditions associated with performance across contexts because previous studies indicated that FQHC services, structures and processes varied by organizational characteristics and organization context.[17,18] In other words, there might be interdependencies between organizational characteristics, organization context and organization performance. Additionally, variation in FQHC organization design suggests that multiple combinations of conditions may contribute to performance independently of one another. CCMs are useful when outcomes may be explained by combinations of specific conditions that occur together, when multiple combinations of conditions produce the same outcome independently of one another, and when the preservation of context through case-based analysis is warranted.

Applying both regression and CCMs helped uncover different mechanisms associated with FQHC performance. This is because regression-based approaches measure the net effect of the variables for the average case. CCMs, on the other hand, represent a case-based analytic method in which observations consist of intact, complex entities (e.g., organizations) that are modeled as a whole.[22] In other words, the regression analysis indicated which FQHC characteristics significantly increased the probability a patient experienced a preventable hospital visit holding other covariates constant, while the configurational comparative analysis uncovered the different combinations of characteristics that high performing organizations had in common across different organizational contexts. Regression analysis focuses on cause-effect pairs and quantifies the impact of the cause on the effect; CCMs take all potential causes of an effect in view and place a Boolean ordering on them, i.e. they determine which causes conjunctively and disjunctively bring about the effect. Moreover, configurational comparative analysis is largely inductive, allowing sometimes unexpected combinations of conditions to emerge.

It is important to note that we estimated patient-level regression models and ran an organization-level configurational comparative analysis for the following reasons: 1) the statistical power generated by a patient-level regression model allowed for inclusion of a variety of patient- and organization-level covariates, and 2) we wanted to make organization-level inferences from the CCM.

This paper is presented in three parts. In part 1, we outline the methods and results for the regression analysis. In part 2, we describe the configurational comparative analysis and results. Because CCMs are relatively new in health services research, we have provided additional background on CCMs in Appendix C. In part 3, we summarize the findings and identify directions for future research.

The analysis sample for both the regression-based and CCMs included North Carolina Medicaid-insured children with asthma. At the time of this analysis, North Carolina had not yet implemented fully capitated Medicaid managed care, which decreased the "noise" present in claims data stemming from variation in managed care plans. For example, managed care plans may have different utilization review and prior authorization restrictions. We focused on pediatric asthma because: there is limited FQHC research in a pediatric population; asthma represents the most commonly diagnosed chronic condition among children[23] and is a leading cause of preventable hospital utilization in a pediatric population;[24] and chronic conditions are better reflections of ongoing care management and systems of care than are acute conditions. Furthermore, asthma morbidity is higher among racial/ethnic minority and low-income children[25] – populations commonly cared for in FQHCs.[1] Therefore, FQHCs represent an ideal setting in which to study quality of asthma care management. Identifying primary care models associated with a reduction in pediatric asthma morbidity can help lower health care spending and improve child health.

Part 1: Regression Analytic Method

Methods

Data Source and Inclusion Criteria

Data included North Carolina Medicaid claims from January 1, 2013 through September 30, 2015 merged with 2013-2015 data from the Uniform Data System (UDS), an FQHC-specific dataset that is updated annually and includes data on FQHC patient characteristics, staffing and utilization, clinical indicators, and financial measures. UDS data are reported at the organization level and not the individual clinic site- or individual patient-level. Medicaid claims dated after September 30, 2015 were excluded from the analysis due to the transition to International Classification of Diseases, 10th Revision, Clinical Modification (ICD-10) coding and unresolved questions regarding the reliability and validity of coding after the transition.[26]

The analysis sample included continuously enrolled pediatric asthma patients aged 2-17 years (inclusive) who utilized FQHCs for the plurality of their primary care services. Children with asthma were identified using International Classification of Diseases, 9th Revision, Clinical Modification (ICD-9) codes 493.0-493.92. Replicating Domino and colleagues' approach, we applied a broad definition of asthma in order to maintain variation in the outcome variables.[27]

Qualifying children were included in the analysis sample beginning the first year (2013-2015) they had a hospital or outpatient clinic claim with an asthma diagnosis. Children remained in the analysis sample regardless of whether they had a visit for asthma in a given analysis year if they demonstrated a pattern of utilization of care for asthma and if they remained an FQHC patient. Roughly 1,400 person-years were excluded because they had a single visit for asthma across three analysis years (5.21% of the sample). Another approximately 1,000 person-years were excluded for having a single asthma visit in the two analysis years those individuals appeared in the dataset (3.92% of the sample).

Diagnosis exclusions included pregnancy, cystic fibrosis or other respiratory system anomalies consistent with the Agency for Healthcare Research and Quality's (AHRQ) Pediatric Quality Indicator for asthma.[28] After exclusions, there were approximately 24,000 patient-years representing FQHC Medicaid-insured children aged 2-17 years with a diagnosis of asthma who were eligible for this study.

Key Variables and Measures

The primary outcome was a binary variable, any hospital utilization with a principal diagnosis of asthma. Any hospital utilization encompassed emergency department (ED) visits, observation or inpatient stays. Refer to Appendix A for more information on the codes and fields used to identify ED visits and observation and inpatient stays.

ED visits represented the majority of hospital utilization, so we modeled a binary indicator for ED visits with a principal diagnosis of asthma as a secondary outcome. Although AHRQ's Pediatric Quality Indicator for asthma is specific to inpatient admissions, previous studies applied the same definition to ED use.[29–31] Secondary model specifications included hospital utilization with any diagnosis of asthma – i.e., if asthma was included in any one of the ten diagnosis claim fields.

To avoid double-counting claims representing a single hospital visit, we prioritized utilization according to how "far" a patient went in the hospital (same hospital or transfer hospital) in decreasing order of severity: inpatient stay, followed by an observation stay, and finally an ED visit. In other words, a visit to the ED counted only if the patient did not also have an observation or inpatient stay during the same visit.

Sensitivity analyses modified the outcome definitions and modeled hospital utilization after a "washout" period. To create a washout period, we excluded patients' hospital utilization if it occurred within 60 days of their first visit to their attributed practice in a given year.

Identifying FQHCs. Organizations were identified as FQHCs in Medicaid claims using the following methods: FQHC taxonomy code, taxonomy qualifier code (provider type and specialty code), place of service code, and billing provider National Provider Identifier (NPI) after an organization name-based search using CMS's National Plan & Provider Enumeration System. To the extent possible given data constraints, this approach mirrored the recommended approach for identifying rural health clinics in claims data.[32] FQHC Look-Alikes, a sub-category of FQHCs, were excluded from the analysis because these organizations are sufficiently different from federally-funded FQHCs.

Attribution to FQHC organization. Patients were attributed to the FQHC organization (billing provider NPI) where they received the plurality of their primary care in a given year.

Attributing patients to a specific organization reflects the value of having a regular source of care for patients with chronic conditions;[33,34] the place where patients receive most of their primary care should have the greatest influence on their outcomes.

Attributing patients to organizations based on where they received the plurality of primary care services has been utilized in previous research[19,42] and by CMS for Accountable Care Organizations.[36] Current Procedural Terminology codes defined as primary or preventive services in the Affordable Care Act or by the American Academy of Pediatrics were used to identify primary care services. A list of these codes can be found in Appendix A. As with CMS's Accountable Care Organization attribution methodology, patients who had the same number of primary care visits to more than one primary care organization in a given year were attributed to the most recent organization.[36] Patients without a primary care visit during the calendar year were assigned to the organization from which they received the plurality of primary care services the previous year. After applying other exclusion criteria, no observations were dropped as a result of having no primary care services in two consecutive years.

FQHC-level covariates: FQHC characteristics were derived from 2012-2015 UDS data and are outlined in Table 4.1. Key variables of interest included FQHC scope of services (a count of the number of non-medical services provided by the FQHC measured by whether the FQHC reported behavioral health, pharmacy and enabling services staff in the UDS), as well as FTEs for behavioral health (mental health and substance abuse), pharmacy, and enabling services. The Akaike Information Criterion indicated better model fit when scope of services was treated as a continuous rather than a discrete variable. Enabling services staff encompassed case managers, patient and community educators, outreach staff, transportation staff, eligibility assistance workers, interpretation and other enabling services staff (primarily care coordinators and referral specialists). Including both the scope of non-medical services and the FTEs for those non-medical services allowed the model to measure the variation in the outcomes as a result of adding an additional service and an additional FTE (a relative increase in capacity) for non-medical services.

Other FQHC organizational characteristics were included in the models because of a documented association with hospital utilization or clinical quality in previous studies, or because they represented actionable characteristics for program improvement. These included: medical staff FTEs, measures of organization size (number of clinic sites and patients), financial resources (operating income, whether the organization represents a “new start”, or newly funded FQHC organization in a given year), FQHC patient characteristics, pediatric clinical quality measures, and health information technology capabilities. Most measures of health information technology capabilities lacked variation across FQHCs, so they were not included in the analysis. For example, nearly every FQHC used an electronic health record (EHR) at all sites during the study period, and nearly every FQHC utilized the EHR for computerized clinical decision support. A variable for patient-centered medical home (PCMH) recognition was only available in 2014 and 2015, so we did not include it in the regression-based analysis.

Patient-level covariates. We adjusted for the following patient characteristics in all multivariate analyses: patient age, race/ethnicity, sex, number of months in calendar year enrolled in Medicaid, rural residence (Rural-Urban Commuting Area code >=4), an indicator for whether the patient utilized specialty care for asthma (relevant taxonomy codes included in Appendix A), an interaction between rural residence and specialty provider utilization, total number of primary care visits to any provider, the number of comorbidities identified using the AHRQ’s Chronic Condition Indicator (CCI)[37], and continuity of care as defined by Breslau and Reeb’s Usual Provider of Care measure.[38]

Sensitivity analyses varied both the measure of patient acuity and the continuity of care definition. Pediatric risk adjustment is complicated by relatively low morbidity and mortality rates, utilization of non-traditional health care sites like school-based health clinics, and different application of diagnoses, drugs and procedures in pediatric populations than adult populations.[39] Therefore, it was important to test for the robustness of results using different patient acuity measures. As an alternative specification for patient acuity, Clinical Classification Software (CCS) diagnosis groups associated with the following asthma comorbidities were included in regression models as individual dummy variables: obesity (CCS 3 - Endocrine; Nutritional; and Metabolic Diseases And Immunity Disorders), mental illness (CCS 5 – Mental Illness), and atopic dermatitis (CCS 12 – Skin and Subcutaneous Tissue Infections).[37,40] Including the CCS category inclusive of allergic reactions (CCS 17 - Symptoms; signs; and ill-defined conditions and factors influencing health status), another co-occurring condition complicating asthma management,[41] created problems with model convergence. An individual's CCS diagnoses were defined on an annual basis.

A modified Wolinsky Continuity[42] measure tested an alternative definition of continuity of care. Using two years of data (current year and prior year), we determined whether patients had at least one primary care visit every six months to their current-year attributed provider to align with the American Academy of Pediatrics' recommendation for visit frequency for children with controlled asthma.[43] The first visit served as the index visit. The models applying this modified Wolinsky Continuity measure also adjusted for number of months enrolled in Medicaid over a two-year period. An additional sensitivity analysis modeled total patient encounters in place of total patients.

Area-level covariates. Using the patient's modal county of residence – where the patient lived for most of the calendar year – we included several county-level measures: percent of population living below the federal poverty line, median household income (in $10,000) and air quality measured as fine particulate matter concentration (annual PM2.5 level). Poverty and income data were from the U.S. Census Bureau's Small Area Income and Poverty Estimates, and air quality data were from the CDC's National Environmental Public Health Tracking Network. The percent of the population living below the federal poverty line has been found to be a valid proxy for area-level socioeconomic deprivation.[44,45] The county-level air pollution measure adjusted for area-level environmental factors affecting hospital utilization. Maps from the North Carolina Rural Health Research Program suggested area-level variation in ambulatory sensitive hospital admissions for asthma.[46] Hereafter, these covariates are referred to under the larger umbrella of patient-level characteristics.

Analytic Approach

We estimated patient-level generalized linear models (GLMs) with a binomial family and logit link given the distribution of the outcome variables. Standard errors were clustered at the individual level to account for correlation across years for the same individual. Models included FQHC and year fixed effects to adjust for time-invariant confounders arising from differences in FQHC organizations and secular time trends. An examination of the quadratic term z-statistics for the number of chronic conditions and county-level median household income indicated improved model fit ($p<.05$). We sequentially tested higher-order terms for other continuous variables, but the z-statistics for these quadratic terms were not significant ($p>.05$). Thus, we removed these terms removed from the final model.

Given the correlation within individuals over time, we prioritized generalized estimating equations (GEE) for the analysis. However, the GEE models did not converge with low-volume FQHCs included. After excluding organizations with fewer than 50 attributed patients, we compared GEE models with unstructured and exchangeable correlation structures to the GLM with clustered standard errors to determine whether the models generated qualitatively similar results. The estimated average marginal effects were comparable across all three models in direction, significance and magnitude with differences at roughly 0.10 of a percentage point.

All regression analyses were conducted using Stata version 13.0. All analyses were conducted using complete case analysis; approximately 44 person-years were dropped as a result.

Results

Sample means for outcomes and model covariates are depicted in Table 4.2. FQHCs offered an average of six non-medical services across their organization clinics. On average, FQHCs staffed approximately four behavioral health (mental health and substance abuse) FTEs and ten pharmacy FTEs. The most common enabling services staff included case manager and eligibility assistance worker FTEs. Transportation FTEs were the least common across FQHCs.

The results of the multivariate analyses are reported in Table 4.3. In the primary models estimating preventable hospital utilization and ED utilization with a principal diagnosis of asthma, neither the scope of services provider nor any of the non-medical services staff had a significant effect on the outcome. Serving more low-income patients (incomes <200% of the federal poverty level) was associated with a small but significant increase in preventable hospital utilization (0.210 percentage points, p<.001) and ED utilization (0.186 percentage points, p<.01). An increase in the percent of eligible children receiving weight assessment and counseling – one of two pediatric quality measures -- was associated with a small but significant decrease in preventable ED utilization with a principal diagnosis of asthma (0.071 percentage points, p<.05).

The models predicting hospital utilization with any diagnosis of asthma included more significant findings for the key variables. For every additional non-medical service offered at the FQHC (a 1-unit increase in scope of services), the probability of any preventable hospital utilization increased by 3.94 percentage points (p<.01) and the probability of a preventable ED visit increased by 4.05 percentage points (p<.01). Similar effects were found for both behavioral health and pharmacy FTEs: an additional FTE significantly increased the probability of both any hospital utilization and ED utilization by roughly two percentage points. Among the enabling services staff, an additional outreach FTE was associated with a two-percentage point increase in any preventable hospital utilization (p<.01) and in preventable ED utilization (p<.01). Interpretation and other enabling services FTEs (e.g., care coordinator and referral staff), on the other hand, were associated with decreases in hospital utilization: any hospital utilization and ED utilization declined by two percentage points for every additional interpretation FTE ($p<.01$ for both any hospital use and ED use). Preventable ED utilization declined by roughly 1.7 percentage points for every additional "other enabling services" FTE ($p<.05$).

As in the models with a principal diagnosis of asthma, a higher concentration of low-income patients was associated with a small but significant increase in preventable hospital utilization and in preventable ED utilization. A greater number of advanced practice clinician FTEs was associated with a two-percentage point increase in preventable hospital utilization and in preventable ED utilization ($p<.05$ for both). Finally, utilizing the electronic health record to extract UDS data was associated with a large decline in both preventable hospital utilization and ED utilization – a 7.9 percentage point decrease ($p<.05$) and a 6.6 percentage point decrease ($p<.05$), respectively.

Sensitivity Analyses

The sensitivity analysis applying a 60-day washout period to the outcome variables produced similar results to the main models in both direction and significance, though the effect sizes were variable across the model specifications. Additionally, pharmacy FTEs and interpretation FTEs no longer had a significant association with the outcome in any of the models.

Models applying the CCS dummy variable-based patient acuity adjustment and the modified Wolinsky continuity of care measure produced results similar to the main model specification in direction, significance and effect size. Finally, the sensitivity analysis that modeled patient encounters in place of total patients found similar effects across the FQHC characteristics but produced larger effect sizes among the enabling services staff categories. Additionally, having more eligibility assistance worker FTEs became statistically significant in this model and was associated with a decrease in preventable hospitalization ($p<.05$) and preventable ED visits ($p<.01$) with any diagnosis of asthma.

Part 2: Configurational Comparative Analysis Using Coincidence Analysis

Methods

Data Source and Inclusion Criteria

The configurational comparative analysis was built on the same dataset utilized for the regression-based methods: North Carolina Medicaid claims from January 1, 2013 through September 30, 2015 for patients who received the plurality of primary care services in FQHCs were merged with 2013-2015 UDS data. Different from the regression analysis, we conducted the configurational analysis at the organization level, so inclusion criteria were assessed at the organization level. We opted to utilize an organization-level CCM because we wanted to apply an organization-level interpretation in order for the results to be most useful for administrators and practitioners.

FQHCs were included in the analysis if more than one Medicaid-insured pediatric patient with asthma was attributed to the organization during the study period (2013-2015) and if they had complete UDS data. Of the 37 federally-funded FQHC organizations in North Carolina, 35 FQHCs were included in this analysis, and all but two of the organizations existed in all three analysis years. (One FQHC was excluded due to insufficient sample size, and one FQHC was excluded due to lack of complete UDS data.)

Key Organizational Characteristics

The primary outcome of interest was whether the FQHC organization was classified as a high performer according to a three-year pooled analysis of Medicaid claims described in Chapter Three. In brief, we applied three different methodologies (unadjusted crude rate, hierarchical generalized linear models and fixed effect models) to two model specifications to rank FQHCs according to preventable hospital utilization rates for asthma. The FQHC-specific performance classification measure for each method represented the average for patients attributed to that organization and was used to generate a method-specific performance ranking. We then assigned an overall performance ranking using the geometric mean of the rankings across the risk-adjusted models. The top-performing 25% of organizations – those that had the best overall performance ranking based on the lowest rate of preventable hospital utilization for asthma – were classified as high performers. Secondary analyses modeled organizational characteristics associated with the absence of the outcome, or *HI_PERF*=0. (From this point forward, the absence of a condition will be denoted with lower-case letters, e.g., *hi_perf*.)

Key explanatory factors consisted of the following modifiable organizational characteristics: staffing ratios, financial resources and PCMH recognition. Focusing on modifiable organizational characteristics is most useful from a policy and practice perspective given the potential to identify actionable conditions for program improvement. The 2013-2015 average for each characteristic was calculated for every organization. A full list of factors and their definitions are included in Table 4.4.

The following factors were considered controls for the analysis: concentration of uninsured patients, operating income, total clinic sites, concentration of pediatric patients, and concentration of low-income patients (income <200% of the federal poverty line). Having a high concentration of patients without insurance influences resources available at FQHCs and directly affects organization structures and services. Organizations with high operating income may have more resources available to improve quality and organization performance. Having a large number of clinic sites could be associated with high performance – a sign of strategic growth – or could signal poor performance if systems and standards are not well integrated across sites. High concentrations of pediatric patients may imply greater experience caring for this patient population. Having high concentrations of low-income patients may imply patients with greater non-medical barriers to good health, thereby influencing an organization's ability to keep these patients out of the hospital.

Set membership definition. CCMs study implication ("if-then") hypotheses that link specific values of variables to the outcomes.[47] In other words, CCMs model the effect of conditions (e.g., high ratio of enabling services staff) on outcomes. Therefore, to conduct the configurational comparative analysis, all factors were "scored" to reflect each FQHC's degree of "membership" in a given factor—for example, the level of membership in the "high enabling services staffing" condition. We applied binary definitions based on break-points in the data distribution. Because some factors had more than one clear break-point in the data distribution, we ran two analyses for each model and outcome – one using the high thresholds, and another using the low thresholds. Figures D.1-D.4 in Appendix D highlight the calibration thresholds for the factors included in the analysis.

Analytic Approach

To date, qualitative comparative analysis, or QCA, represents the more commonly utilized CCM in health services research.[48–50] However, we elected to use a new method within the CCM family known as coincidence analysis, or CNA, [51,52] because it has improved upon some of the shortcomings of QCA.[53,54] Appendix C includes a description of the CNA algorithm used to identify conditions associated with the outcome.

Configurational comparative methods including CNA represent an iterative process with refinements made to model inputs and factor calibration throughout the analysis. Iterative model-building and testing is necessary in part because researchers are limited in the number of factors included in configurational analyses; for each additional factor, k, included in the model, there are 2^k logically plausible configurations. For example, including 10 factors in the model produces 1,024 configurations. With only 35 organizations in this analysis, including a large number of factors would result in logically possible configurations without data, also known as limited diversity. Limited diversity can produce large numbers of potential solutions, adversely affecting the informativeness of the resulting model solutions.

Given the need to limit the number of factors included in the analysis, we chose to reduce the number of control factors included by first homogenizing the data on two control factors. (Homogenizing on more than two controls did not leave sufficient cases for analysis.)

We created four subsets of the full dataset comprised of cases that were homogenous in their configuration of two of the controls (1/1, 1/0, 0/1 and 0/0 configurations). The configuration of high concentration of uninsured patients with the absence of a high concentration of pediatric patients contained sufficient diversity to permit analysis (N=11 cases in both the high- and low-threshold specifications). Two other configurations – organizations without high concentrations of both low-income patients and pediatric patients, and organizations without high concentrations of low-income patients but with high concentrations of uninsured patients – also contained sufficient diversity for analysis, but there were no commonalities across model solutions. Thus, these results are not reported here. Two other control conditions -- high operating income and large number of clinic sites -- were included in the analytical models. When models included a third control, high concentration of low-income patients, the results were inconclusive. All results should be interpreted relative to organizations with high concentrations of uninsured patients but without high concentrations of pediatric patients.

After deciding on the controls, we established two different model specifications to incorporate all factors of interest in the analysis. For model 1, we included the control conditions and the individual enabling services FTEs. To further increase the diversity index, i.e. the ratio of observed configurations to all logically possible configurations in the dataset, we included only four enabling service FTE categories – case manager FTEs, a combined outreach measure that summed outreach and patient/community educator FTEs into a single category, eligibility assistance FTEs and interpretation FTEs – in addition to the two controls, operating income and total sites. Model 2 comprised seven conditions including the two control conditions, requiring us to disjunctively aggregate two of the remaining key conditions of interest to increase the diversity index. Disjunctively aggregating conditions is a common approach in CCMs to maintain the properties of the conditions in the models but to limit the number of factors included in the analytical model given limited diversity. The five key factors for Model 2 included: ratio of advanced practice clinicians to physicians, patient-centered medical home recognition, as well as pharmacy, behavioral health and total enabling services FTEs. We disjunctively aggregated behavioral health and total enabling services FTEs because these staff could help to address non-medical causes of poor health.

CNA then determined which conditions were minimally necessary and minimally sufficient for the outcome within these subsets of the full data set by searching the data for single conditions then combinations of conditions that met pre-specified consistency and coverage thresholds. Consistency measures how often a combination of conditions leads to the outcome, or the degree to which the cases sharing a particular combination also share the same outcome.[55] Lower consistency values may indicate lower confidence in the causal relationship between conditions and the outcome. Coverage measures the proportion of cases with the outcome that also have a particular condition[56] – the “empirical importance” of a given configuration.[55] Conditions meeting the consistency and coverage thresholds were aggregated to form model solutions.

We ran CNA on both the high- and low-threshold specifications for Models 1 and 2 for a total of four analyses with the outcome *HI_PERF*. We ran the same four analyses on the absence of high performance, or *hi_perf* (hi_perf=1 when HI_PERF=0). All analyses were conducted using the cna package in R.[57] Initial analyses set consistency and coverage thresholds at 100% and gradually lowered to 75% if there were no solutions. We increased the maximum complexity of model solutions from default settings.

Results

According to traditional cross-case analysis, the following conditions had the strongest associations with the outcome, high performance, in both the high- and low-threshold datasets: having a high concentration of uninsured patients, the absence of a high concentration of pediatric patients, high ratios of behavioral health FTEs to medical patients, and the absence of high ratios of advanced practice clinicians to physicians (Tables D.1 and D.2 in Appendix D).

Among all 35 organizations in the analysis, only two pairs of two organizations shared the same configuration of conditions in the high-threshold dataset; no organizations shared identical configurations in the low-threshold dataset.

Tables 4.5 and 4.6 include the CNA results -- the solutions for Models 1 and 2 for both the *HI_PERF* and *hi_perf* analyses with high- and low-threshold specifications for the included factors. As shown in Table 4.5, both the high- and low-calibration thresholds for Model 1 produced the same results when modeling the outcome *HI_PERF*:

(1) TOTAL_SITES + *combout*interp_ratio* <-> *HI_PERF*

(2) TOTAL_SITES + *combout*ELIGASST_RATIO*interp_ratio* <-> *HI_PERF*

In words, solution 1 translates to: high performance was associated with having a large number clinic sites OR the absence of a high outreach/patient and community educator-to-patient ratio AND the absence of a high interpretation FTE-to-patient ratio. (The + symbol connotes “OR”, the * symbol connotes “AND,” and lower-case letters symbolize the absence of a condition.) This solution was observed in the high- and low-threshold specifications with 86% consistency and 100% coverage, meaning that the outcome of high performance was observed nearly 86% of the time in which this configuration was also observed. Moreover, all of the organizations classified as high performers exhibited this configuration.

Solution 2 is similar to Solution 1 but suggests that the combination of the absence of a high outreach/patient and community educator FTE-to-patient ratio AND having high eligibility assistance FTE-to-patient ratio AND the absence of a high interpretation FTE-to-patient ratio was associated with high performance. Solution 2 occurred with 100% consistency and 83% coverage in the homogenized dataset for both the high- and low-threshold specifications. The common core for both Solutions 1 and 2 was: *TOTAL_SITES* + *combout*interp_ratio.*

This common core was well-represented in the full dataset. In the full dataset with 35 cases and high-threshold calibration, *TOTAL_SITES* was associated with the outcome in roughly 36% of cases (i.e., when cases exhibited *TOTAL_SITES*, 36% of those cases also exhibited the outcome). Approximately 44% of the high performers exhibited the condition *TOTAL_SITES*. The same consistency and coverage measures were observed for the low-threshold dataset.

In the high-threshold dataset, the condition *combout*interp_ratio* was associated with the outcome in approximately 29% of the cases in which it appeared, and nearly 67% of the high performers exhibited this configuration. Consistency and coverage scores for this configuration were only slightly lower in the low-threshold dataset.

CNA for the outcome *hi_perf* (the absence of high performance) generated nine potential solutions across the two threshold calibrations for Model 1. Even so, eight of the nine potential solutions contained the following common core: *total_sites*INTERP_RATIO*, which means the absence of a large number of clinic sites AND having a high interpreter FTE-to-patient ratio was linked directly to the absence of high performance. This configuration exhibited 25% consistency and nearly 78% coverage in both the high- and low-threshold calibrations of the full dataset (all 35 cases). Further, *total_sites*INTERP_RATIO* represented a negation of the conditions associated with the outcome *HI_PERF*.

As shown in Table 4.6, the CNA on *HI_PERF* for Model 2 produced one solution in the high-threshold dataset and three potential solutions for the low-threshold calibrations. These solutions contained the following common core, *OP_INC*pcmh_recog* + *TOTAL_SITES,* which translates to: having a higher operating income AND no PCMH recognition OR having a large number of clinic sites was associated with high performance. The configuration *OP_INC*pcmh_*recog was present in all four solution models, and *TOTAL_*SITES was present in three of the four solution models. As with Model 1, the condition *TOTAL_SITES* demonstrated good consistency and coverage in the full, 35-case dataset. However, the configuration *OP_INC*pcmh_recog* was instantiated by only one case in the full dataset, producing very low coverage (11%) for this configuration.

For the analysis on *hi_perf* using Model 2, the high-threshold dataset generated two model solutions, but the low-threshold dataset produced 12 model solutions. The condition *total_sites*PCMH_RECOG* – the absence of a large number of clinic sites and having PCMH recognition – appeared in both solutions for the high-threshold calibration and in four of the 12 solutions in the low-threshold calibration. However, this configuration exhibited low consistency (11%) and coverage (11%) in both the high and low-threshold calibrations of the full dataset (where N=35 organizations).

<u>Part 3: Discussion</u>

To improve upon previous studies examining FQHC organizational characteristics associated with organization performance, this analysis applied both regression-based and configurational comparative methods. The regression analysis helped identify which FQHC characteristics were associated with the probability a patient experienced a preventable hospital visit, while the configurational comparative analysis using CNA uncovered different combinations of characteristics that high performing organizations had in common across an array of contexts (i.e., organization configurations). The decision to use patient-level regression models was motivated by statistical power, which permitted inclusion of a variety of both patient- and organization-level covariates. The decision to use an organization-level CNA was motivated by previous research indicating that FQHC services, structures and processes varied across organizational characteristics and organization context, suggesting there might be interdependencies among organizational characteristics, context and performance. Indeed, CCMs are useful when outcomes may be explained by combinations of specific conditions that occur together, when multiple combinations of conditions produce the same outcome, and when a case-based unit of analysis is important to account for an array of contexts.

Both the regression and CNA results indicated that certain non-medical services were associated with higher preventable hospital utilization and lower organization performance, disproving the study hypothesis that these services would be associated with lower preventable hospital use and higher performance. The regression results indicated that having a broader scope of FQHC services and greater numbers of behavioral health, pharmacy and outreach FTE staff were associated with significantly higher likelihood of preventable hospital utilization with any diagnosis of asthma after controlling for patient and area-level characteristics. However, more interpretation and other enabling services FTEs (care coordinators and referral specialists) were associated with approximately a 1-2 percentage point decrease in the likelihood of preventable hospital utilization with any diagnosis of asthma, respectively ($p<.05$).

Results from the configurational comparative analysis provided insights into “typologies” of high-performing FQHCs among organizations with high percentages of uninsured patients and low percentages of pediatric patients. Overall, the CNA results indicated that having a large number of clinic sites was associated with the outcome of high performance in both Models 1 and 2 and across both high- and low-threshold calibrations. Further, analysis for the absence of the outcome, *hi_perf,* suggested the negation of the positive outcome: having fewer clinic locations was associated with the absence of high performance across all model specifications. This finding aligns with previous research that indicated having more clinic sites was associated with higher odds of Level 3 PCMH recognition among FQHCs.[58] Moreover, having a large number of clinic sites despite having high concentrations of uninsured patients likely indicates strategic leadership and greater access to other revenue sources and community partnerships that facilitate expanding access to care.

The strongest conclusions can be drawn from Model 1. Although we found two potential model solutions and thus could not identify which causal structure was operative, the fact that these solutions were replicated across both the high- and low-threshold calibration suggested robust findings for the *HI_PERF* outcome in Model 1. Model 1 solutions suggested that having low ratios of FTEs-to-patients for outreach/patient and community educators and interpretation staff were also connected to high performance. While these results are surprising, they could signal a systematic difference in organizations exhibiting these characteristics that is not being captured in the data. To borrow Cross and colleagues' hypothesis regarding why quality of care measures were lower in practices with higher concentrations of high-needs patients,[16] perhaps organizations with higher ratios of outreach and interpretation staff have patients with more complex social, economic and environmental needs that detract attention and resources away from medical management of chronic disease.

Definitive conclusions could not be drawn from Model 2. The dataset for CNA was highly fragmented (i.e., exhibited low diversity), so most logically possible configurations were not observed in the data. For this reason, Model 2 results revealed only portions of the underlying causal structures.

It is important to note that an organization-level measure for scope of services and non-medical services staffing does not necessarily imply that these services are equally available to and accessed by pediatric patients. FQHCs, for example, may target enabling services to adult populations, or may only offer services at some clinic locations. In other words, the results of this study should not be interpreted as a reflection of the effectiveness of non-medical services in FQHCs since we did not have patient-level utilization measures for non-medical services. In fact, previous research has underscored the importance of non-medical services on improving patient outcomes,[59–62] particularly among vulnerable patient populations. For example, Vest and colleagues[62] used patient-level encounter data and found that receipt of one of five "wraparound services" – behavioral health, social work, dietetics, respiratory therapy and patient navigation services – in a large, urban FQHC significantly reduced subsequent high-cost hospital utilization among adult patients.

Another potential explanation for this study's surprising results could be that organizations with more non-medical services and greater staffing of non-medical services generate more patient "touches," which could identify underlying health problems that warrant more immediate medical attention in the hospital, thereby increasing hospital utilization rates.

Limitations

This study has several limitations. First, the FQHC characteristics included in the UDS are measured at an organization-level and may not reflect services available at individual delivery sites. In other words, non-medical services may not be equally accessible to all patients within an FQHC organization. Furthermore, neither Medicaid claims data nor UDS data indicate which patients are accessing enabling services at FQHCs. Children may be accessing enabling services less frequently than adults, for example.

Second, this analysis was limited to the organizational characteristics available in UDS data. Other organizational factors (e.g., leadership, community partnerships) not available in these data may be contributing to the observed relationships. Furthermore, UDS data are self-reported and unaudited, potentially introducing measurement error in model covariates and biasing results. Third, FQHC patients do not randomly select into FQHCs. However, North Carolina FQHCs have historically had distinct service areas, so patients likely had limited opportunity to utilize more than one FQHC organization. Additionally, the FQHC fixed effects control for unobserved, time-invariant differences within FQHCs which could influence patient selection. Fourth, the study included only nine months of data for analysis year 2015 given the transition to ICD-10 coding; however, analyses adjusted for total months of Medicaid enrollment in a calendar year. Additionally, we assumed in 2015 that the outcomes were linear in the number of months on Medicaid – that the outcomes for those enrolled in Medicaid for 12 months would be twice as high compared to those enrolled for six months.

Finally, CCMs can produce ambiguous results when data are highly fragmented, i.e., when there are logically plausible configurations of conditions without observed data. Because we examined six conditions in each analysis sample, the CNA explored 128 (2^6) logically plausible configurations. However, we only had 35 organizations, or cases, for analysis, resulting in highly fragmented data. In order to reduce fragmentation, we homogenized our dataset on two of the control factors, which in turn limited the generalizability of the results.

Therefore, the utility of CCMs was diminished in this study given the high degree of data fragmentation.

Conclusion

Overall, we found that a broader scope of services and more full-time equivalent staff for certain non-medical services were associated with increases in preventable hospital use. However, the FQHC services included in this study were measured at an organization-level and did not reflect patient-level utilization of those services. Therefore, our ability to make inferences about these organization-level characteristics and patient-level outcomes was limited.

The results of this study highlight the need for additional research that utilizes patient-level encounter data for non-medical services to better understand the effect of accessing non-medical services on preventable hospital utilization. Additionally, future research could explore whether non-medical services have a different effect on inpatient hospital utilization versus ED utilization. Because this study focused on pediatric asthma, ED utilization comprised the majority of hospital use.

Qualitative interviews would also be beneficial for identifying how organizational factors not available in quantitative data (e.g., leadership, community partnerships) may be contributing to the observed relationships between organizational characteristics and organization performance. Furthermore, qualitative interviews could identify organizational structures and processes underlying chronic disease care and access to non-medical services.

Finally, as the health care system continues to move toward value-based payment, policymakers and payers might consider including revenue codes for non-medical services to permit future examination of the effectiveness of these services in reducing health care costs and utilization and improving patient outcomes across both FQHC and non-FQHC organizations. Without the ability to examine the association between organizations' services and patient-level utilization and outcomes on a systems-level, quantitative research to identify organizational characteristics associated with high performance will be limited.

Table 4.1. Covariates Derived from FQHC Uniform Data System (UDS) data

Category	Variables
Key explanatory factors	
FQHC scope of services	A count of the non-medical services relevant to asthma care provided by the FQHC organization (measured by whether the FQHC reported FTE staff for those services in the UDS). Range: 0-9.
FTE staff for non-medical services	Behavioral health providers (mental health and substance abuse)
	Pharmacy staff
	Enabling services staff
	Case managers
	Patient/Community education specialists
	Outreach workers
	Transportation staff
	Eligibility assistance workers
	Interpretation staff
	Other enabling services staff (e.g., care coordinators and referral specialists)
Other explanatory factors	
Medical staff FTEs	Primary care physician (MD/DOs) FTEs
	Advanced practice provider (NPs, PAs, CNMs) FTEs
Organization size	Number of clinic sites
	Number of patients
Financial resources	Three-year average operating income (prior year, current year and subsequent year net revenue less expenses)
	Indicator for whether FQHC was a "new start" (newly funded) FQHC organization in analysis year
FQHC patient profile	% pediatric patients
	% of patients with asthma
	% of patients who report incomes ≤ 200% of the federal poverty level
	% of patients uninsured
Clinical quality	Percent of eligible children receiving weight assessment and counseling
	Percent of eligible children fully immunized by third birthday
Health information technology capabilities	EHR utilized to extract UDS data
	Electronic health information exchange with other health care organizations
	Patient engagement through health information technology

Table 4.2. Descriptive Statistics, 2013-2015 FQHC and Patient Characteristics

	Mean or mean % (SD)
N (person-years)	23,982
Unique individuals	13,292
Any hospital utilization with a principal diagnosis of asthma	9.5%
Emergency department visit with a principal diagnosis of asthma	8.6%
Any hospital utilization with any diagnosis of asthma	25.5%
Emergency department visit with any diagnosis of asthma	23.8%
FQHC Characteristics	
FQHC scope of services (range: 0-9)	5.54 (1.76)
Behavioral health FTEs	4 (3.71)
Pharmacy FTEs	9.7 (11.2)
Enabling services FTEs	
Case manager FTEs	3.34 (3.85)
Patient/Community Education Specialist FTEs	1.57 (2.22)
Outreach worker FTEs	1.75 (1.79)
Transportation staff FTEs	0.408 (1.01)
Eligibility assistance worker FTEs	3.97 (3.45)
Interpretation staff FTEs	1.71 (2.48)
Other enabling services FTEs (e.g., care coordinator and referral specialists)	1.68 (3.21)
Primary care physician (MD/DOs) FTEs	12 (6.04)
Advanced practice provider (NPs, PAs, CNMs) FTEs	9.9 (5.15)
Indicator for whether FQHC was a "new start" (newly funded) FQHC organization in analysis year	8.2%
3-year average operating income (prior year, current year and subsequent year), in $10,000	-62.8 (171)
Number of clinic sites	8.58 (5.47)
Number of patients (in 10,000)	2.58 (1.16)
Proportion of pediatric patients	37.0 (23.1)
Proportion of patients with asthma	6.36 (4.34)
Proportion of patients with incomes ≤ 200% of the federal poverty level	61.2 (27.9)
Proportion of patients uninsured	36.8 (20.4)
Percent of eligible children receiving weight assessment and counseling	57.0 (20.1)
Percent of eligible children fully immunized	81.2 (16.9)
Electronic health information exchange with other health care organizations	80.7%
Patient engagement through health information technology	81.8%
EHR utilized to extract UDS data	87.6%
Patient characteristics (in person-years)	
Age	9.3 (4.43)
Female enrollee	43.3%
Race/Ethnicity	

White, not Hispanic	16.2%
Black, not Hispanic	49.4%
Hispanic	27.0%
Multiple/Other, not Hispanic	3.2%
Unknown	4.2%
Months of Medicaid coverage in calendar year	10.4 (2.18)
Rural residence	28.5%
Specialty provider utilization in calendar year	6.8%
Number of primary care visits in calendar year	4.07 (3.63)
Number of chronic conditions	1.63 (1.10)
Continuity of care (% of primary care visits with attributed organization in calendar year)	83.8 (0.224)
County-level measures	
Percent living under poverty	18.9 (4.98)
Median household income (in $10,000)	4.55 (0.946)
Annual concentration of air particulate matte	9.8 (0.903)
Year	
2013	29.4%
2014	35.9%
2015	34.8%

Standard deviation (SD) in parentheses.

Table 4.3. Average Marginal Effects of FQHC Characteristics on Preventable Hospital Utilization, 2013-2015

	Model 1 Any hospital utilization (ED, observation or inpatient stay) with a principal diagnosis of asthma	**Model 2** ED visit with principal diagnosis of asthma	**Model 3** Any hospital utilization (ED, observation or inpatient stay) with any diagnosis of asthma	**Model 4** ED visit with any diagnosis of asthma
FQHC Scope of Services (count of non-medical services offered, 0-9)	0.0141	0.0142	0.0394^{**}	0.0405^{**}
	(0.0108)	(0.0102)	(0.0142)	(0.0139)
Behavioral health FTEs (mental health/substance abuse)	0.00858	0.00588	0.0217^{**}	0.0187^{**}
	(0.00504)	(0.00491)	(0.00688)	(0.00692)
Pharmacy FTEs	0.00279	0.00141	0.0202^{**}	0.0179^{**}
	(0.00441)	(0.00421)	(0.00639)	(0.00628)
Case manager FTEs	0.000615	0.00159	0.00734	0.00747
	(0.00302)	(0.00291)	(0.00465)	(0.00464)
Patient/Community Education Specialist FTEs	-0.00448	-0.00242	-0.00831	-0.0125
	(0.00620)	(0.00601)	(0.00880)	(0.00902)
Outreach FTEs	-0.00361	-0.00413	0.0216^{**}	0.0195^{**}
	(0.00520)	(0.00498)	(0.00754)	(0.00750)
Eligibility Assistance FTEs	-0.00155	-0.00218	-0.00795	-0.0106
	(0.00389)	(0.00375)	(0.00569)	(0.00565)
Interpretation FTEs	0.00454	0.00116	-0.0203^{**}	-0.0219^{**}
	(0.00544)	(0.00530)	(0.00777)	(0.00777)
Other Enabling Services FTEs	-0.00526	-0.00290	-0.0156	-0.0172^{*}
	(0.00598)	(0.00574)	(0.00824)	(0.00816)
Transportation FTEs	0.00883	-0.00785	-0.00493	-0.0137
	(0.0285)	(0.0279)	(0.0409)	(0.0411)

Primary care physician FTEs	0.00362	0.00424	0.000826	0.00327
	(0.00440)	(0.00419)	(0.00630)	(0.00622)
Advanced practice provider FTEs	0.0103	0.00798	0.0218*	0.0213*
	(0.00728)	(0.00709)	(0.0103)	(0.0102)
New FQHC organization in analysis year (*ref.* existing FQHC)	-0.0500	-0.0532	-0.0377	-0.0377
	(0.0329)	(0.0290)	(0.0684)	(0.0666)
Three-year average operating income (in $10,000)	-0.000142	-0.000102	0.000318	0.000287
	(0.000140)	(0.000131)	(0.000200)	(0.000198)
Number of clinical delivery sites	-0.00305	-0.00267	-0.00185	-0.00563
	(0.00540)	(0.00518)	(0.00827)	(0.00809)
Total patients (in 10,000)	-0.0815	-0.0739	-0.0789	-0.0976
	(0.0464)	(0.0443)	(0.0706)	(0.0701)
Proportion of pediatric patients	-0.00300	-0.00305	0.000648	0.000830
	(0.00212)	(0.00204)	(0.00298)	(0.00294)
Proportion of asthma patients	-0.00404	-0.00324	-0.00187	-0.000399
	(0.00279)	(0.00264)	(0.00421)	(0.00415)
Proportion of patients with incomes <200% FPL	0.00210***	0.00186**	0.00326***	0.00328***
	(0.000627)	(0.000613)	(0.000880)	(0.000888)
Proportion of patients uninsured	-0.00207	-0.00197	-0.00117	-0.00157
	(0.00133)	(0.00129)	(0.00202)	(0.00198)
Percent of eligible children receiving weight assessment and counseling	-0.000583	-0.000717*	0.000149	-0.000114
	(0.000364)	(0.000339)	(0.000484)	(0.000475)
Percent of eligible children fully immunized by third birthday	0.000303	0.000158	0.000491	0.000625
	(0.000356)	(0.000342)	(0.000474)	(0.000465)

Electronic health information exchange with other health care organizations	-0.0302	-0.0283	-0.0198	-0.0241
	(0.0169)	(0.0166)	(0.0208)	(0.0210)
Patient engagement through health information technology	0.0276*	0.0216	0.0351	0.0439*
	(0.0137)	(0.0136)	(0.0217)	(0.0207)
EHR utilized to extract UDS data	-0.0618	-0.0408	-0.0788*	-0.0660*
	(0.0326)	(0.0295)	(0.0339)	(0.0332)
N (person-years)	23,982	23,982	23,982	23,982

Standard errors in parentheses.
*** p < 0.001, ** p < 0.01, * p < 0.05
Models also adjusted for the following patient- and area-level characteristics: age, sex, race/ethnicity, months of Medicaid coverage in the calendar year, rural residence, specialty provider utilization for asthma in calendar year, an interaction between rural residence and specialty provider utilization, total number of primary care visits to any provider, total number of chronic conditions, Breslau & Reeb's continuity of care measure, percent of population living below the federal poverty line, median household income, air particulate matter concentration (annual PM2.5 level), as well as year and FQHC fixed effects.

Table 4.4. Organizational Characteristics, Factor Names and Set Membership Definitions for Coincidence Analysis

Organizational characteristics (Factor name)	High-threshold definitions	Low-threshold definitions
Outcome		
High performer (HI_PERF)	Top 25% of organizations based on Aim 2 analysis=1; 0 otherwise	Same as high-threshold definition
Controls		
High concentration of patients without insurance (PERC_UNINSURED)	Organizations with >50% uninsured patients =1; 0 otherwise	Same as high-threshold definition
High concentration of pediatric patients (PERCPEDS)	Organizations with >27% pediatric patients =1; 0 otherwise	Same as high-threshold definition
High operating income (OP_INC)	Organizations with >$440,000 in operating income =1; 0 otherwise	Same as high-threshold definition
Large number of clinic sites	Organizations with >6 clinic sites =1; 0 otherwise	Same as high-threshold definition
Explanatory factors		
High advanced practice clinician (NP, PA, CNM) to physician (MD, DO) full-time equivalent (FTE) ratio (AP_PCP)	Organizations with >1.9 advanced practice providers per physician=1; 0 otherwise	Organizations with >1.3 advanced practice providers per physician=1; 0 otherwise
High behavioral health provider (mental health and substance abuse) FTE to medical patient ratio (BH_RATIO)	Organizations with > 1.99 behavioral health providers per 10,000 medical patients =1; 0 otherwise	Same as high-threshold definition
High pharmacy FTE to medical patient ratio (PHARMACY_RATIO)	Organizations with > 5 pharmacy staff per 10,000 medical patients =1; 0 otherwise	Organizations with > 3.71 pharmacy staff per 10,000 medical patients =1; 0 otherwise
High enabling services FTE to medical patient ratio (TOTAL_ES)	Organizations with > 14 enabling services FTEs per 10,000 medical patients =1; 0 otherwise	Organizations with > 9 enabling services FTEs per 10,000 medical patients =1; 0 otherwise
High case manager FTE to medical patient ratio (CASEMNGR_RATIO)	Organizations with >3.1 case manager staff per 10,000 medical patients; 0 otherwise.	Organizations with >1.99 case manager staff per 10,000 medical patients; 0 otherwise.
High outreach and patient education FTE to medical patient ratio (COMBOUT)	Organizations with >3.1 outreach/education staff per 10,000 medical patients; 0 otherwise.	Organizations with >2.09 outreach/education staff per 10,000 medical patients; 0 otherwise.

High eligibility assistance FTE to medical patient ratio ELIGASST_RATIO)	Organizations with >4.2 eligibility assistance staff per 10,000 medical patients; 0 otherwise.	Same as high-threshold definition
High interpretation FTE to medical patient ratio (INTERP_RATIO)	Organizations with >1.2 interpretation staff per 10,000 medical patients; 0 otherwise.	Same as high-threshold definition
At least one site with patient-centered medical home (PCMH) recognition (PCMH_RECOG)	1 if yes; 0 if no (2014/2015 data only)	Same as high-threshold definition

Table 4.5. Model 1 Coincidence Analysis Results for Organizations with High Concentrations of Uninsured Patients and Low Concentrations of Pediatric Patients (N=11 cases)

Model specification	Explanatory factor specification	Model solutions (CNA results)	Consistency & coverage
HI_PERF=1 (HI_PERF)			
High-threshold calibration	**Model 1:** OP_INC, TOTAL_SITES, CASEMNGR_RATIO, COMBOUT, ELIGASST_RATIO, INTERP_RATIO	(1) TOTAL_SITES + combout*interp_ratio <-> HI_PERF (2) TOTAL_SITES + combout*ELIGASST_RATIO*interp_ratio <-> HI_PERF	(1) Consistency: 85%; coverage: 100% (2) Consistency: 100%; coverage: 83%
Low-threshold calibration	**Model 1:** OP_INC, TOTAL_SITES, CASEMNGR_RATIO, COMBOUT, ELIGASST_RATIO, INTERP_RATIO	(1) TOTAL_SITES + combout*interp_ratio <-> HI_PERF (2) TOTAL_SITES + combout*ELIGASST_RATIO*interp_ratio <-> HI_PERF	(1) Consistency: 86%; coverage: 100% (2) Consistency: 100%; coverage: 83%
HI_PERF=0 (hi_perf)			
High-threshold calibration	**Model 1:** OP_INC, TOTAL_SITES, CASEMNGR_RATIO, COMBOUT, ELIGASST_RATIO, INTERP_RATIO	(1) total_sites*COMBOUT + total_sites*INTERP_RATIO <-> HI_PERF (2) total_sites*INTERP_RATIO + COMBOUT*ELIGASST_RATIO <-> HI_PERF (3) total_sites*INTERP_RATIO + op_inc*casemngr_ratio*COMBOUT <-> HI_PERF (4) total_sites*INTERP_RATIO + casemngr_ratio*COMBOUT*interp_ratio <-> HI_PERF	(1) Consistency: 100%; coverage: 80% (2) Consistency: 100%; coverage: 80% (3) Consistency: 100%; coverage: 80% (4) Consistency: 100%; coverage: 80%

Low-threshold calibration	**Model 1:** OP_INC, TOTAL_SITES, CASEMNGR_RATIO, COMBOUT, ELIGASST_RATIO, INTERP_RATIO	(1) total_sites*COMBOUT + total_sites*INTERP_RATIO <-> HI_PERF (2) total_sites*COMBOUT + combout*INTERP_RATIO <-> HI_PERF (3) total_sites*COMBOUT + ELIGASST_RATIO*INTERP_RATIO <-> HI_PERF (4) total_sites*INTERP_RATIO + COMBOUT*ELIGASST_RATIO <-> HI_PERF (5) total_sites*INTERP_RATIO + casemngr_ratio*COMBOUT*interp_ratio <-> HI_PERF	(1) Consistency: 100%; coverage: 80% (2) Consistency: Consistency: 100%; coverage: 80% (3) Consistency: 100%; coverage: 80% (4) Consistency: 100%; coverage: 80% (5) Consistency: 100%; coverage: 80%

Table 4.6. Model 2 Coincidence Analysis Results for Organizations with High Concentrations of Uninsured Patients and Low Concentrations of Pediatric Patients (N=11 cases)

Model specification	Explanatory factor specification	Model solutions (CNA results)	Consistency & coverage
HI_PERF=1 (HI_PERF)			
High-threshold calibration	**Model 2:** OP_INC, TOTAL_SITES, AP_PCP, PCMH_RECOG, PHARMACY_RATIO, BH_RATIO, TOTALES_RATIO	(1) OP_INC*pcmh_recog + ap_pcp*PCMH_RECOG*pharmacy_ratio<-> HI_PERF	(1) Consistency: 83%; coverage: 83%
Low-threshold calibration	**Model 2:** OP_INC, TOTAL_SITES, AP_PCP, PCMH_RECOG, PHARMACY_RATIO, BH_RATIO, TOTALES_RATIO	(1) TOTAL_SITES + OP_INC*pcmh_recog + AP_PCP*PHARMACY_RATIO <-> HI_PERF (2)TOTAL_SITES + OP_INC*pcmh_recog + PHARMACY_RATIO*bh_ratio_total_es <-> HI_PERF (3) TOTAL_SITES + OP_INC*pcmh_recog + op_inc*PCMH_RECOG*PHARMACY_RATIO <-> HI_PERF	(1) Consistency: 100%; coverage: 83% (2) Consistency: 100%; coverage: 83% (3) Consistency: Consistency: 100%; coverage: 83%
HI_PERF=0 (hi_perf)			
High-threshold calibration	**Model 2:** OP_INC, TOTAL_SITES, AP_PCP, PCMH_RECOG, PHARMACY_RATIO, BH_RATIO, TOTALES_RATIO	(1) op_inc*PHARMACY_RATIO + total_sites*PCMH_RECOG <-> HI_PERF (2) total_sites*PCMH_RECOG + PHARMACY_RATIO*bh_ratio_total_es <-> HI_PERF	(1) Consistency: 80%; coverage: 80% (2) Consistency: 80%; coverage: 80%

Low-threshold calibration	**Model 2:** OP_INC, TOTAL_SITES, AP_PCP, PCMH_RECOG, PHARMACY_RATIO, BH_RATIO, TOTALES_RATIO	(1) total_sites*PCMH_RECOG+ op_inc*total_sites*BH_RATIO_TOTAL_ES <-> HI_PERF (2) total_sites*PCMH_RECOG+ op_inc*pcmh_recog*PHARMACY_RATIO <-> HI_PERF (3) total_sites*PCMH_RECOG+ op_inc*pcmh_recog*BH_RATIO_TOTAL_ES <-> HI_PERF (4) total_sites*pharmacy_ratio + op_inc*total_sites*BH_RATIO_TOTAL_ES <-> HI_PERF (5) total_sites*pharmacy_ratio + op_inc*pcmh_recog*PHARMACY_RATIO <-> HI_PERF (6) total_sites*pharmacy_ratio + op_inc*pcmh_recog*BH_RATIO_TOTAL_ES <-> HI_PERF (7) pharmacy_ratio*bh_ratio_total_es + op_inc*total_sites*BH_RATIO_TOTAL_ES <-> HI_PERF (8) pharmacy_ratio*bh_ratio_total_es + op_inc*pcmh_recog*PHARMACY_RATIO <-> HI_PERF (9) pharmacy_ratio*bh_ratio_total_es + op_inc*pcmh_recog*BH_RATIO_TOTAL_ES <-> HI_PERF (10) total_sites*PCMH_RECOG + op_inc*total_sites *ap_pcp*PHARMACY_RATIO <-> HI_PERF (11) total_sites*pharmacy_ratio + op_inc*total_sites * ap_pcp*PHARMACY_RATIO <-> HI_PERF (12) pharmacy_ratio*bh_ratio_total_es + op_inc*total_sites * ap_pcp*PHARMACY_RATIO <-> HI_PERF	All 12 solutions: Consistency: 80%; coverage: 80%

REFERENCES

1. Bureau of Primary Health Care. 2016 Health Center Data - National Program Grantee Data. Uniform Data System. https://bphc.hrsa.gov/uds/datacenter.aspx. Published 2017. Accessed October 4, 2017.

2. Geiger HJ. The first community health centers: a model of enduring value. *J Ambul Care Manage*. 2005;28(4):313-320. http://www.ncbi.nlm.nih.gov/pubmed/16172560. Accessed September 14, 2017.

3. Bureau of Primary Health Care. Summary of Program Requirements. https://bphc.hrsa.gov/programrequirements/summary.html. Accessed August 9, 2017.

4. Wright B. Who governs federally qualified health centers? *J Health Polit Policy Law*. 2013;38(1):27-55. doi:10.1215/03616878-1898794.

5. *Section 330 of the Public Health Service Act*. http://uscode.house.gov/view.xhtml?edition=prelim&req=42+usc+254b&f=treesort&fq=true&num=20&hl=true. Accessed August 9, 2017.

6. Lebrun LA, Shi L, Zhu J, et al. Racial/ethnic differences in clinical quality performance among health centers. *J Ambul Care Manage*. 2013;36(1):24-34. doi:10.1097/JAC.0b013e3182473523.

7. Goldman LE, Chu PW, Tran H, Romano MJ, Stafford RS. Federally Qualified Health Centers and Private Practice Performance on Ambulatory Care Measures. *Am J Prev Med*. 2012;43(2):142-149. doi:10.1016/j.amepre.2012.02.033.

8. Falik M, Needleman J, Wells BL, Korb J. Ambulatory care sensitive hospitalizations and emergency visits: experiences of Medicaid patients using federally qualified health centers. *Med Care*. 2001;39(6):551-561. http://www.ncbi.nlm.nih.gov/pubmed/11404640. Accessed August 24, 2016.

9. Laiteerapong N, Kirby J, Gao Y, et al. Health care utilization and receipt of preventive care for patients seen at federally funded health centers compared to other sites of primary care. *Health Serv Res*. 2014;49(5):1498-1518. doi:10.1111/1475-6773.12178.

10. Wright B, Potter AJ, Trivedi A. Federally Qualified Health Center Use Among Dual Eligibles: Rates Of Hospitalizations And Emergency Department Visits. *Health Aff*. 2015;34(7):1147-1155. doi:10.1377/hlthaff.2014.0823.

11. Mukamel DB, White LM, Nocon RS, et al. Comparing the Cost of Caring for Medicare Beneficiaries in Federally Funded Health Centers to Other Care Settings. *Health Serv Res*. 2016;51(2):625-644. doi:10.1111/1475-6773.12339.

12. Richard P, Ku L, Dor A, Tan E, Shin P, Rosenbaum S. Cost savings associated with the use of community health centers. *J Ambul Care Manage*. 2012;35(1):50-59. doi:10.1097/JAC.0b013e31823d27b6.

13. Nocon RS, Lee SM, Sharma R, et al. Health Care Use and Spending for Medicaid Enrollees in Federally Qualified Health Centers Versus Other Primary Care Settings. *Am J Public Health*. 2016;106(11):1981-1989. doi:10.2105/AJPH.2016.303341.

14. Bruen B, Ku L. *Community Health Centers Reduce the Costs of Children's Health Care*.; 2017. http://publichealth.gwu.edu/projects/geiger-gibson-program-community-health-policy. Accessed June 28, 2017.

15. Shi L, Lebrun LA, Zhu J, et al. Clinical quality performance in U.S. health centers. *Health Serv Res*. 2012;47(6):2225-2249. doi:10.1111/j.1475-6773.2012.01418.x.

16. Cross DA, Cohen GR, Lemak CH, Adler-Milstein J. Outcomes For High-Needs Patients: Practices With A Higher Proportion Of These Patients Have An Edge. *Health Aff*. 2017;36(3):476-484. doi:10.1377/hlthaff.2016.1309.

17. Gurewich D, Capitman J, Sirkin J, Traje D. Achieving excellence in community health centers: implications for health reform. *J Health Care Poor Underserved*. 2012;23(1):446-459. doi:10.1353/hpu.2012.0008.

18. Wells R, Punekar RS, Vasey J. Why do some health centers provide more enabling services than others? *J Health Care Poor Underserved*. 2009;20(2):507-523. doi:10.1353/hpu.0.0151.

19. Wright DB. Consumer governance and the provision of enabling services that facilitate access to care at community health centers. *Med Care*. 2012;50(8):668-675. doi:10.1097/MLR.0b013e3182551763.

20. Donaldson L. *The Contingency Theory of Organizations*. Thousand Oaks, California: SAGE Publications, Inc.; 2001.

21. Institute for Alternative Futures. *Community Health Centers Leveraging the Social Determinants of Health*. Alexandria, VA; 2012. http://www.altfutures.org/pubs/leveragingSDH/IAF-CHCsLeveragingSDH.pdf.

22. Rihoux B, Lobe B. The Case for Qualitative Comparative Analysis (QCA): Adding Leverage for Thick Cross-Case Comparison. In: Byrne D, Ragin C, eds. *The SAGE Handbook of Case-Based Methods*. London : SAGE Publications Ltd; 2009:222-242. doi:10.4135/9781446249413.n13.

23. Pardue Jones B, Fleming GM, Otillio JK, Asokan I, Arnold DH. Pediatric acute asthma exacerbations: Evaluation and management from emergency department to intensive care unit. *J Asthma*. 2016;53(6):607-617. doi:10.3109/02770903.2015.1067323.

24. Pearson WS, Goates SA, Harrykissoon SD, Miller SA. State-Based Medicaid Costs for Pediatric Asthma Emergency Department Visits. *Prev Chronic Dis*. 2014;11:140139. doi:10.5888/pcd11.140139.

25. Centers for Disease Control. Asthma - Data, Statistics and Surveillance. http://www.cdc.gov/asthma/asthmadata.htm. Published 2016. Accessed October 13, 2016.

26. Elixhauser A, Heslin K, PL O. *Healthcare Cost and Utilization Project (HCUP) Recommendations for Reporting Trends Using ICD-9-CM and ICD-10-CM/PCS Data*.; 2017. www.hcup - us.ahrq.gov/datainnovations/icd10_resources.jsp.

27. Domino ME, Humble C, Lawrence WW, Wegner S. Enhancing the Medical Homes Model for Children With Asthma. *Med Care*. 2009;47(11):1113-1120. doi:10.1097/MLR.0b013e3181adcc65.

28. Barrett ML, Wier LM, Washington R. *Trends in Pediatric and Adult Hospital Stays for Asthma, 2000–2010. HCUP Statistical Brief #169*. Rockville, MD; 2014. http://www.hcup-us.ahrq.gov/reports/statbriefs/sb169-Asthma-Trends-Hospital-Stays.pdf. Accessed November 23, 2016.

29. Nath JB, Hsia RY. Children's emergency department use for asthma, 2001-2010. *Acad Pediatr*. 2015;15(2):225-230. doi:10.1016/j.acap.2014.10.011.

30. Tang N, Stein J, Hsia RY, Maselli JH, Gonzales R. Trends and Characteristics of US Emergency Department Visits, 1997-2007. *JAMA*. 2010;304(6):664. doi:10.1001/jama.2010.1112.

31. Johnson PJ, Ghildayal N, Ward AC, Westgard BC, Boland LL, Hokanson JS. Disparities in Potentially Avoidable Emergency Department (ED) Care. *Med Care*. 2012;50(12):1020-1028. doi:10.1097/MLR.0b013e318270bad4.

32. Domino M, Tyree S, Rutledge R, Holmes M. *Findings Brief: Identifying Rural Health Clinics in Medicaid Data*.; 2016. https://www.ruralhealthresearch.org/publications/1036.

33. Raphael JL, Cooley WC, Vega A, et al. Outcomes for Children with Chronic Conditions Associated with Parent- and Provider-reported Measures of the Medical Home. *J Health Care Poor Underserved*. 2015;26(2):358-376. doi:10.1353/hpu.2015.0051.

34. Spatz ES, Ross JS, Desai MM, Canavan ME, Krumholz HM. Beyond insurance coverage: Usual source of care in the treatment of hypertension and hypercholesterolemia. Data from the 2003-2006 National Health and Nutrition Examination Survey. *Am Heart J*. 2010;160(1):115-121. doi:10.1016/j.ahj.2010.04.013.

35. Gurewich D, Tyo KR, Zhu J, Shepard DS. Comparative Performance of Community Health Centers and Other Usual Sources of Primary Care. *J Ambul Care Manage*. 2011;34(4):380-390. doi:10.1097/JAC.0b013e31822cbc59.

36. *Medicare Shared Savings Program: Shared Savings and Losses and Assignment Methodology Specifications*. Baltimore; 2015. https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/sharedsavingsprogram/Downloads/Shared-Savings-Losses-Assignment-Spec-V4.pdf. Accessed April 18, 2017.

37. Agency for Healthcare Research and Quality. HCUP Chronic Condition Indicator. Healthcare Cost and Utilization Project (HCUP). https://www.hcup-us.ahrq.gov/toolssoftware/chronic/chronic.jsp. Accessed April 21, 2017.

38. Breslau N, Reeb KG. Continuity of care in a university-based practice. *J Med Educ*. 1975;50(10):965-969. http://www.ncbi.nlm.nih.gov/pubmed/1159765. Accessed April 22, 2017.

39. Kuhlthau K, Ferris TGG, Iezzoni LI. Risk Adjustment for Pediatric Quality Indicators. *Pediatrics*. 2004;113(1):210-216. http://pediatrics.aappublications.org/content/pediatrics/113/Supplement_1/210.full.pdf. Accessed October 11, 2016.

40. Cazzola M, Segreti A, Calzetta L, Rogliani P. Comorbidities of asthma. *Curr Opin Pulm Med*. 2013;19(1):36-41. doi:10.1097/MCP.0b013e32835b113a.

41. Tan RA, Corren J. The relationship of rhinitis and asthma, sinusitis, food allergy, and eczema. *Immunol Allergy Clin North Am*. 2011;31(3):481-491. doi:10.1016/j.iac.2011.05.010.

42. Wolinsky FD, Miller TR, Geweke JF, et al. An interpersonal continuity of care measure for Medicare Part B claims analyses. *Journals Gerontol Ser B Psychol Sci Soc Sci*. 2007;62(3):S160-8. http://www.ncbi.nlm.nih.gov/pubmed/17507591. Accessed November 8, 2018.

43. American Academy of Pediatrics. Key Points for Asthma Guideline Implementation. https://www.aap.org/en-us/Documents/medicalhome_resources_keypointsforasthma.pdf. Published 2013.

44. Krieger N, Chen JT, Waterman PD, Soobader M-J, Subramanian S V, Carson R. Choosing area based socioeconomic measures to monitor social inequalities in low birth weight and childhood lead poisoning: The Public Health Disparities Geocoding Project (US). *J Epidemiol Community Health*. 2003;57(3):186-199. doi:10.1136/jech.57.3.186.

45. Diez-Roux A V, Kiefe CI, Jacobs DR, et al. Area characteristics and individual-level socioeconomic position indicators in three population-based epidemiologic studies. *Ann Epidemiol*. 2001;11(6):395-405. http://www.ncbi.nlm.nih.gov/pubmed/11454499. Accessed September 15, 2017.

46. *Ambulatory Care Sensitive Condition Hospital Admissions (2004) for Asthma*. http://www.shepscenter.unc.edu/rural/maps/ACS2004_18underNC.pdf.

47. Thiem A, Baumgartner M, Bol D. Still Lost in Translation! A Correction of Three Misunderstandings Between Configurational Comparativists and Regressional Analysts. *Comp Polit Stud*. 2016;49(6):742-774. doi:10.1177/0010414014565892.

48. Baumgartner M, Ambühl M. Causal Modeling with Multi-Value and Fuzzy-Set Coincidence Analysis. *Polit Sci Res Method*. 2018:1-17. doi:10.1017/psrm.2018.45.

49. Medical Resource Council. *A Framework for Development and Evaluation of RCTs for Complex Interventions to Improve Health*.; 2000. https://mrc.ukri.org/documents/pdf/rcts-for-complex-interventions-to-improve-health/.

50. Pfadenhauer L, Gerhardus A, Mozygemba, K et al. Making sense of complexity in context and implementation: the Context and Implementation of Complex Interventions (CICI) framework. *Implement Sci*. 2013;12(1):21.

51. Baumgartner M. Uncovering deterministic causal structures: a Boolean approach. *Synthese*. 2009;170(1):71-96. doi:10.1007/s11229-008-9348-0.

52. Baumgartner M. Inferring Causal Complexity. *Sociol Methods Res*. 2009;38(1):71-101. doi:10.1177/0049124109339369.

53. Baumgartner M, Thiem A. Model Ambiguities in Configurational Comparative Research. *Sociol Methods Res*. October 2015. doi:10.1177/0049124115610351.

54. Baumgartner M. Parsimony and Causality. *Qual Quant*. 2015;49(2):839-856. doi:10.1007/s11135-014-0026-7.

55. Ragin CC. Set Relations in Social Research: Evaluating Their Consistency and Coverage. *Polit Anal*. 2006;14(03):291-310. doi:10.1093/pan/mpj019.

56. Kahwati LC, Lewis MA, Kane H, et al. Best Practices in the Veterans Health Administration's MOVE! Weight Management Program. *Am J Prev Med*. 2011;41(5):457-464. doi:10.1016/j.amepre.2011.06.047.

57. Ambuehl M, Baumgartner M. cna: Causal modeling with Coincidence Analysis. 2017. https://cran.r-project.org/package=cna.

58. Kahn KL, Timbie JW, Friedberg MW, et al. *Evaluation of CMS's Federally Qualified Health Center (FQHC) Advanced Primary Care Practice (APCP) Demonstration*. Santa Monica; 2016. https://downloads.cms.gov/files/cmmi/fqhc-finalevalrpt.pdf.

59. Bradley EH, Elkins BR, Herrin J, Elbel B. Health and social services expenditures: associations with health outcomes. *BMJ Qual Saf*. 2011;20(10):826-831. doi:10.1136/bmjqs.2010.048363.

60. Bradley EH, Canavan M, Rogan E, et al. Variation In Health Outcomes: The Role Of Spending On Social Services, Public Health, And Health Care, 2000-09. *Health Aff*. 2016;35(5):760-768. doi:10.1377/hlthaff.2015.0814.

61. Gottlieb LM, Hessler D, Long D, et al. Effects of Social Needs Screening and In-Person Service Navigation on Child Health. *JAMA Pediatr*. 2016;170(11):e162521. doi:10.1001/jamapediatrics.2016.2521.

62. Vest JR, Harris LE, Haut DP, Halverson PK, Menachemi N. Indianapolis Provider's Use Of Wraparound Services Associated With Reduced Hospitalizations And Emergency Department Visits. *Health Aff*. 2018;37(10):1555-1561. doi:10.1377/hlthaff.2018.0075.

CHAPTER FIVE: DISCUSSION

Overview of Findings

The purpose of this research was to examine organizational characteristics associated with high performance among federally qualified health centers (FQHCs). We narrowly defined our study sample to include North Carolina FQHCs and Medicaid-insured children with asthma because North Carolina had yet to implement full Medicaid managed care, which reduced the "noise" present in claims data stemming from multiple insurance companies influencing practice patterns (e.g., imposing their own utilization review or quality management systems). Additionally, asthma is one of the mostly commonly diagnosed chronic diseases in children,[1] has strong face validity as an ambulatory care sensitive condition,[2,3] and disproportionately affects low-income and minority children.[4]

Our research consisted of three studies. In Aim 1, we estimated the association of FQHC use with preventable hospital utilization in a population of Medicaid-insured children with asthma. The purpose of this analysis was to: 1) measure the association of FQHC use in a pediatric population, a group that has been understudied in the FQHC literature, and 2) to assess FQHC performance relative to other primary care practices in North Carolina to help contextualize the results of Aims 2 and 3.

In Aim 2, we applied three different performance classification methodologies (unadjusted crude rate, hierarchical generalized linear models and fixed effect models) across two model specifications (with and without risk adjustment for the percent of patients without insurance) to rank FQHCs according to preventable hospital utilization rates. Since no "gold standard" in performance classification exists, we sought to incorporate performance classification results across multiple statistical methods and model specifications in order to generate a more robust performance classification. In Aim 3, we utilized both regression-based and configurational comparative methods to identify FQHC characteristics associated with lower preventable hospital utilization. In particular, we were interested in the association of non-medical services with preventable hospital use.

The results of these studies add to the literature on FQHC performance and performance classification. In particular, we found that FQHC use was associated with higher preventable hospital utilization among Medicaid-insured children with asthma even after controlling for patient selection into FQHCs and a range of patient characteristics such as race/ethnicity, number of chronic conditions, utilization of specialty care for asthma and continuity of care. Because emergency department (ED) utilization comprised the majority of hospital utilization for pediatric asthma in this study, ED use likely drove the magnitude of the FQHC effect. Higher rates of ED utilization among FQHC patients compared to non-FQHC patients align with the results of previous studies in adult populations.[5–7]

Community Care of North Carolina's (CCNC) primary care case management and medical home model also likely influenced the differential effect of FQHC use in this patient population. CCNC has been shown to reduce hospital utilization, lower costs and improve health outcomes.[8] Moreover, Medicaid-insured patients enrolled in CCNC have better process and outcome quality measures for chronic disease management relative to patients enrolled in Medicaid managed care programs in other states.[9] CCNC may influencing Medicaid enrollees' health outcomes and utilization in ways not duplicated in other states.

Greater ED utilization among FQHC patients may also be driven by FQHC appointment availability or clinic accessibility.[10] Moreover, non-hospital-based urgent care resources are less common in low-income communities[11] – communities often served by FQHCs – potentially causing more people to utilize the ED in these areas.

Among patients attributed to FQHC practices, we found substantial variation in hospital utilization rates across organizations. After testing three different methodologies across two model specifications, we found variation in FQHC rankings across the five methodologies. However, the organizations in the top and bottom 25% of the rankings remained relatively consistent across methods. Therefore, minimal variation existed in the top and bottom organizations' absolute rankings across methods. We demonstrated that the geometric mean could be used to generate an overall ranking across methodologies because it is indifferent to the various methods used to generate the rankings, it incorporates all data points, and it is not as susceptible to outlier rankings across methodologies. A similar approach may be useful for researchers, policymakers or payers who seek to generate relative performance rankings across organizations but who are concerned about the limitations associated with any one statistical method.

In the final study examining FQHC organizational characteristics associated with high performance, we found surprising results. We expected the provision of non-medical services in FQHCs would be associated with lower preventable hospital use, but neither the regression-based nor the configurational comparative analysis findings supported our hypothesis. Across these two methodological approaches, the results indicated that certain non-medical services were associated with higher preventable hospital utilization and lower organization performance. These results are surprising because, according to structural contingency theory,[12] FQHCs offering a broader scope of services and greater non-medical FTE staff have recognized and responded to the greater health and social needs of their patient population. Vulnerable patients are more likely to face social, economic and resource barriers to good health, and providing non-medical services and enabling services are intended to help address or alleviate some of these barriers.[13] Indeed, previous research found reduced hospital utilization following receipt of certain non-medical services.[14] Perhaps FQHCs with more non-medical services and greater staffing of non-medical services have more frequent patient "touches," which could identify underlying health problems that warrant more immediate medical attention in the hospital. Alternatively, FQHCs with a broader scope of non-medical services and more non-medical services staffing may be prioritizing patient's non-medical causes of poor health ahead of routine clinical care.[15]

These findings are associated with substantial limitations. The FQHC characteristics included in this study were measured at an organization-level and did not reflect patient-level utilization. In other words, non-medical services might not be equally accessible to all patients within an FQHC organization. Furthermore, neither Medicaid claims data nor UDS data indicated which patients accessed enabling services at FQHCs. Children might access FQHCs' non-medical services less frequently than adult populations, for example. Therefore, our ability to make inferences about these organization-level characteristics and patient-level outcomes was limited.

Policy Implications

Our findings highlight the importance of identifying processes of care within FQHCs or structural barriers within communities served by FQHCs that may encourage patients to utilize the hospital more frequently.

Furthermore, our analysis suggests that health care organization performance profiling with research or policy applications should examine the influence of methodology and risk adjusters on performance and determine whether results are robust to the methodological approach and model specification. Policymakers and researchers might consider utilizing an overall ranking that encompasses results from multiple methodologies and model specifications.

Finally, our results highlight the need for policymakers and payers to consider including non-medical service revenue codes in claims to encourage system-wide examination of the effectiveness of these services in reducing health care costs and utilization and improving patient outcomes. Having a revenue code for non-medical services in claims data would permit researchers to model health care utilization, costs and outcomes as a function of receipt of non-medical services.

Limitations and Directions for Future Research

There are several important limitations to this research that are worth reiterating. First, the study design presents a time-ordering problem for hospital use – patients could be going to the hospital before or after seeing a provider. Despite this concern, all model specifications comparing FQHC to non-FQHC patients found similar results in both direction and significance.

Another limitation is the challenge associated with risk adjustment in a pediatric population given relatively low morbidity and mortality rates and the different application of diagnoses, drugs and procedures in pediatric populations than adult populations.[16] Furthermore, FQHCs are known to under-code diagnoses on claims because they are paid on a per-visit basis; reimbursement is not tied to services and diagnosis codes as under traditional fee-for-service reimbursement models.[17,18] Our analysis somewhat mitigated this under-coding bias by utilizing both outpatient and hospital-based claims for measuring patient acuity. Even so, we may not have captured something related to patient acuity in a pediatric population that could be driving observed relationships.

Importantly, UDS data were self-reported and unaudited. As a result, there may be measurement error in our model covariates, potentially biasing our results. Finally, our analysis was limited to the organizational characteristics available in UDS data. Other organizational factors (e.g., leadership, community partnerships) not available in these data might be contributing to observed relationships. For example, the configurational comparative results indicated that having a large number of clinic sites was associated with high performance. Having a large number of clinic sites could be a reflection of leadership that is more proactive in meeting community needs.

Directions for Future Research

Our analyses utilized organization-level UDS data that could not be linked to patient-level data. Future research examining FQHC services should explore electronic health record data to better assess the effect of non-medical services on patient-level utilization, cost and outcomes. Additionally, the International Statistical Classification of Diseases and Related Health Problems, Tenth Revision (ICD-10) diagnosis codes for non-medical causes of poor health present exciting opportunities for research into risk adjustment algorithms potentially important for FQHC to non-FQHC comparisons if more health care providers utilize these codes.[19]

Because our research focused narrowly on pediatric asthma, future studies could replicate these analyses in different study populations or with different disease categories. Future studies should ensure the study population exhibits variation in inpatient hospital use to determine whether the effect of FQHC use, as well as FQHC characteristics, vary according to ED versus inpatient hospital utilization.

Finally, qualitative research could help identify how organizational factors not available in quantitative data (e.g., leadership, community partnerships) may contribute to the observed relationships between organizational characteristics and organization performance. Furthermore, qualitative interviews could identify organizational structures and processes underlying chronic disease care and access to non-medical services. For example, qualitative interviews could assess how pediatric patients access non-medical services within FQHCs. At the time of this writing, few studies examining FQHC performance and FQHC organizational characteristics have utilized qualitative interviews to verify quantitative findings and generate a more in-depth understanding of contextual factors influencing performance that are not observed in standard data sets.

Conclusion

Federally qualified health centers are vital primary care providers for low-income, uninsured and underinsured populations. Measuring their performance relative to other providers is an important endeavor for addressing the Triple Aim of lower costs, better patient outcomes and better population health. Moreover, identifying “successful” FQHC practice models could encourage their replication across the FQHC program and in other practice settings.

In this study, FQHC use was associated with a higher likelihood of preventable hospital utilization among Medicaid-insured children with asthma in North Carolina. Patients using FQHCs with a broader scope of non-medical services and more of certain types of non-medical services staff were more likely to have preventable hospital utilization. Understanding the organizational characteristics associated with lower preventable hospital utilization rates among FQHCs is both timely and policy-relevant given the growth of the FQHC program[20] and ongoing health care payment and delivery system reforms. However, the FQHC characteristics in this study did not reflect patient-level utilization, and non-medical services might not be equally accessible to all patients within an FQHC organization.

The results of this research provide additional insight into the complexities inherent in measuring the effect of FQHCs in pediatric populations. The surprising and counterintuitive finding that certain non-medical services are associated with higher hospital utilization should encourage future research using FQHCs' electronic health record data and qualitative interviews to best identify organization structures and processes associated with performance. These findings also underscore the need for policymakers and payers to incorporate encounter-level data on non-medical services in claims submissions in order to better measure the effect of non-medical services on health care costs, utilization and outcomes across all provider types.

REFERENCES

1. Pardue Jones B, Fleming GM, Otillio JK, Asokan I, Arnold DH. Pediatric acute asthma exacerbations: Evaluation and management from emergency department to intensive care unit. *J Asthma*. 2016;53(6):607-617. doi:10.3109/02770903.2015.1067323.

2. Billings J, Parikh N, Mijanovish T. *Emergency Department Use in New York City: A Substitute for Primary Care?*; 2000.

3. Faculty & Research. NYU Center for Health and Public Service Research. https://wagner.nyu.edu/faculty/billings/nyued-background. Accessed October 3, 2017.

4. Centers for Disease Control. Asthma - Data, Statistics and Surveillance. http://www.cdc.gov/asthma/asthmadata.htm. Published 2016. Accessed October 13, 2016.

5. Potter AJ, Trivedi AN, Wright B. Younger Dual-Eligibles Who Use Federally Qualified Health Centers Have More Preventable Emergency Department Visits, but Some Have Fewer Hospitalizations. *J Prim Care Community Health*. 2017;8(1):3–8. doi:10.1177/2150131916657081.

6. Wright B, Potter AJ, Trivedi A. Federally Qualified Health Center Use Among Dual Eligibles: Rates Of Hospitalizations And Emergency Department Visits. *Health Aff*. 2015;34(7):1147-1155. doi:10.1377/hlthaff.2014.0823.

7. Wright B, Potter AJ, Trivedi AN. Use of Federally Qualified Health Centers and Potentially Preventable Hospital Utilization Among Older Medicare-Medicaid Enrollees. *J Ambul Care Manage*. 2017;40(2):139-149. doi:10.1097/JAC.0000000000000158.

8. Jackson CT, Trygstad TK, DeWalt DA, DuBard CA. Transitional Care Cut Hospital Readmissions For North Carolina Medicaid Patients With Complex Chronic Conditions. *Health Aff*. 2013;32(8):1407-1415. doi:10.1377/hlthaff.2013.0047.

9. DuBard AC. Improving the Quality of Care for Medicaid Patients with Chronic Diseases: Community Care of North Carolina. *N C Med J*. 2013;74(2):142-147.

10. Kangovi S, Barg FK, Carter T, Long JA, Shannon R, Grande D. Understanding Why Patients Of Low Socioeconomic Status Prefer Hospitals Over Ambulatory Care. *Health Aff*. 2013;32(7):1196-1203. doi:10.1377/hlthaff.2012.0825.

11. Le ST, Hsia RY. Community characteristics associated with where urgent care centers are located: a cross-sectional analysis. *BMJ Open*. 2016;6(4):e010663. doi:10.1136/bmjopen-2015-010663.

12. Donaldson L. *The Contingency Theory of Organizations*. Thousand Oaks, California: SAGE Publications, Inc.; 2001.

13. Institute for Alternative Futures. *Community Health Centers Leveraging the Social Determinants of Health*. Alexandria, VA; 2012. http://www.altfutures.org/pubs/leveragingSDH/IAF-CHCsLeveragingSDH.pdf.

14. Vest JR, Harris LE, Haut DP, Halverson PK, Menachemi N. Indianapolis Provider's Use Of Wraparound Services Associated With Reduced Hospitalizations And Emergency Department Visits. *Health Aff*. 2018;37(10):1555-1561. doi:10.1377/hlthaff.2018.0075.

15. Cross DA, Cohen GR, Lemak CH, Adler-Milstein J. Outcomes For High-Needs Patients: Practices With A Higher Proportion Of These Patients Have An Edge. *Health Aff*. 2017;36(3):476-484. doi:10.1377/hlthaff.2016.1309.

16. Kuhlthau K, Ferris TGG, Iezzoni LI. Risk Adjustment for Pediatric Quality Indicators. *Pediatrics*. 2004;113(1):210-216. http://pediatrics.aappublications.org/content/pediatrics/113/Supplement_1/210.full.pdf. Accessed October 11, 2016.

17. Gurewich D, Tyo KR, Zhu J, Shepard DS. Comparative Performance of Community Health Centers and Other Usual Sources of Primary Care. *J Ambul Care Manage*. 2011;34(4):380-390. doi:10.1097/JAC.0b013e31822cbc59.

18. Nocon RS, Lee SM, Sharma R, et al. Health Care Use and Spending for Medicaid Enrollees in Federally Qualified Health Centers Versus Other Primary Care Settings. *Am J Public Health*. 2016;106(11):1981-1989. doi:10.2105/AJPH.2016.303341.

19. Gottlieb L, Tobey R, Cantor J, Hessler D, Adler NE. Integrating Social And Medical Data To Improve Population Health: Opportunities And Barriers. *Health Aff*. 2016;35(11):2116-2123. doi:10.1377/hlthaff.2016.0723.

20. Bureau of Primary Health Care. Health Center Program: Impact and Growth. https://bphc.hrsa.gov/about/healthcenterprogram/index.html. Accessed August 9, 2017.

APPENDIX A: VARIABLE DEFINITIONS FOR AIMS 1-3

Primary care provider definition:

We utilized rendering and billing provider taxonomy codes to identify primary care providers according to the classifications and taxonomy codes outlined in the table below:

Classification	*Taxonomy code*
Midwives	176B00000X
Nurse practitioners & physician assistants	363A00000X, 363L00000X, 364S00000X, 367A00000X
Internal medicine physicians	207R00000X, 207RA0000X
Pediatric physicians	208000000X, 2080A0000X
Family medicine physicians	207Q00000X, 207QA0000X
OBGYN physicians	207V00000X, 207VG0400X, 207VM0101X, 207VX0000X
Preventive medicine physicians	2083P0500X, 2083P0901X, 2083X0100X
General practice physicians	208D00000X
Rural health clinic, community clinic and public health	261QC1500X, 261QP0905X, 261QR1300X
Federally qualified health center	261QF0400X

The primary care provider definition also included practices flagged as Community Care of North Carolina (CCNC) practices in Medicaid management claims. Specialty providers were not included.

Primary care and preventive services definition:

The following Current Procedural Terminology codes were used to identify primary care and preventive services:

ACA-defined primary care visits	
99201-99205	Preventive medicine service code
99211-99215	Preventive medicine service code
99324-99328	New patient domiciliary, rest home, or custodial care visit
99334-99337	Established patient domiciliary, rest home, or custodial care visit
99339-99340	Individual physician supervision of a patient in home, domiciliary or rest home
99341-99345	New patient home visit

99347-99350	Established patient home visit
AAP-identified codes for preventive services	
99382-99385	Preventive medicine service code
99392-99395	Preventive medicine service code
99429	Unlisted preventive medicine service
90460-90461	Immunizations
90471-90474	Immunizations (non-age specific)
S0302	Early and Periodic Screening, Diagnostic & Treatment (EPSDT)
Other preventive services	
99499	Other Evaluation & Management
99354	Prolonged physician services
99355	Prolonged physician services
G0463	Hospital outpatient clinic visit for assessment & management (OPPS)
T1015	All-inclusive visit (FQHC code)

Patients were attributed to the primary care organization (billing provider NPI) from which they received the plurality of primary and preventive care services.

Specialty provider definition:

Specialists for asthma care were identified using the following billing and rendering provider taxonomy codes:

Classification	*Taxonomy code*
Allergy & Immunology	207K00000X, 207KA0200X
Internal Medicine, Pulmonary Disease	207RP1001X
Pediatrics, Pediatric Pulmonology	2080P0214X
Internal Medicine, Allergy & Immunology	207RA0201X
Otolaryngology, Otolaryngic Allergy	207YX0602X
Pediatrics, Pediatric Allergy/Immunology	2080P0201X

Community Care of North Carolina-participating organization:

Practices were flagged as CCNC practices according to the following algorithm:

- For 2012 claims (reference year): Procedure codes W9920, W9921 and W9925 represent per member per month payments to practices for an individual enrollee.
- For claims after 2013: Claim Type Code = M and Managed Care Cohort ID = 8, 10 and Claim Base Amount Source Code = HE, HA.

Identifying hospital utilization:

Emergency department (ED) visits were identified using revenue codes 0450-0459 and 0981. Observation stays were identified using either revenue codes (0760 and 0762) or Current Procedural Terminology codes (99217-9920, 99224-99226, 99234-99236, G0378 and G0379).[1,2] Inpatient stays were identified using place of service code 21 and header type code "I" for inpatient. (All room and board revenue codes indicating an inpatient stay corresponded with the header type code = "I".)

REFERENCES

1. Lind KD, Noel-Miller CM, Sangaralingham LR, et al. Increasing Trends in the Use of Hospital Observation Services for Older Medicare Advantage and Privately Insured Patients. *Med Care Res Rev*. July 2017:107755871771802. doi:10.1177/1077558717718026.

2. Centers for Medicare & Medicaid Services. *January 2006 Update of the Hospital Outpatient Prospective Payment System (OPPS) Manual Instruction: Changes to Coding and Payment for Observation*.; 2005. https://www.cms.gov/Regulations-and-Guidance/Guidance/Transmittals/downloads/r787cp.pdf.

APPENDIX B: AIM 1 SENSITIVITY ANALYSES

Table B.1. Differential Effect of Federally Qualified Health Center (FQHC) Use in All Model Specifications

	Model specification - Attribution method and outcome definition	Model 1 Any hospital utilization (ED, observation or inpatient stay) with a principal diagnosis of asthma	Model 2 ED visit with principal diagnosis of asthma	Model 3 Any hospital utilization (ED, observation or inpatient stay) with any diagnosis of asthma	Model 4 ED visit with any diagnosis of asthma
1	Plurality of services attribution *(Main model specification)*	0.0121**	0.0125***	0.0286***	0.0311***
2	Plurality of services attribution with 60-day washout period for hospital utilization	0.0121**	0.0126***	0.0227***	0.0239***
3	CCNC medical home-based attribution	0.0169***	0.0178***	0.0384***	0.0436***
4	Ever FQHC patient	0.0114***	0.0117***	0.0291***	0.0318***
5	Lagged FQHC attribution	0.0134**	0.0141**	0.0452***	0.0438***

Note: The analysis sample varied across the five sensitivity analyses.
*** p<0.001, ** p<0.01, * p<0.05

Table B.2. Average Marginal Effects of Model Covariates on Preventable Hospital Utilization with a 60-Day Washout Period

	Model 1 Any hospital utilization (ED, observation or inpatient stay) with a principal diagnosis of asthma	Model 2 ED visit with principal diagnosis of asthma	Model 3 Any hospital utilization (ED, observation or inpatient stay) with any diagnosis of asthma	Model 4 ED visit with any diagnosis of asthma
FQHC patient	0.0121**	0.0126***	0.0227***	0.0239***
	(0.00374)	(0.00371)	(0.00502)	(0.00471)
Age	-0.00475***	-0.00345***	-0.00591***	-0.00439***
	(0.000139)	(0.000125)	(0.000198)	(0.000187)
Race/Ethnicity (*ref. White. not Hispanic*)				
Black, not Hispanic	0.0465***	0.0426***	0.0603***	0.0575***
	(0.00109)	(0.00099)	(0.00166)	(0.00161)
Hispanic	0.00447***	0.00320**	-0.0325***	-0.0328***
	(0.00132)	(0.00118)	(0.00213)	(0.00203)
Multiple/Other, not Hispanic	0.00821***	0.00611**	-0.0104**	-0.0125***
	(0.00225)	(0.00212)	(0.00377)	(0.00362)
Unknown	0.00910***	0.00767***	-0.00159	-0.00597
	(0.00218)	(0.00203)	(0.00364)	(0.00365)
Female sex (*ref. male*)	-0.00690***	-0.00592***	-0.00309*	-0.00239
	(0.000934)	(0.000879)	(0.00136)	(0.00133)
Months of Medicaid coverage in calendar year	0.00128***	0.00149***	0.00451***	0.00512***
	(0.000233)	(0.000225)	(0.000354)	(0.000358)
Rural residence (*ref. non-rural*)	0.00556***	0.00626***	0.0241***	0.0256***
	(0.00129)	(0.00118)	(0.00200)	(0.00192)
Utilized specialty care for asthma	0.0314***	0.0220***	0.000232	-0.00316
	(0.00174)	(0.00160)	(0.00213)	(0.00207)
Total primary care visits	0.00179***	0.00146***	0.00449***	0.00326***
	(0.000119)	(0.000112)	(0.000187)	(0.000185)
Number of chronic conditions	0.00556***	0.00443***	0.0394***	0.0292***
	(0.000361)	(0.000343)	(0.000594)	(0.000582)
Continuity of care in calendar year	0.0371***	0.0309***	0.0361***	0.0259***
	(0.00318)	(0.00299)	(0.00450)	(0.00442)

County-level covariates				
Percent of population living below federal poverty line	0.00191***	0.00157***	0.000205	-0.00042
	(0.000233)	(0.000215)	(0.000366)	(0.000347)
Median household income (in $10,000)	0.00640***	0.00400***	-0.00225	-0.00591**
	(0.00128)	(0.00119)	(0.00196)	(0.00188)
Annual concentration of air particulate matter	-0.000888	-0.00133	0.00108	0.00139
	(0.000760)	(0.000703)	(0.00118)	(0.00115)
Number of Medicaid patients with asthma served by attributed provider organization in calendar year (in 10,000)	0.000198***	0.000156**	0.000362***	0.000283***
	(0.0000551)	(0.0000516)	(0.0000843)	(0.0000821)
Year (*ref. 2013*)				
2014	-0.0137***	-0.0127***	-0.0324***	-0.0345***
	(0.00165)	(0.00155)	(0.00247)	(0.00240)
2015	-0.0375***	-0.0326***	-0.0670***	-0.0654***
	(0.00159)	(0.00145)	(0.00251)	(0.00245)
Pearson residual	-0.00145	-0.00139	-0.00132	-0.000938
	(0.000752)	(0.000735)	(0.000953)	(0.000844)
Observations	381,723	381,723	381,723	381,723

Bootstrapped standard errors in parentheses.

*** p<0.001, ** p<0.01, * p<0.05

Table B.3. Average Marginal Effects of Model Covariates on Preventable Hospital Utilization - CCNC Medical Home Attribution

	Model 1 Any hospital utilization (ED, observation or inpatient stay) with a principal diagnosis of asthma	Model 2 ED visit with principal diagnosis of asthma	Model 3 Any hospital utilization (ED, observation or inpatient stay) with any diagnosis of asthma	Model 4 ED visit with any diagnosis of asthma
FQHC patient	0.0169***	0.0178***	0.0384***	0.0436***
	(0.00490)	(0.00490)	(0.00788)	(0.00816)
Age	-0.00500***	-0.00355***	-0.00586***	-0.00413***
	(0.000160)	(0.000145)	(0.000220)	(0.000213)
<u>Race/Ethnicity (*ref. White. not Hispanic*)</u>				
Black, not Hispanic	0.0545***	0.0497***	0.0685***	0.0653***
	(0.00141)	(0.00134)	(0.00220)	(0.00216)
Hispanic	0.00379**	0.00227	-0.0422***	-0.0426***
	(0.00138)	(0.00132)	(0.00243)	(0.00238)
Multiple/Other, not Hispanic	0.00958***	0.00716**	-0.0112*	-0.0142**
	(0.00277)	(0.00254)	(0.00456)	(0.00443)
Unknown	0.0104***	0.00897***	-0.00602	-0.00983*
	(0.00271)	(0.00250)	(0.00423)	(0.00422)
Female sex (*ref. male*)	-0.00711***	-0.00611***	-0.00204	-0.0011
	(0.00117)	(0.00107)	(0.00166)	(0.00160)
Months of Medicaid coverage in calendar year	-7.26E-05	0.000347	0.000909*	0.00175***
	(0.000285)	(0.000268)	(0.000430)	(0.000407)
Rural residence (*ref. non-rural*)	0.00681***	0.00767***	0.0292***	0.0311***
	(0.00152)	(0.00142)	(0.00226)	(0.00220)
Utilized specialty care for asthma	0.0288***	0.0188***	-0.0169***	-0.0202***
	(0.00193)	(0.00175)	(0.00249)	(0.00240)
Total primary care visits	0.00115***	0.000876***	0.00203***	0.00103***
	(0.000130)	(0.000120)	(0.000217)	(0.000211)
Number of chronic conditions	0.00538***	0.00430***	0.0445***	0.0324***
	(0.000484)	(0.000443)	(0.000727)	(0.000696)

Continuity of care in calendar year	0.0182***	0.0142***	-0.0270***	-0.0303***
	(0.00330)	(0.00305)	(0.00469)	(0.00455)
<u>County-level covariates</u>				
Percent of population living below federal poverty line	0.00237***	0.00189***	0.000587	-0.000245
	(0.000274)	(0.000259)	(0.000428)	(0.000413)
Median household income (in $10,000)	0.00853***	0.00520***	-0.000509	-0.00565**
	(0.00151)	(0.00143)	(0.00221)	(0.00216)
Annual concentration of air particulate matter	0.00066	-4.23E-05	0.00528***	0.00498***
	(0.000922)	(0.000864)	(0.00133)	(0.00125)
Number of Medicaid patients with asthma served by attributed provider organization in calendar year (in 10,000)	0.000158*	0.000106	0.000294**	0.000173
	(0.0000685)	(0.0000633)	(0.000106)	(0.000101)
<u>Year (*ref. 2013*)</u>				
2014	-0.0202***	-0.0187***	-0.0450***	-0.0461***
	(0.00199)	(0.00184)	(0.00272)	(0.00259)
2015	-0.0513***	-0.0448***	-0.0973***	-0.0934***
	(0.00199)	(0.00184)	(0.00273)	(0.00264)
Pearson residual	-0.00162	-0.00164	-0.00218	-0.00266
	(0.000990)	(0.000984)	(0.00170)	(0.00176)
Observations	315,562	315,562	315,562	315,562

Bootstrapped standard errors in parentheses.

*** p<0.001, ** p<0.01, * p<0.05

Table B.4. Average Marginal Effects of Model Covariates on Preventable Hospital Utilization - Ever-FQHC Attribution

	Model 1 Any hospital utilization (ED, observation or inpatient stay) with a principal diagnosis of asthma	Model 2 ED visit with principal diagnosis of asthma	Model 3 Any hospital utilization (ED, observation or inpatient stay) with any diagnosis of asthma	Model 4 ED visit with any diagnosis of asthma
Ever FQHC patient	0.0114***	0.0117***	0.0291***	0.0318***
	(0.00288)	(0.00279)	(0.00397)	(0.00359)
Age	-0.00513***	-0.00364***	-0.00562***	-0.00396***
	(0.000147)	(0.000131)	(0.000203)	(0.000189)
Race/Ethnicity (*ref. White. not Hispanic*)				
Black, not Hispanic	0.0544***	0.0497***	0.0678***	0.0649***
	(0.00119)	(0.00108)	(0.00179)	(0.00173)
Hispanic	0.00471***	0.00343**	-0.0423***	-0.0421***
	(0.00141)	(0.00126)	(0.00228)	(0.00218)
Multiple/Other, not Hispanic	0.0104***	0.00788***	-0.0117**	-0.0146***
	(0.00255)	(0.00236)	(0.00418)	(0.00402)
Unknown	0.0110***	0.00980***	-0.00506	-0.00819*
	(0.00242)	(0.00225)	(0.00403)	(0.00399)
Female sex (*ref. male*)	-0.00703***	-0.00608***	-0.00148	-0.000418
	(0.00102)	(0.000965)	(0.00147)	(0.00145)
Months of Medicaid coverage in calendar year	-0.000479*	1.07E-05	0.000726	0.00180***
	(0.000242)	(0.000233)	(0.000376)	(0.000372)
Rural residence (*ref. non-rural*)	0.00533***	0.00644***	0.0260***	0.0282***
	(0.00139)	(0.00129)	(0.00215)	(0.00208)
Utilized specialty care for asthma	0.0242***	0.0155***	-0.0174***	-0.0204***
	(0.00172)	(0.00159)	(0.00215)	(0.00209)
Total primary care visits	0.000613***	0.000430***	0.00126***	0.000263
	(0.000122)	(0.000118)	(0.000195)	(0.000188)
Number of chronic conditions	0.00540***	0.00431***	0.0476***	0.0350***
	(0.000387)	(0.000367)	(0.000665)	(0.000630)

<u>County-level covariates</u>				
Percent of population living below federal poverty line	0.00233***	0.00190***	0.000391	-0.000399
	(0.000254)	(0.000237)	(0.000397)	(0.000377)
Median household income	0.00805***	0.00502***	-0.00202	-0.00673***
	(0.00140)	(0.00130)	(0.00209)	(0.00202)
Annual concentration of air particulate matter	-0.000262	-0.000975	0.00457***	0.00424***
	(0.000836)	(0.000773)	(0.00127)	(0.00126)
<u>Year (*ref. 2013*)</u>				
2014	-0.0190***	-0.0174***	-0.0442***	-0.0455***
	(0.00186)	(0.00173)	(0.00267)	(0.00262)
2015	-0.0526***	-0.0456***	-0.100***	-0.0958***
	(0.00174)	(0.00160)	(0.00276)	(0.00266)
Pearson residual	-7.89E-05	-3.89E-05	6.25E-05	5.41E-05
	(0.000541)	(0.000517)	(0.000740)	(0.000560)
Observations	381,723	381,723	381,723	381,723

Bootstrapped standard errors in parentheses.
*** p<0.001, ** p<0.01, * p<0.05

Table B.5. Average Marginal Effects of Model Covariates on Preventable Hospital Utilization with a Principal Diagnosis of Asthma and Lagged FQHC Attribution, 2014-2015

	Model 1 - Lagged	**Model 1 - Not lagged**	**Model 2 - Lagged**	**Model 2 - Not lagged**
	Any hospital utilization with a principal diagnosis of asthma	**Any hospital utilization with a principal diagnosis of asthma**	**ED visit with principal diagnosis of asthma**	**ED visit with principal diagnosis of asthma**
FQHC patient - lagged attribution	0.0134**		0.0141**	
	(0.00501)		(0.00504)	
FQHC patient - unlagged attribution		0.0132**		0.0138**
		(0.00458)		(0.00429)
Age	-0.00362***	-0.00362***	-0.00266***	-0.00266***
	(0.000171)	(0.000171)	(0.000160)	(0.000160)
<u>Race/Ethnicity (*ref. White. not Hispanic*)</u>				
Black, not Hispanic	0.0490***	0.0490***	0.0452***	0.0452***
	(0.00151)	(0.00150)	(0.00142)	(0.00142)
Hispanic	0.00321*	0.00330*	0.00296*	0.00305*
	(0.00150)	(0.00150)	(0.00135)	(0.00134)
Multiple/Other, not Hispanic	0.0120***	0.0121***	0.0101***	0.0101***
	(0.00293)	(0.00293)	(0.00274)	(0.00274)
Unknown	0.0107***	0.0107***	0.0103***	0.0104***
	(0.00273)	(0.00272)	(0.00252)	(0.00252)
Female sex (*ref. male*)	-0.00506***	-0.00506***	-0.00412***	-0.00412***
	(0.00118)	(0.00118)	(0.00113)	(0.00113)
Months of Medicaid coverage in calendar year	0.000392	0.000396	0.000416	0.00042

	(0.000518)	(0.000519)	(0.000475)	(0.000477)
Rural residence (*ref. non-rural*)	0.00479**	0.00483**	0.00607***	0.00610***
	(0.00165)	(0.00165)	(0.00159)	(0.00159)
Utilized specialty care for asthma	0.0395***	0.0395***	0.0280***	0.0279***
	(0.00229)	(0.00229)	(0.00204)	(0.00203)
Total primary care visits	0.00132***	0.00132***	0.00110***	0.00110***
	(0.000152)	(0.000151)	(0.000141)	(0.000140)
Number of chronic conditions	0.00939***	0.00939***	0.00787***	0.00788***
	(0.000449)	(0.000449)	(0.000405)	(0.000405)
Continuity of care in calendar year	0.0234***	0.0233***	0.0187***	0.0186***
	(0.00383)	(0.00383)	(0.00355)	(0.00354)
<u>County-level covariates</u>				
Percent of population living below federal poverty line	0.00244***	0.00245***	0.00194***	0.00195***
	(0.000320)	(0.000320)	(0.000295)	(0.000294)
Median household income (in $10,000)	0.00830***	0.00832***	0.00533***	0.00537***
	(0.00161)	(0.00160)	(0.00151)	(0.00150)
Annual concentration of air particulate matter	0.00212*	0.00211*	0.00154	0.00152
	(0.000924)	(0.000920)	(0.000853)	(0.000849)
Number of Medicaid patients with asthma served by attributed provider organization	7.09E-05		4.04E-05	

in prior year (in 10,000)				
	(0.0000675)		(0.0000638)	
Number of Medicaid patients with asthma served by attributed provider organization in current year (in 10,000)		0.000139		0.000108
		(0.0000722)		(0.0000673)
<u>Year (*ref. 2014 for lagged attribution*)</u>				
2015	-0.0267***	-0.0265***	-0.0234***	-0.0232***
	(0.00184)	(0.00184)	(0.00171)	(0.00172)
Pearson residual	0.000104	-0.000278	-9.13E-05	-0.000198
	(0.00094)	(0.00079)	(0.00094)	(0.00071)
Observations	198,807	198,807	198,807	198,807

Bootstrapped standard errors in parentheses.

*** p<0.001, ** p<0.01, * p<0.05

Table B.6. Average Marginal Effects of Model Covariates on Preventable Hospital Utilization with Any Diagnosis of Asthma and Lagged FQHC Attribution, 2014-2015

	Model 3 - Lagged	Model 3 - Not lagged	Model 4 - Lagged	Model 4 - Not lagged
	Any hospital utilization (ED, observation or inpatient stay) with any diagnosis of asthma	**Any hospital utilization (ED, observation or inpatient stay) with any diagnosis of asthma**	**ED visit with any diagnosis of asthma**	**ED visit with any diagnosis of asthma**
FQHC patient - lagged attribution	0.0452***		0.0438***	
	(0.00773)		(0.00745)	
FQHC patient - unlagged attribution		0.0403***		0.0399***
		(0.00784)		(0.00768)
Age	-0.00443***	-0.00442***	-0.00341***	-0.00340***
	(0.000263)	(0.000263)	(0.000261)	(0.000261)
Race/Ethnicity (*ref. White. not Hispanic*)				
Black, not Hispanic	0.0687***	0.0691***	0.0657***	0.0660***
	(0.00241)	(0.00241)	(0.00233)	(0.00232)
Hispanic	-0.0284***	-0.0278***	-0.0283***	-0.0278***
	(0.00257)	(0.00256)	(0.00249)	(0.00248)
Multiple/Other, not Hispanic	9.83E-05	0.000223	-0.00274	-0.00263
	(0.00520)	(0.00519)	(0.00495)	(0.00494)
Unknown	0.00221	0.00254	-0.000667	-0.000383
	(0.00458)	(0.00457)	(0.00442)	(0.00443)
Female sex (*ref. male*)	-0.00136	-0.00133	-0.000356	-0.000325
	(0.00190)	(0.00190)	(0.00182)	(0.00182)

Months of Medicaid coverage in calendar year	0.00414***	0.00416***	0.00448***	0.00450***
	(0.000730)	(0.000730)	(0.000695)	(0.000695)
Rural residence (*ref. non-rural*)	0.0262***	0.0261***	0.0279***	0.0279***
	(0.00259)	(0.00259)	(0.00252)	(0.00252)
Utilized specialty care for asthma	0.0119***	0.0117***	0.00649*	0.00624*
	(0.00298)	(0.00297)	(0.00282)	(0.00281)
Total primary care visits	0.00309***	0.00306***	0.00195***	0.00192***
	(0.000262)	(0.000262)	(0.000261)	(0.000261)
Number of chronic conditions	0.0516***	0.0516***	0.0411***	0.0411***
	(0.000743)	(0.000742)	(0.000727)	(0.000726)
Continuity of care in calendar year	-0.0123*	-0.0130*	-0.0221***	-0.0227***
	(0.00562)	(0.00561)	(0.00530)	(0.00529)
<u>County-level covariates</u>				
Percent of population living below federal poverty line	0.00286***	0.00286***	0.00224***	0.00225***
	(0.000500)	(0.000499)	(0.000483)	(0.000482)
Median household income (in $10,000)	0.0125***	0.0125***	0.00836***	0.00834***
	(0.00249)	(0.00249)	(0.00246)	(0.00246)
Annual concentration of air particulate matter	0.00688***	0.00684***	0.00595***	0.00591***
	(0.00139)	(0.00139)	(0.00132)	(0.00131)

Number of Medicaid patients with asthma served by attributed provider organization in prior year (in 10,000)	0.000199		0.000145	
	(0.000110)		(0.000106)	
Number of Medicaid patients with asthma served by attributed provider organization in current year (in 10,000)		0.000384***		0.000324**
		(0.000114)		(0.000110)
<u>Year (*ref. 2014 for lagged attribution*)</u>				
2015	-0.0299***	-0.0293***	-0.0280***	-0.0274***
	(0.00269)	(0.00271)	(0.00255)	(0.00257)
Pearson residual	-0.00114	-0.00104	-0.000663	-0.000655
	(0.00151)	(0.00151)	(0.00142)	(0.00141)
Observations	198,807	198,807	198,807	198,807

Bootstrapped standard errors in parentheses.

*** p<0.001, ** p<0.01, * p<0.05

APPENDIX C: OVERVIEW OF CONFIGURATIONAL COMPARATIVE METHODS INCLUDING COINCIDENCE ANALYSIS

Configurational comparative methods (CCMs) such as coincidence analysis (CNA) represent a family of cross-case comparative methods that apply Boolean algebra to identify logical combinations of conditions associated with an outcome in a set of data. These methods have been used in the social sciences since the 1980s, but CCMs are only recently becoming common in health services research.[1–4] In particular, these methods are well-suited for implementation and organization science researchers as well as health care practitioners who are interested in evaluating multifaceted interventions in complex, real-world settings. Under these conditions, interventions can represent constellations of both independent and interdependent factors, and the relationship between individual factors and the outcomes can be challenging to isolate. Moreover, boundaries between an intervention, its implementation, and its contextual features are often blurred.[5,6]

Because of the complexities associated with organization-based observational research, theories and methodological approaches that support complex causality are needed.[7] Complex causality maintains that conditions may influence an outcome only in combination with other conditions (conjunctural causality);[1] conditions can have variable effects on an outcome depending on their configuration (asymmetric causality);[1] multiple combinations of conditions can produce equivalent outcomes (disjunctive causality); and outcomes can produce further outcomes along causal chains (sequential causality). CCMs represent one tool for modeling complex causality.

Introduction to CCMs. To help orient the reader to the language associated with CCMs, Table C.1 includes a brief glossary of terms. CCMs conceptualize cases (the unit of analysis) as configurations of conditions that are either present or absent (e.g., *A* denotes the presence of a condition, A; *a* denotes the absence of condition A). In other words, CCMs do not examine a single condition in isolation but within the context of the presence or absence of other conditions.[8]

Configurations of conditions can be conjunctively (*A* AND *B*), disjunctively (*A* OR *B*), or sequentially related to one another in a solution set that is linked to a given outcome. The goal of configurational comparative research is to identify the groupings of conditions that are causally related to an outcome.[9] If, for example, Organization 1 exhibits the configuration *ABC,* Organization 2 exhibits the configuration *AbC,* and both Organization 1 and Organization 2 exhibit the outcome, *E,* then it can be said that *ABC* OR *AbC* produce the outcome *E* $(ABC + AbC \rightarrow E)$. More analysis is needed to determine whether these conditions are causally related to the outcome, however.

Groupings of conditions are determined to be causally related based on the regularity theory of causation, which has its roots in the work of philosophers David Hume[10], John Stuart Mill[11] and John Mackie.[5] Understanding the theory of causality applied to CCMs is important for assessing the validity of the method. Regularity theory defines a cause as one that is sufficient and necessary for a given effect.[5] In his contribution to regularity theory, Mackie maintained that in order for a set of conditions to be causally interpretable, the set must contain no redundant elements—the conditions must be "difference-makers" for their effects.[5] In other words, a condition cannot be causal if it can be removed from a sufficient condition without affecting the sufficiency of the condition. In this scenario, the condition does not make a difference for the presence of the outcome and is therefore redundant and not a cause of the outcome.

Mackie referred to these conditions as "INUS conditions:" an INUS condition of an outcome Y is an <u>I</u>nsufficient but <u>N</u>ecessary part of a condition that is itself <u>U</u>nnecessary but <u>S</u>ufficient for Y. He illustrated INUS conditions using an example of a fire starting in a building. In this example, fires can start as a result of a short circuit or other causes like arson or lightning. In order for the short-circuit to start a fire, there must be other conditions present, such as flammable material nearby and the lack of a sprinkler system. Therefore, the short-circuit represents an INUS condition—it is a necessary part of a sufficient condition for a fire.[5]

CCMs utilize Boolean algebra – the algebra of logic rather than linear algebra – to apply Mackie's theory of causation and systematically minimize a set of conditions to identify those that are minimally sufficient and minimally necessary for an outcome. Only after this process of minimization are conditions considered causally interpretable.[9] CCM solutions are minimal theories of causation and are represented by a Boolean expression -- a minimally necessary disjunction of minimally sufficient conditions. These expressions can be causally interpreted according to regularity theory because they are redundancy-free. The goal of CCMs is to identify all minimal theories that fit the data.

Two parameters of fit – consistency and coverage – provide insight into the strength of the causal relationship between conditions and the outcome.[12] Consistency measures how often a combination of conditions leads to the outcome, or the degree to which the cases sharing a combination also share the same outcome.[12] Lower consistency values may indicate lower confidence in the causal relationship between conditions and the outcome. Coverage measures the proportion of cases with the outcome that also have a particular condition.[1] In other words, coverage measures the "empirical importance" of a given configuration.[12] Coverage is only relevant for conditions that meet the minimum consistency threshold.[1,12] Low coverage for a solution set may indicate that there are confounding conditions not included in the model.[13]

CNA as a variant of CCMs. To date, qualitative comparative analysis, or QCA, has been more commonly utilized in health services research.[13–15] However, we used a new method within the CCM family known as CNA [16,17] because it has improved upon some of the shortcomings of QCA.[18,19] The CNA program executes the minimization algorithm in three primary steps[13,20]:

1. CNA builds a set of minimally sufficient conditions for each outcome by first analyzing a single condition at a time to determine whether the condition meets

an indicated minimum consistency threshold (i.e., is “sufficient” to produce the outcome). Then, CNA examines combinations of two, three, etc. conditions that were not previously determined to be sufficient for the outcome. Meeting the consistency threshold implies that the specified proportion of cases displaying the condition or combination of conditions also displays the outcome.

2. Once the set of minimally sufficient conditions have been identified, a similar approach is applied to determine whether those conditions meet the minimum coverage threshold. Meeting the coverage threshold implies that the required proportion of cases that display the outcome also display the indicated condition(s) or path to the outcome. Conditions that meet the minimal coverage threshold are included in the solution set. To accomplish this step, the minimally sufficient conditions are disjunctively concatenated and tested first as single conditions, disjuncts of two conditions, and so on until all logically possible disjuncts of conditions have been evaluated against the coverage threshold.
3. Minimally sufficient conditions meeting the coverage threshold are then included in the solution set for the data.

Distinguishing CCMs from Econometric Methods. Econometric methods (i.e., regression analytic methods) and CCMs like CNA apply different theories of causation (statistical and probabilistic versus regularity theories, respectively). Therefore, these methods are complementary rather than in competition with each other.[13] Additionally, CCMs study hypotheses that link specific values of variables, thereby modeling the association of conditions with the outcome. Econometric methods, on the other hand, study covariation hypotheses – i.e., how the outcome varies given a one-unit change in an explanatory variable.

Another key distinction between CCMs and regression analysis is the way in which CCMs conceptualize the “case”, or the unit of analysis: CCMs retain the composition of each case in the analysis instead of deconstructing cases into a series of variables as in regression analysis. CCM results indicate all the possible conditions that consistently produce the outcome across all cases. A regression model, on the other hand, deconstructs the unit of analysis into a series of variables and estimates the net effect of each explanatory variable on the outcome for the average case. Taken together, the results of a regression model indicate how much variation in the outcome can be explained by the included variables. CCMs, on the other hand, identify causal “recipes” – configurations of conditions that are associated with the outcome across cases. Both CCMs and regression analysis are valuable methods but seek to answer different questions.

Table C.1. Brief Glossary for Configurational Comparative Methods

CCM Terminology	Definition
Boolean algebra	The algebra of logic and the formal language for CCMs. Conceives of conditions as present or absent in contrast to linear algebra that conceives of variables as increasing or decreasing.[8] Key operators in Boolean algebra include: 1) the implication operator, $\rightarrow$, which allows for causal dependencies between conditions, 2) the conjunction ("and") operator signified by concatenated letters or a * symbol, and 3) the disjunction ("or") operator signified by a + symbol.[19]
Case	The unit of analysis in CCM.
Factor	Conceptually similar to a variable in econometric methods.
Condition	The value assigned to a given factor for analysis (e.g., a high concentration of uninsured patients).
Calibration	To align with the properties of Boolean algebra, CCMs transform factor values into set membership values through a process of calibration. Factors are calibrated to align with crisp-set, fuzzy-set or multi-value membership definitions prior to analysis. (There are additional calibration sets, but these three encompass the membership set definitions available to both QCA and CNA.[20,21]) Crisp-set calibration transforms factor values to 0 or 1; fuzzy-set calibration transforms linear factors into a range of values from 0-1 inclusive; and multi-value calibration transforms factor values into nominal scales. Factor values can be calibrated using theoretical and empirical justification.
Configuration	An arrangement of conditions into conjunctions or disjunctions.
Minimally sufficient condition	A minimally sufficient condition can either be a single condition (e.g., *A*) or a combination of conditions (e.g., *ABC)* that is free of redundant elements and exhibits a causal dependency with the outcome. In CNA, minimally sufficient conditions must meet the minimum consistency threshold.
Solution set	A solution set contains the various minimally sufficient conditions for the outcome. Solutions for CCMs take the form of a minimally necessary disjunction of minimally sufficient conditions. Conditions that appear in different disjuncts represent alternative pathways to the outcome. Solution formulas appear with the equivalence operator ($\Leftrightarrow$).

REFERENCES

1. Kahwati LC, Lewis MA, Kane H, et al. Best Practices in the Veterans Health Administration's MOVE! Weight Management Program. *Am J Prev Med*. 2011;41(5):457-464. doi:10.1016/j.amepre.2011.06.047.

2. Kane H, Lewis MA, Williams PA, Kahwati LC. Using qualitative comparative analysis to understand and quantify translation and implementation. *TBM*. 2014;4(2):201-208.

3. Roberts MC, Murphy T, Moss JL, Wheldon CW, Psek W. A Qualitative Comparative Analysis of Combined State Health Policies Related to Human Papillomavirus Vaccine Uptake in the United States. *Am J Public Health*. 2018;108(4):493-499. doi:10.2105/AJPH.2017.304263.

4. Mendel P, Chen EK, Green HD, et al. Pathways to Medical Home Recognition: A Qualitative Comparative Analysis of the PCMH Transformation Process. *Health Serv Res*. December 2017. doi:10.1111/1475-6773.12803.

5. Mackie JL. *The Cement of the Universe: A Study of Causation*. Oxford: Clarendon Press; 1974.

6. Baumgartner M. Regularity Theories Reassessed. *Philosophia (Mendoza)*. 2008;36(3):327-354. doi:10.1007/s11406-007-9114-4.

7. Misangyi VF, Greckhamer T, Furnari S, Fiss PC, Crilly D, Aguilera R. Embracing Causal Complexity. *J Manage*. 2017;43(1):255-282. doi:10.1177/0149206316679252.

8. Ragin CC. *The Comparative Method: Moving beyond Qualitative and Quantitative Strategies*. Oakland: University of California Press; 1987. https://books.google.com/books?hl=en&lr=&id=zLinAwAAQBAJ&oi=fnd&pg=PP1&dq=Ragin+Comparative+Strategies+Boolean+Algebraic+Approach+to+Qualitative&ots=_GcumUs084&sig=nJbrwa5qBeYPPXzyu4FJeOQww_Q#v=onepage&q=Ragin Comparative Strategies Boolean Algebr. Accessed November 7, 2017.

9. Thiem A. Conducting Configurational Comparative Research With Qualitative Comparative Analysis. *Am J Eval*. 2017;38(3):420-433. doi:10.1177/1098214016673902.

10. Hume D. An Enquiry Concerning Human Understanding. 1748.

11. Mill JS. Of the Four Methods of Experimental Inquiry. In: *A System of Logic*. London: John W. Parker; 1843.

12. Ragin CC. Set Relations in Social Research: Evaluating Their Consistency and Coverage. *Polit Anal*. 2006;14(03):291-310. doi:10.1093/pan/mpj019.

13. Baumgartner M, Ambühl M. Causal Modeling with Multi-Value and Fuzzy-Set Coincidence Analysis. *Polit Sci Res Method*. 2018:1-17. doi:10.1017/psrm.2018.45.

14. Medical Resource Council. *A Framework for Development and Evaluation of RCTs for Complex Interventions to Improve Health*.; 2000. https://mrc.ukri.org/documents/pdf/rcts-for-complex-interventions-to-improve-health/.

15. Pfadenhauer L, Gerhardus A, Mozygemba, K et al. Making sense of complexity in context and implementation: the Context and Implementation of Complex Interventions (CICI) framework. *Implement Sci*. 2013;12(1):21.

16. Baumgartner M. Uncovering deterministic causal structures: a Boolean approach. *Synthese*. 2009;170(1):71-96. doi:10.1007/s11229-008-9348-0.

17. Baumgartner M. Inferring Causal Complexity. *Sociol Methods Res*. 2009;38(1):71-101. doi:10.1177/0049124109339369.

18. Baumgartner M, Thiem A. Model Ambiguities in Configurational Comparative Research. *Sociol Methods Res*. October 2015. doi:10.1177/0049124115610351.

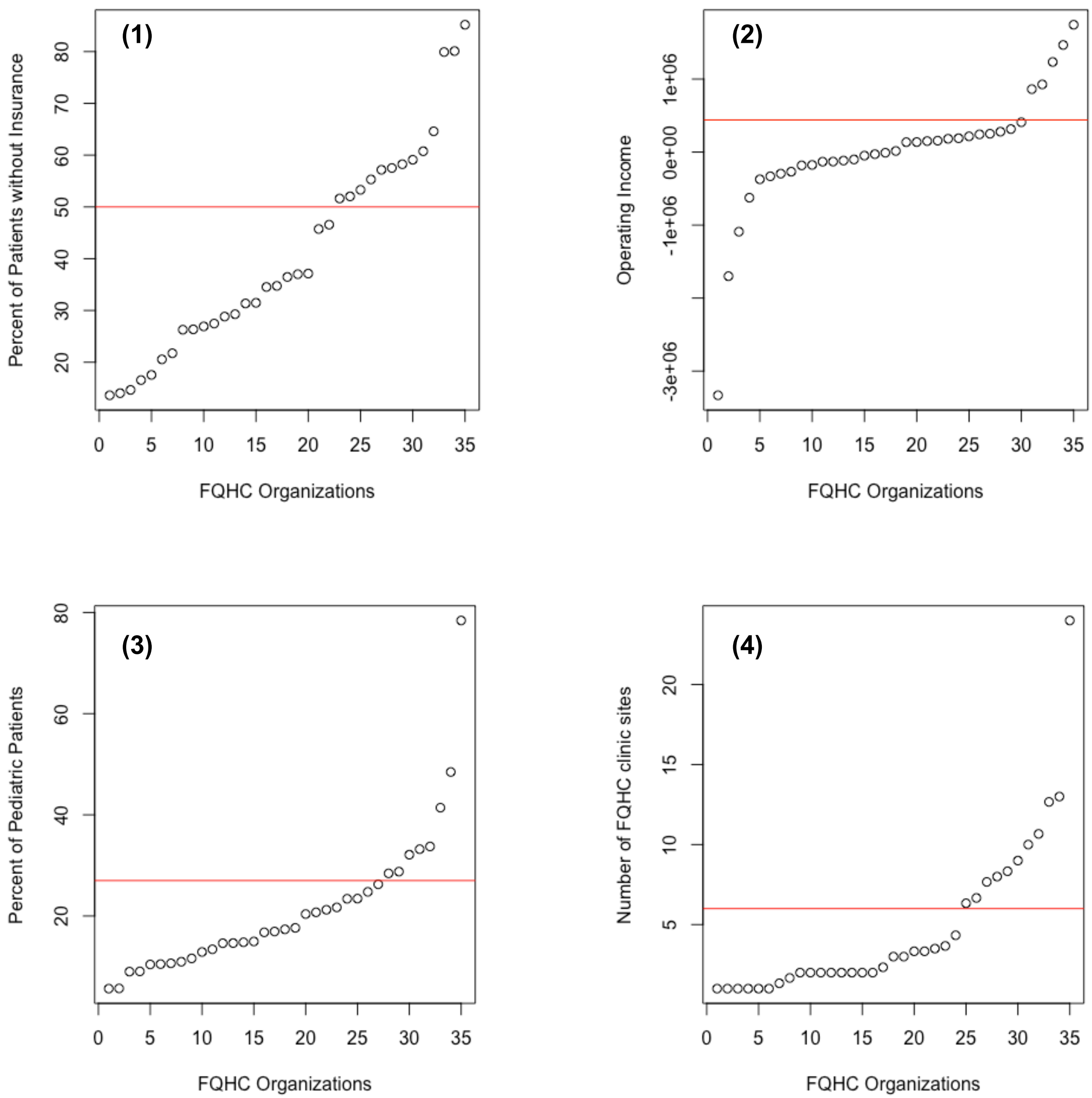
19. Baumgartner M. Parsimony and Causality. *Qual Quant*. 2015;49(2):839-856. doi:10.1007/s11135-014-0026-7.

20. Ambuehl M, Baumgartner M. cna: Causal modeling with Coincidence Analysis. 2017. https://cran.r-project.org/package=cna.

21. Thiem A, Dua A. QCA: A Package for Qualitative Comparative Analysis. *R J*. 2013;5(1):87-97. https://journal.r-project.org/archive/2013-1/thiem-dusa.pdf. Accessed April 27, 2017.

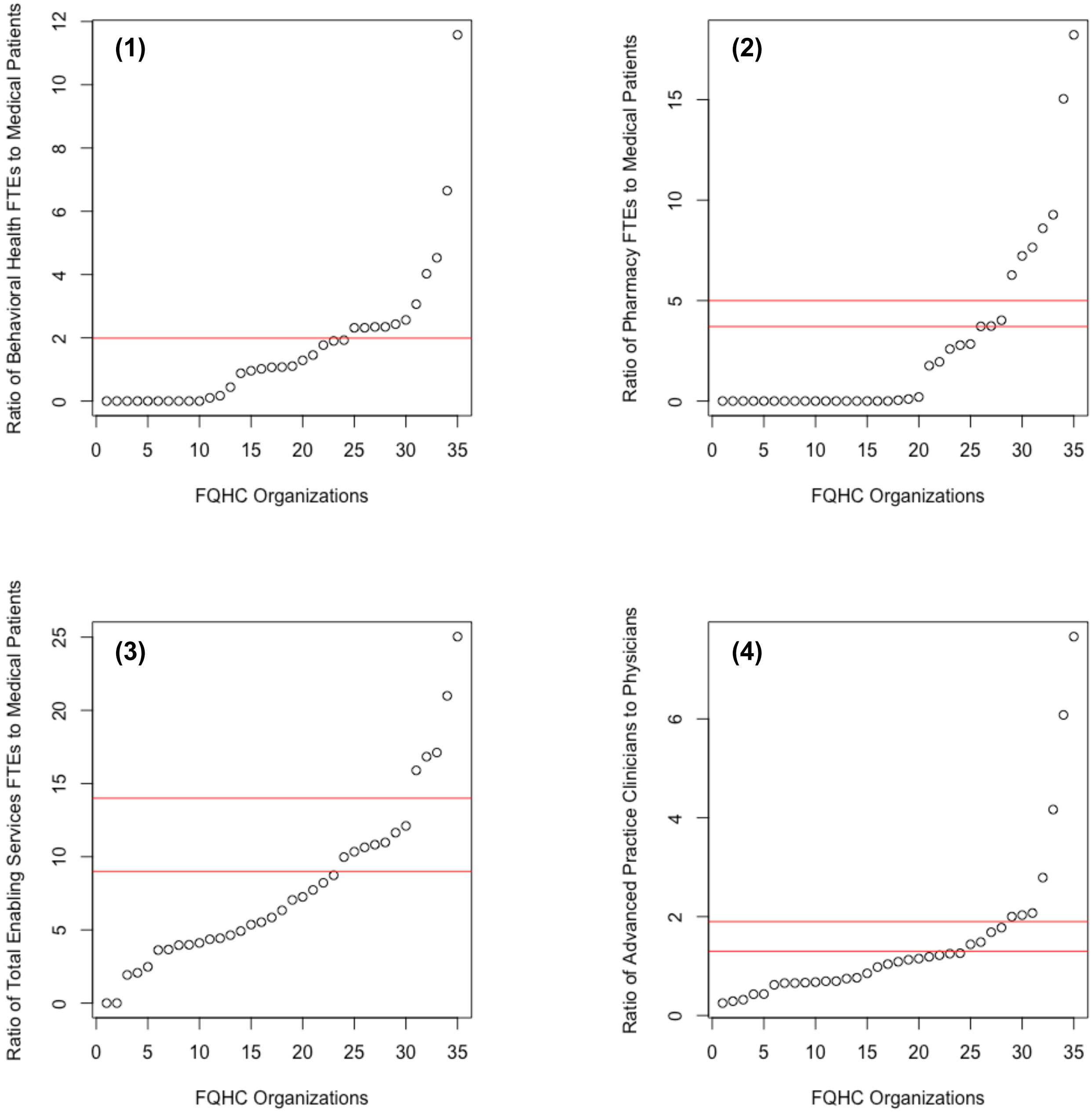
APPENDIX D: THRESHOLD PLACEMENT AND CALIBRATION FOR COINCIDENCE ANALYSIS

Figure D.1. Threshold Placement for Control Factors



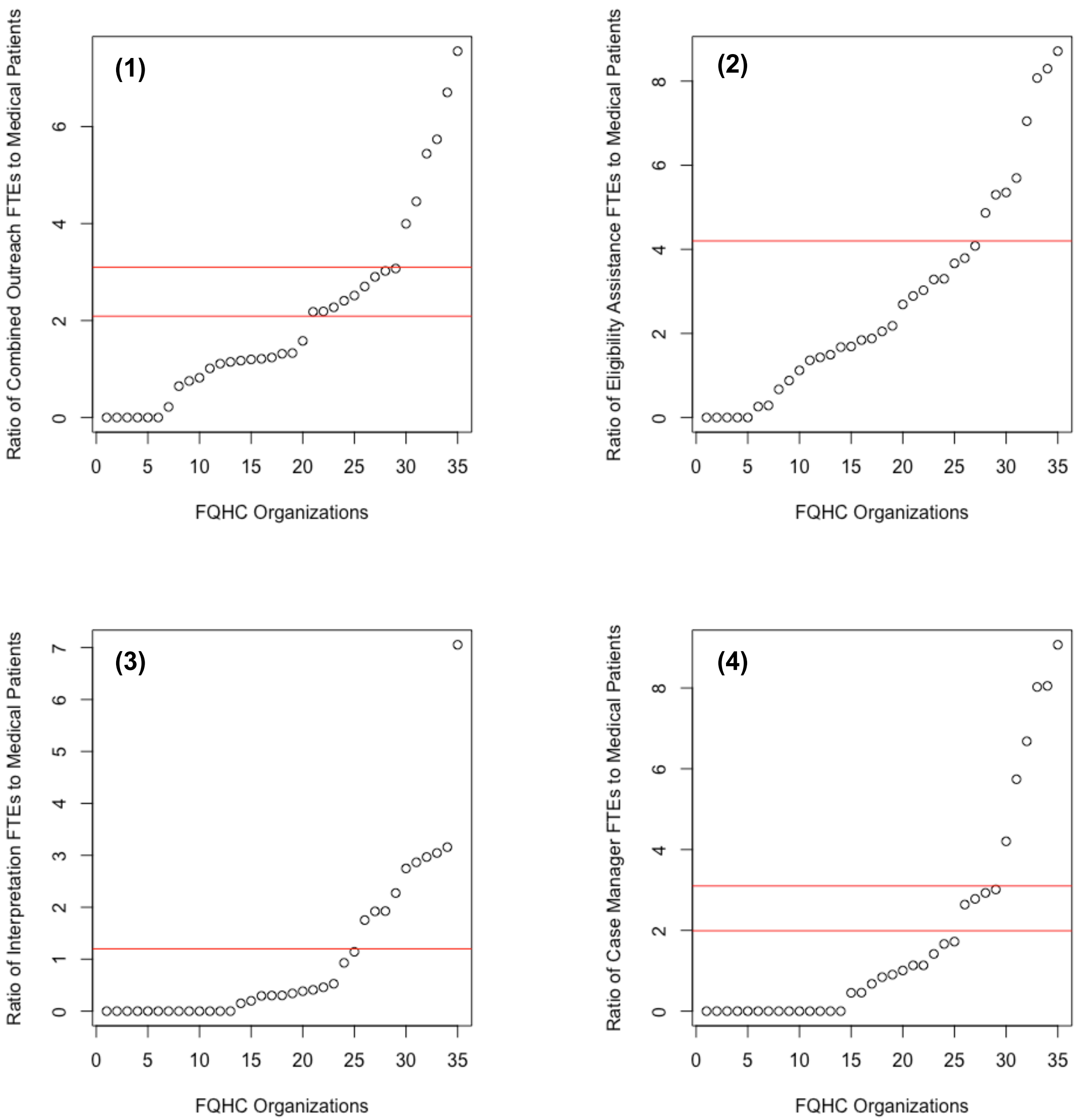
(1) Percent of patients without insurance; (2) organization operating income; (3) percent of pediatric patients; (4) Number of FQHC clinic sites

Figure D.2. Threshold Placement for Staffing Ratios



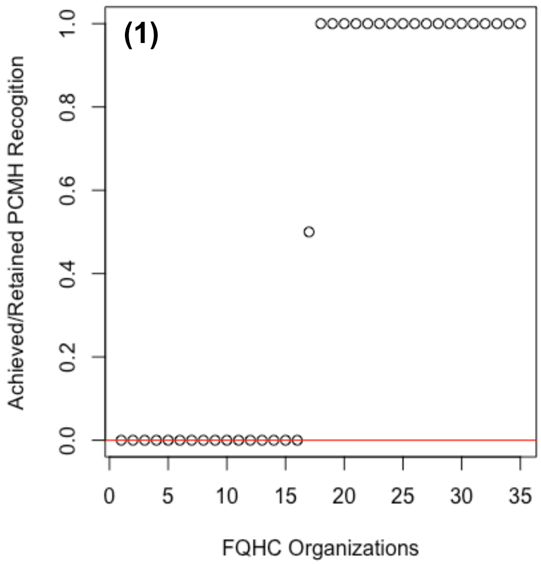
(1) Ratio of behavioral health FTEs to 10,000 medical patients; (2) ratio of pharmacy FTEs to 10,000 medical patients; (3) ratio of total enabling services FTEs to 10,000 medical patients; (4) ratio of advanced practice clinicians to physician FTEs

Figure D.3. Threshold Placement for Individual Enabling Services Staffing Ratios



(1) Ratio of outreach/patient and community education FTEs to 10,000 medical patients; (2) ratio of eligibility assistance FTEs to 10,000 medical patients; (3) ratio of interpretation FTEs to 10,000 medical patients; (4) ratio of case manager FTEs to 10,000 medical patients

Figure D.4. Threshold Placement for Patient-Centered Medical Home (PCMH) Recognition



Represents organizations' that achieved or retained PCMH recognition at at least one site during a calendar year. Organizations that ever-achieved PCMH recognition over the three-year study period were coded as having PCMH recognition.

Table D.1. High-threshold Calibration for Coincidence Analysis

FQHC_ID	HI_PERF	PERC_UNINSURED	PERCPEDS	PT_INCOME	OP_INC	TOTAL_SITES	BH_RATIO	PHARMACY_RATIO	CASEMNGR_RATIO	COMBOUT	ELIGASST_RATIO	INTERP_RATIO	TOTAL_ES	AP_PCP	PCMH_RECOG
1	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
7	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0
8	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1
9	0	0	1	1	0	1	0	1	0	0	0	0	0	0	1
10	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1
11	0	0	1	1	0	0	1	0	0	0	0	0	0	1	0
13	0	1	0	0	1	0	0	1	1	0	1	1	1	0	1
14	0	0	1	0	0	0	0	0	0	0	0	1	0	1	0
15	0	1	1	1	0	0	0	0	1	1	1	1	1	0	1
16	0	1	0	0	0	0	0	0	0	0	1	1	0	1	1
17	0	0	0	0	1	1	0	0	0	0	0	1	0	0	1
18	0	0	1	0	0	1	0	1	0	0	0	0	0	0	1
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
23	0	0	0	0	0	1	1	0	1	0	0	1	1	1	1
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
27	0	1	0	0	0	0	0	1	0	1	1	0	0	0	0
28	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0
29	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
31	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
33	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0
34	0	0	0	0	0	0	0	1	0	0	1	0	0	1	1
3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	1	1	0	0	0	1	1	0	1	1	0	0	1	0	1
19	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1
22	1	1	0	0	1	1	1	0	0	1	0	1	0	0	1
25	1	1	0	1	1	0	1	1	1	0	1	0	1	0	0
26	1	0	0	0	0	0	1	0	0	0	1	0	0	0	0
32	1	1	1	0	1	1	1	1	0	0	0	0	0	0	1
35	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0
36	1	1	0	0	0	1	1	0	0	0	0	1	0	0	1
	Consistency*	54%	13%	17%	60%	36%	55%	29%	33%	33%	38%	20%	40%	0%	26%
	Coverage**	78%	11%	11%	33%	44%	67%	22%	22%	22%	33%	22%	22%	0%	56%

*% of organizations with factor and HI_PERF=1
**% of HI_PERF=1 with factor

Table D.2. Low-threshold Calibration for Coincidence Analysis

FQHC_ID	HI_PERF	PERC_UNINSURED	PERCPEDS	PT_INCOME	OP_INC	TAL_SIT	BH_RATIO	PHARMACY_RATIO	CASEMNGR_RATIO	COMBOUT	ELIGASST_RATIO	INTERP_RATIO	TOTAL_ES	AP_PCP	PCMH_RECOG
1	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
4	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0
6	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1
7	0	0	0	1	0	0	0	0	1	1	0	1	1	1	0
8	0	0	1	1	0	1	0	0	0	0	0	0	0	0	1
9	0	0	1	1	0	1	0	1	1	0	0	0	0	0	1
10	0	1	0	1	0	0	0	0	0	0	0	0	0	1	1
11	0	0	1	1	0	0	1	0	0	0	0	0	0	1	0
13	0	1	0	1	1	0	0	1	1	1	1	1	1	0	1
14	0	0	1	0	0	0	0	0	0	1	0	1	0	1	0
15	0	1	1	1	0	0	0	0	1	1	1	1	1	0	1
16	0	1	0	0	0	0	0	0	0	0	1	1	0	1	1
17	0	0	0	0	1	1	0	0	0	0	0	1	0	0	1
18	0	0	1	1	0	1	0	1	0	0	0	0	0	0	1
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1
23	0	0	0	1	0	1	1	0	1	1	0	1	1	1	1
24	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
27	0	1	0	0	0	0	0	1	0	1	1	0	1	0	0
28	0	0	0	1	0	0	1	0	1	1	0	0	1	0	0
29	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1
31	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
33	0	1	0	1	0	0	0	0	0	1	0	1	0	0	0
34	0	0	0	0	0	0	0	1	0	0	1	0	0	1	1
3	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0
12	1	1	0	0	0	1	1	0	1	1	0	0	1	0	1
19	1	1	0	0	0	0	0	1	0	0	0	0	0	1	1
22	1	1	0	0	1	1	1	1	1	1	0	1	1	0	1
25	1	1	0	1	1	0	1	1	1	0	1	0	1	0	0
26	1	0	0	0	0	0	1	0	0	0	1	0	1	0	0
32	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1
35	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0
36	1	1	0	1	0	1	1	1	0	1	0	1	1	0	1
Consistency*		54%	13%	18%	60%	36%	55%	50%	30%	27%	38%	20%	42%	9%	26%
Coverage**		78%	11%	33%	33%	44%	67%	56%	33%	44%	33%	22%	56%	11%	56%

*% of organizations with factor and HI_PERF=1

**% of HI_PERF=1 with factor