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Patient-Centered Innovation and Clinician Network Influences on Chronic Disease Prevention and Management

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By

Rachel Ross

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in

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Abstract

Patient-Centered Innovation and Clinician Network Influences on Chronic Disease Prevention and Management

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Doctor of Philosophy in Health Policy

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This dissertation explores the dynamics of patient engagement and clinical collaboration within the framework of patient-centered care, following a four-paper format. The research is divided into two main themes: the application of decision aids to enhance shared decision-making in breast cancer screening, and the examination of clinician networks to improve care coordination for Federally Qualified Health Center (FQHC) patients with chronic diseases.

Paper 1 examines physician practices' adoption of decision aids for breast cancer screening. Findings suggest that practices with limited health information technology, higher barriers to innovation adoption, and larger or system-owned organizational structures face significant challenges in widespread decision aid adoption. Paper 2 then assesses the association between decision aid use and mammography uptake among older women, highlighting that despite the potential for decision aids to improve patient-provider communication and informed decision-making, inconsistent implementation limits their observed impact on mammography rates.

Paper 3 investigates the restructuring of patient-sharing clinician networks in FQHCs during the COVID-19 pandemic, revealing increases in overall network dispersion. This study emphasizes the need for adaptive care coordination strategies that leverage network structures to enhance collaborative dynamics during public health crises. Paper 4 builds upon this work by focusing on the role of clinician network brokerage in managing chronic conditions within FQHCs. While brokerage showed no significant association with blood pressure outcomes, it was correlated with improved diabetes management, suggesting that structural network characteristics may have potential implications for chronic disease outcomes in FQHC settings.

Overall, this dissertation underscores the necessity of integrating patient-centered tools like decision aids into clinical practice and utilizing network analysis to inform and optimize healthcare delivery and policy in complex care settings. Future research should continue to explore these approaches to further enhance engagement and collaboration, ultimately improving health outcomes in diverse patient populations.

To my mother & to my father,
who instilled in me a deep love of learning
and the values of persistence, humility, and compassion.

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CHAPTER 1

INTRODUCTION

1.1 ENGAGING PATIENTS THROUGH SHARED DECISION-MAKING

In response to the dynamic complexities of the American healthcare system, the Institute of Medicine issued a landmark report in 2001 that called for reforms to our current practices, envisioning a system that was truly "patient-centered."[1] The key provision of patient-centered care is that an individual's holistic health needs and preferences remain as the driving force behind decisions throughout the care continuum.[2] Largely from this movement, the field of patient engagement emerged.

Although a uniform definition has yet to be recognized, the core concept behind "patient engagement" is true partnership between patients and clinicians.[3,4] Patient engagement efforts primarily involve interventions designed to increase patients' self-efficacy and promote positive health behaviors.[5]

Shared decision-making (SDM) is one component of this broader concept, and refers to processes in which a patient and doctor jointly reach an agreement on condition management, treatment, or screening.[6] Key steps of SDM include: defining or explaining the problem, presenting options, discussing the risks and benefits associated with each option, eliciting patients' values and concerns, discussing patients' abilities, sharing doctors' knowledge and recommendations, checking for understanding, making or explicitly deferring decisions, and arranging follow-up conversation(s).[7] This concept diverges from traditional models of medical decision-making that solely rely upon physician paternalism, in which patients more passively respond to doctors' established professional authority.[8]

It is important to note that SDM does not preclude the ability for patients to solicit physicians' expertise. In many cases, patients may display preferences for physicians who present clear recommendations when faced with difficult decisions.[9] So long as the decision to rely on physician guidance was deliberately made by the patient, with alternative options presented appropriately, this paradigm remains congruent with the shared decision-making model.

SDM efforts are associated with improvements in knowledge and attitudinal patient outcomes, such as understanding, satisfaction, and trust.[10] Additionally, SDM has shown promise for improving patient-reported health outcomes and reducing healthcare utilization.[11] The potential for health improvement and cost reduction has led to the inclusion of SDM incentives in state and federal policy-making,[12] as well as increased attention among health services researchers.

Despite these benefits, however, the importance of substantive clinician-led discussion has historically remained under-appreciated in practice.[13] Observational studies examining the discourse between patients and clinicians indicate that less than 10% of decisions meet the criteria for completeness of informed decision-making.[14] While physicians appeared to consistently describe the nature of a healthcare decision, there are less frequent discussions of the risks and benefits associated with various treatment options, and assessment of patients' understanding and appropriate follow-up are rare.[13] Although patients' involvement in decision-making has increased over time, this pattern does not apply uniformly for all patients, suggesting that improvements are still seriously warranted.[15]

The challenge of incorporating SDM strategies into clinical workflows has been described in the literature as needing to "balance an ethical ideal with a practical reality."[14] One of the most commonly cited barriers is physicians' perceptions of a lack of time to engage with patients in extended discussions.[16,17] The organizational and structural support to implement SDM interventions in light of these time constraints is routinely lacking.[16] Specifically, there widely exists a lack of training on effective informed decision-making within care delivery organizations, decreased time spent with each patient, increased burden of administrative tasks, and lower reimbursements from third-party payers.[14,18]

In addition to these persistent logistical barriers, many physicians challenge the overall importance of SDM, questioning the degree to which patients actually want to be involved in their personal medical decisions.[16] Further, there is frequently a failure to recognize that lower-risk procedures warrant meaningful attention to patient involvement, as is traditionally given to more invasive procedures.[14] Too often, these perceptions persist despite the increasing evidence that practices with more patient-centered cultures are more likely to have more engaged patients, who in turn report better emotional, physical, and social health outcomes.[19]

To illustrate one example of SDM, the present body of work considers a use case for decision aids (DAs): DAs are evidence-driven tools designed to structure patient-clinician conversations and elevate the patient's voice, with the understanding that unique clinical considerations vary from patient to patient. Importantly, DAs are not general health information materials, nor are they designed to simply promote compliance with a clinician-recommended option.[20] They are particularly beneficial for preference-sensitive conditions, such as breast cancer screening: while screenings allow for timely detection of malignancies, they also pose specific risks for older women, which encompass pain, anxiety, and the risk of false positive results.[21] Thus, this population may particularly benefit from such interventions to ensure their unique risks and preferences are incorporated into screening decisions. Recent evidence highlights that women prefer to share screening decisions with their clinicians, and that DAs improve knowledge and successfully promote informed decision-making.[20,22,23]

To address the failures of the medical system to routinely incorporate patients' voices into their care decisions, there have been calls to incorporate the topic into medical training. Additionally, policymakers have turned their attention to patient engagement efforts in recent years by incorporating clinician reimbursement mechanisms that are tied to patient satisfaction. Thus, robust evidence is still needed to expand our understanding of the organizational barriers and facilitators to increased adoption of SDM strategies.

1.2 COORDINATING PATIENT CARE IN COMPLEX SETTINGS

While the importance of the patient-clinician relationship cannot be overstated, to develop a robust understanding of the patient care continuum, we must also take into consideration the complexities associated with the coordination of care between multiple clinicians. One recent study found that over the past 20 years, the proportion of Medicare beneficiaries seeing five or more doctors per year rose from about 19% in 2000 to 35% in 2019.[24] While updated statistics on this in light of the pandemic are not yet unavailable, this trend makes logical sense in the context of people living longer with chronic diseases, and requiring more complex care.[25]

The concept of care coordination encapsulates multiple aspects of health care delivery, with an explicit focus on the provision of services that are clinically appropriate and delivered in a timely manner.[26] No formal consensus exists in the medical community regarding a precise definition of "care coordination." In fact, one systematic review identified 57 unique definitions of the concept. From these diverse descriptions, five common themes emerged: care coordination involves numerous participants, is necessitated by interdependence among participants and activities, aims to facilitate appropriate health care delivery, requires knowledge of others' roles and resources, and relies on information exchange.[27] The proliferation in publications on the topic led the Agency for Healthcare Research and Quality (AHRQ) to broadly conceptualize care coordination as "the deliberate organization of patient care activities between two or more participants [...] involved in a patient's care to facilitate the appropriate delivery of health care services."[28]

One of the major components of successful cancer care coordination identified by physicians is effective communication and cooperation among those delivery health services.[29] The absence of such cooperation poses direct threats to patients' well-being because it can lead to interruptions in clinicians' receipt of diagnostic findings, delays in clinicians' awareness of complications from recent procedures, and failures to adequately update treatment plans in electronic charting systems, among other issues, all of which require doctors to operate with incomplete clinical knowledge when giving advice or making care decisions for their patients.[26] Unfortunately, the lack of effective information transfer between physicians in different specialties remains one of the most prominently cited reasons for poorly coordinated care,[29] which is associated with reductions in patients' health outcomes and care experiences.[30]

1.3 THE APPLICATION OF SOCIAL NETWORK THEORY TO CARE COORDINATION

The interpersonal exchange of information across intra- and inter-organizational boundaries is the most frequently identified concept among the various theoretical frameworks seeking to explain successful care coordination.[31] Thus, a network approach to the empirical investigation of care coordination activities is warranted because it focuses specifically on individuals' relationships to one another.[32]

Social networks in organizations are increasingly understood as optimal structures to understand how groups work together collaboratively. In social network analysis, networks are composed of "nodes," or the individual actors within the network, as well as "ties," or the relationships between the nodes. The overall structure of a network is formed by these ties, with each node occupying a unique position within that structure.[32]

Recent advancements in the field of health services research has demonstrated that social network analysis can be used to examine interactions among medical staff in clinical settings.[33] In such work, nodes are often represented as providers, or the agents of interest who typically engage with one another, and ties are represented as interactions between them.[34] Interactions are defined in a variety of ways, such as the sharing of care for a single patient, referral activity, or self-reported advice seeking behavior.[33–35] This dissertation draws upon the definition of a "tie" between two clinicians as sharing care for at least one patient.

CHAPTER 2

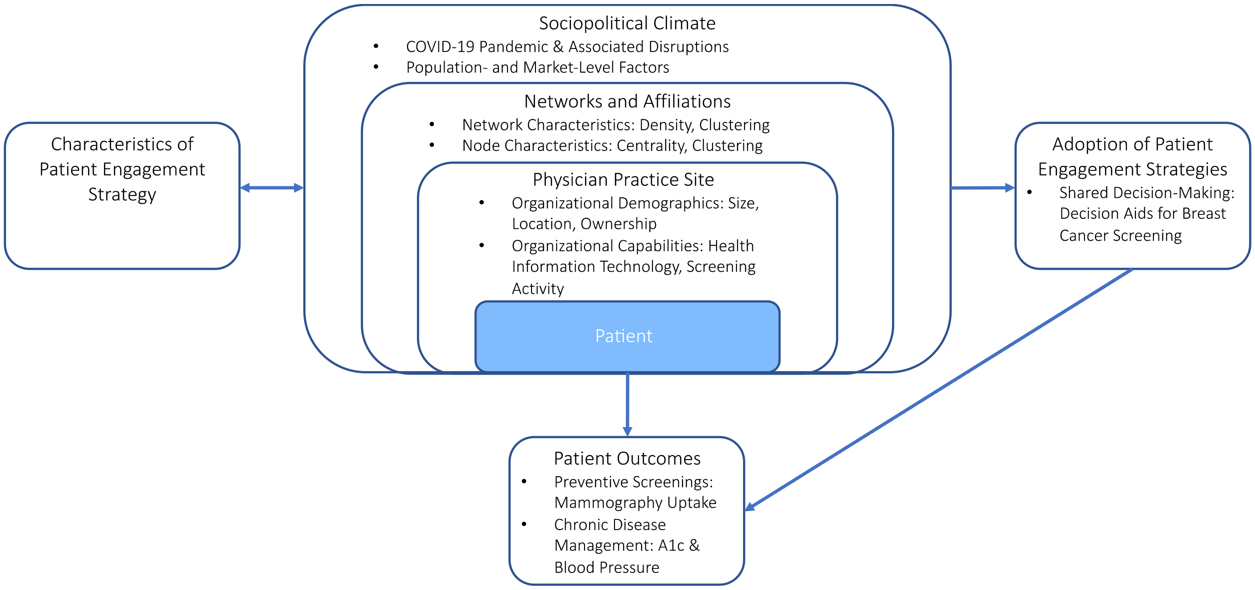
CONCEPTUAL MODEL & SPECIFIC AIMS

2.1 CONCEPTUAL MODEL

Building upon existing theoretical and empirical literature in the health services and patient engagement domains, the integrated conceptual model outlined in Figure 1 was developed. The model first draws upon the socioecological model, which identifies the multifaceted factors that are related to patients' health outcomes. Specifically, this model acknowledges that an individual's health outcomes are not solely a function of individual characteristics, but rather a reflection of the broader environment in which an individual exists.[36] Here, we focus largely on the health care context: while non-medical factors such as social determinants of health (SDOH) and lifestyle behaviors are important contributors to health outcomes, medical care remains a critical component of the overall health system, and can have a significant impact on specific health outcomes.[1,37]

Specifically, the present domains were adapted from work published by Miller-Rosales et al.[38] In their work, the authors present a framework for understanding organizations' adoption of patient engagement strategies, such as physician practice characteristics, and the broader environment in which they exist. Of note, Miller-Rosales' original "networks and affiliations" category focused on formal organizational partnerships. The present work builds upon existing literature on patient engagement efforts and lends a novel perspective through the incorporation of a social network lens: thus, the proposed "networks and affiliations" category in the present proposal emphasizes patient-sharing provider networks that may exist within and across organizational boundaries.

Figure 1. [Adapted] Conceptual Model.



2.2 SPECIFIC AIMS

This collection of work contributes to our understanding of the influences of organizational and network characteristics on patient outcomes by examining four specific aims, addressing several gaps in the existing literature. The proceeding chapters are divided conceptually into two main themes: patient engagement (through the examination of one decision aid use case) and clinical collaboration (through the lens of network theory). Thus, this dissertation aims to:

1. Assess the relationship between physician practice and community characteristics and increased adoption of decision aid use for breast cancer screening;
2. Assess the relationship between increased decision aid use and actual mammography uptake;
3. Examine how local and global clinician network characteristics changed following the onset of the COVID-19 pandemic among Federally Qualified Health Center clinicians caring for individuals with chronic diseases; and
4. Investigate the association between network brokerage and high priority outcome measures for Federally Qualified Health Centers.

CHAPTER 3

ORGANIZATIONAL AND COMMUNITY CHARACTERISTICS ASSOCIATD WITH THE USE OF DECISION AIDS FOR BREAST CANCER SCREENING

3.1 BACKGROUND

BREAST CANCER PREVALENCE AND MAMMOGRAPHY POLICY CONTEXT

Among health services scholars, breast cancer is acknowledged as a major public health problem and is the target of research efforts across a variety of specialty fields. Epidemiologists in the United States began the formal tracking of cases through cancer registries in the 1930s. Since this time, breast cancer diagnosis rates have been rising steadily; while increases in early screening and detection capabilities may contribute to a modest rise in incidence reports, this trend is thought to explain only a small portion of the overall long-term increases in breast cancer incidence over the years.[39]

Today, breast cancer is the second most common type of cancer overall, and represents the most commonly diagnosed cancer among women worldwide.[40] It is estimated that approximately one in eight women in the United States will develop breast cancer over the course of their lifetime.[41] The rising prevalence of breast cancer has placed increasing pressures on the health care delivery system to develop strategies to improve both treatment and preventive service options for this disease.

The preventive service coverage requirement under the Affordable Care Act stipulates that private insurance plans and state Medicaid expansion programs must provide full coverage for screening mammography for women between the ages of 40 and 74 who present an average risk for developing breast cancer.[42] While guidelines from the U.S. Preventive Service Task Force (USPSTF) currently recommend that eligible women receive biennial mammograms until they reach the age of 74,[43] evidence is mixed regarding the utility of universal screening beyond the age of 70 years.[44–46]

DECISION AIDS AS TOOLS TO DISCUSS THE POTENTIAL RISKS ASSOCIATED WITH BREAST CANCER SCREENING IN OLDER WOMEN

While cancer screenings may allow for the early detection of illnesses and timely interventions that can lead to improved patient outcomes, they also pose significant risks of overdiagnosis and overtreatment. *Overdiagnosis* occurs when malignancies are detected that would not have resulted in clinical significance; it is estimated that up to 25% of breast cancer cases may be over-diagnosed.[47–49] *Overtreatment* occurs when patients receive services that do not actually provide clinical benefit.[50] The implications of these risks, particularly for breast cancer screenings, vary by age and the presence of potential comorbidities.[21] Therefore, it is important for patients to actively engage in conversations with their providers around their individual health-related goals and risks when deciding whether or not to undergo a screening.

Given the rise in the percentage of older adults in the U.S. population,[51] it is especially important to consider the risks of breast cancer screening in older women: these include pain, anxiety, false positives leading to additional tests that carry their own risks of complications, and over-diagnosis leading to unnecessary treatments and their associated risks.[52] Decision aids (DAs) for breast cancer screening have been shown to increase patients' awareness of such risks.[22] It is not yet known the extent to which these trends impact diagnosis rates and subsequent health outcomes, and how such effects might vary across age, race, and socioeconomic status. While such analyses are outside of the scope of this dissertation, this remains an important area of future research.

Despite stating their intentions to use a DA, evidence shows that substantially fewer clinicians follow through with their sustained adoption into clinical workflows,[53] suggesting that barriers to successful implementation warrant additional investigation. To date, the scholars have documented that the integration of DAs into clinical practice is widely perceived as difficult. This is in part due to time pressures, concerns about shifting the "onus of responsibility" onto the patient, costs to develop and maintain the tools themselves, general lack of DA knowledge, and concerns about usability by diverse populations.[54–56] Evidence is limited regarding the organizational and population-level factors that are associated with increased use of DAs for breast cancer screening.

STUDY AIMS

DAs for breast cancer screening can be categorized as evidence-driven "innovations," with the understanding of "innovations" as ideas or practices that are perceived to be novel to an organization.[57] Thus, two measures relating to innovation in care delivery settings will be examined in relation to DA use frequency: a composite score of practices' cultures of innovation, and a scale of the barriers to innovation practices face. Furthermore, the Strengths-Based Innovation Framework posits that practices are most likely to embrace those changes, or innovations, that align with what they are already doing well.[58] Given that DAs are increasingly being utilized in computer-based modalities,[12] it is therefore plausible that practices who already demonstrate proficiency in the effective implementation of technology-enabled workflows are more likely than their less tech-savvy counterparts to utilize breast cancer screening DAs. A composite score of advanced health information technology capabilities will therefore serve as the third independent variable in this analysis. Therefore, the following organizational hypotheses will be tested to address Aim 1 of this dissertation:

1. More advanced HIT capacity will be associated with more frequent DA use;
2. More barriers to innovation will be associated with less frequent DA use; and
3. A stronger culture of innovation will be associated with more frequent DA use.

Additionally, lack of time is one of the most frequently cited barriers to successful implementation of shared decision-making (SDM) efforts.[59,60] Thus, shortages of primary care physicians may result in less available time to spend with each patient, and therefore less frequent DA use.[61,62] Parallel to concerns about clinical bandwidth, clinicians perceive patients with more comorbidities as having less time to engage in shared decision-making,[63] and clinicians' perception of their patients' willingness to engage in SDM is known to affect DA use.[59] Thus, a more clinically complex population, as defined by the CMS Hierarchical Conditions Category (HCC) Score, may be associated with less frequent DA use. Lastly, various studies reference age as a factor in patients' willingness to engage in SDM, with older patients often demonstrating a lesser preference for sharing decision-making autonomy with their provider.[59] Thus, an older population may be associated with less frequent DA use. Therefore, the following population hypotheses will be tested to address Aim 1 of this dissertation:

4. A greater number of primary care providers per 10,000 residents will be associated with more frequent DA use;
5. A higher aggregate CMS HCC Score will be associated with less frequent DA use; and
6. A higher percentage of female residents age 65 and older will be associated with less frequent DA use.

3.2 METHODS

ANALYTIC SAMPLE

To address Aim 1 of this dissertation, data from the 2017/2018 National Survey of Healthcare Organizations and Systems (NSHOS) of physician practices were analyzed. NSHOS uses a stratified-cluster sampling design (which approximates a census of clinician organizations) to select eligible physician practices with three or more adult primary care physicians.[64] The response rate was 48.6% and the analytic sample includes 2,190 physician practices.[65] For the purposes of this survey, practice characteristics were categorized by a commercially available database from health innovation firm, IQVIA, and merged with practices' responses.

Additional data pertaining to community-level characteristics were sourced from the 2017 Area Health Resource Files (AHRF) by the Health Resources & Services Administration (HRSA).[66] The AHRF consolidates information from over 50 federal and non-governmental databases, encompassing more than 1,000 variables that describe a wide range of county-specific attributes. These variables include demographic data, details on the healthcare workforce, information about healthcare facilities, health spending figures, and other indicators that represent key social determinants of health. These data were linked to the 2017/2018 NSHOS responses via a ZIP/FIP code crosswalk data file.

MEASURE SELECTION

The outcome of interest in this study is frequency of DA use for breast cancer screening. DAs were defined in the 2017/2018 NSHOS as providing "objective information on benefits and harms to help patients clarify their goals, values and preferences and make decisions that are consistent with their goals." Respondents reported the extent to which "eligible patients" in their practice received DAs for breast cancer screening "none", "some", "most", or "all" of the time.

The remaining practice and community covariates are described in detail in Table 1 below.

Table 1. Descriptions of Physician Practice and Community Characteristics.

Variable Name	Variable Description	Variable Type
Practice Characteristics from the 2017/2018 National Survey of Healthcare Organizations & Systems (NSHOS)		
Advanced HIT Index	Participants were asked if their practices' health information systems (including their electronic health record) allowed for five advanced HIT functions: patients' access to electronic health records, patients' ability to electronically comment on these records, physicians' and patients' ability to communicate with each other via secure email, physicians' ability to know if patients filled prescriptions, and the presence of advanced analytic systems.[67] The index reflects a transformed sum of the number of positive responses (range= -2.54 - 2.12).	Independent Variable
Barriers to Innovation Scale	Respondents responded to six questions about the degree to which their practice experienced various barriers to evidence-based care delivery innovations: lack of a process for identifying beneficial innovations, lack of a process for disseminating information about innovations, not having enough time to implement these innovations, having insufficient financial resources for implementation, lacking the necessary knowledge/experience to implement, and lacking incentives to implement. Positive responses to these questions were summed and transformed to produce this scale (range= -2.48 - 2.20).	Independent Variable
Culture of Innovation Scale	The innovation culture items were informed by the Competing Values Framework, which categorizes cultures on the basis of two dimensions (control vs. flexibility and internal vs. external focus), depicts "innovative" cultures as those that support development and experimentation.[68] NSHOS respondents reported the degree to which their practice culture is "innovative" and indicated "never," "sometimes," "often," or "always" to six questions that have been previously demonstrated to effectively measure innovation culture: "there is protected time given to generate new ideas and innovations," "successful care delivery innovations are highly publicized," "we encourage trying new ideas to see if they work," and "we consider ourselves to be a testing ground for new approaches to engage patients in their care." This scale represents a transformed score of positive responses to these questions (range= -1.87 - 1.52).	Independent Variable
Practice Size	Practice size was calculated based on the total number of practicing physicians at each practice. The measure includes 5 categories of practice size: 3 physicians, 4–7 physicians, 8–12 physicians, 13– 19 physicians, and >20 physicians.	Control Variable
Practice Ownership	Practice ownership was categorized into the following groups: hospital/healthcare system-owned, large physician group-owned, independent, community health center, and other.	Control Variable
Rurality	Practice locations were dichotomously classified as "rural" or "urban."	Control Variable
Medicare ACO Participation	Practices were asked if they were participating in any risk-bearing ACO; practices were categorized as participating if their participation was current. Alternatively, practices were categorized as not participating if they answered "no" or that they had participated in an ACO in the past.	Control Variable
Medicaid Revenue Scale	Percentage of annual patient care revenue coming from Medicaid was classified as follows: No Medicaid Revenue = 0%, Low Medicaid Revenue = 1-29%, and High Medicaid Revenue = 30% or greater.	Control Variable

Training in SDM	Practices were provided with the definition of "shared decision-making" as "informing patients of their options and the benefits or harms of those options, supporting them to compare those options and then make choices that are aligned with their informed goals and values. Then, respondents were asked how many of the physicians and staff in their practice were formally trained in shared decision-making. Response options included "none," "some," "most," or "all."	Control Variable
Specialty Mix	Specialty mix was calculated as the ratio of specialist physicians to primary care physicians within a practice. The cut-off points for the low, moderate, and high categories are as follows: No = no specialists, Low = 0–33rd percentile, Moderate = 33rd–66th percentile, High = 66th–100th percentile. Advanced Practice Clinicians	Control Variable
Advanced Practice Clinicians	This variable is a count of the total number of advanced practice clinicians within a physician practice. Advanced practice clinicians include nurse practitioners, physician assistants, and clinical nurse specialists.	Control Variable
	Community Characteristics from the 2017 Area Health Resource File (AHRF)	
PCPs per 10,000 Residents	The adjusted number of primary care physicians per county was constructed by taking the total number of primary care physicians in each county, dividing by the county population estimate, and multiplying by 10,000.	Independent Variable
CMS HCC Score	Hierarchical condition category (HCC) coding is a risk-adjustment model used by the Centers for Medicare and Medicaid Services (CMS).[69] Constructed with ICD-9 diagnostic codes, a mean HCC score was provided in the AHRF file for each county.	Independent Variable
Percent of Females 65+	The estimated percent of females over the age of 65 was constructed by first calculating the proportion of females in each county (total female population/total population), then multiplying the proportion of females by the number of residents over the age of 65 in each county, and multiplying by 100. The available statistics were pulled from the AHRF file.	Independent Variable
Median Household Income	Annual median household income in the ZIP code of residence was included in the AHRF file for each county.	Control Variable

DATA ANALYSIS

Mixed-effect regression models estimated the association of DA use with physician practice capabilities and community effects, adjusting for control variables, and with fixed and random effects at the zip code level to account for potential clustering of responses within the same geographical areas. The model's covariance structure was unspecified, allowing for an unstructured covariance matrix among the random effects. The breast cancer DA use outcome was normally distributed, justifying the use of an OLS specification. To mitigate concerns about linear regression modeling using a continuous specification of the ordinal outcome variable, a sensitivity analysis using an ordinal logistic specification of the mixed-effect model was conducted and the results were compared with the linear results.

Descriptive analyses were conducted using chi-square tests to elucidate the distribution of DA use for breast cancer screening among the sample population of participating practices. The main independent variables were standardized to improve interpretability of the results.

3.3 RESULTS

DESCRIPTIVE STATISTICS

Most physician practices adopted DAs for breast cancer screening (70.3%), but there was high variation in frequency of use: 30.0% of practices used DAs some of the time, 26.6% of practices used them most of the time, and 13.7% of practices used them all of the time (Table 2).

Table 2. Local Characteristics and Decision Aid Use for Breast Cancer Screening.

Practice or Zip Code Characteristic	**Frequency of Decision Aid Use**			
	None of the Time	Some of the Time	Most of the Time	All of the Time
Physician Practice Characteristics: N (%)				
Size				
3 Physicians	156 (29.16)	143 (26.73)	148 (27.66)	88 (16.45)
4-7 Physicians	228 (27.77)	246 (29.96)	223 (27.16)	124 (15.10)
8-12 Physicians	97 (29.57)	105 (32.01)	82 (25.00)	44 (13.41)
13-19 Physicians	39 (23.78)	58 (35.37)	55 (33.54)	12 (7.32)
20+ Physicians	83 (28.14)	104 (35.25)	75 (25.42)	33 (11.19)
				x^2 = 21.17, p = 0.05
Ownership				
Hospital/Healthcare System	326 (32.76)	304 (30.55)	248 (24.92)	117 (11.76)
Large Physician Group	61 (25.42)	57 (23.75)	88 (36.67)	34 (14.17)
Independent Practice	131 (23,69)	172 (31.10)	157 (28.39)	93 (18.82)
Community Health Center	76 (24.84)	106 (34.64)	72 (23.53)	52 (16.99)
Other	9 (18.37)	17 (34.69)	18 (36.73)	5 (10.20)
				x^2 = 42.94, $p < 0.001$
Rurality				
Rural	51 (27.13)	66 (35.11)	52 (27.66)	10 (10.11)
Urban	552 (28.24)	590 (30.18)	531 (27.16)	282 (14.42)
				x^2 = 3.73, p = 0.29
Medicare ACO Participation				
Yes (Current)	443 (28.75)	482 (31.28)	410 (26.61)	206 (13.37)
No	160 (26.58)	174 (28.90)	173 (28.74)	95 (15.78)
				x^2 = 26.30, $p < 0.001$
Medicaid Scale				
No Medicaid	68 (24.03)	73 (25.80)	83 (29.33)	59 (20.85)
Low Medicaid	393 (28.23)	435 (31.25)	382 (27.44)	182 (13.07)
High Medicaid	142 (30.34)	148 (31.62)	118 (25.21)	60 (12.82)
				x^2 = 16.95 , p = 0.01
Training in SDM				
None of the Physicians/Staff	322 (53.44)	156 (25.74)	90 (14.85)	38 (6.27)
Some of the Physicians/Staff	174 (23.39)	313 (42.07)	189 (25.40)	68 (9.14)
Most of the Physicians/Staff	70 (14.47)	123 (25.89)	203 (42.74)	79 (16.63)
All of the Physicians/Staff	33 (10.89)	62 (20.46)	94 (31.02)	114 (37.62)
				x^2 = 492.83, $p < 0.001$
Physician Practice Characteristics: Mean (SD)				
Advanced HIT Capabilities	48.58 (20.11)	53.45 (20.29)	58.27 (20.83)	61.81 (24.02)

				F = 35.09, p < 0.001
Barriers to Innovation Scale	65.51 (26.98)	56.31 (28.17)	51.73 (27.33)	31.71 (31.71)
				F = 61.88, p < 0.001
Culture of Innovation Scale	44.69 (20.45)	52.10 (20.07)	56.45 (20.00)	64.57 (22.04)
				F = 71.01, p < 0.001
Specialist Mix	3.59 (10.18)	4.94 (24.44)	4.11 (19.31)	2.94 (13.15)
				F = 1.01, p = 0.385
Advanced Practice Clinicians	3.08 (5.27)	3.28 (5.04)	2.91 (4.79)	2.45 (4.49)
				F = 2.01, p = 0.11
Community Characteristics: Mean (SD)				
Percent of Females 65+	15.56 (3.27)	15.65 (3.68)	15.58 (3.37)	15.41 (3.15)
				F = 0.35, p < 0.001
PCPs per 10,000 Residents	8.69 (3.18)	8.56 (3.24)	8.43 (3.15)	8.38 (2.78)
				F = 0.95, p = 0.415
CMS HCC Score	1.00 (0.10)	0.99 (0.09)	1.01 (0.11)	1.01 (0.11)
				F = 5.80, p < 0.001
Median Household Income	$62,796.34 ($15,552.17)	$64,449.78 ($17,001.04)	$64,913.17 ($17,312.76)	$65,765.54 ($17,750.56)
				F = 2.65, p = 0.047

Unadjusted comparisons indicated a significant increase in DA use correlating with advanced HIT capabilities, reflected in a gradient from lower to higher usage as capabilities improved (F = 35,09, p < 0.001). Practices reporting higher barriers to innovation showed a marked decrease in DA use (F = 61.88, p < 0.001), while practice reporting increased scores on the culture of innovation scale showed an increase in DA use (F = 71.01, p < 0.001).

The distribution of percentage of females over the age of 65, the density of PCPs, and CMS HCC scores did not show meaningful differences across DA use frequencies.

REGRESSION RESULTS

In the multi-level regression analyses, advanced HIT capabilities (β = 0.135, p < 0.001) and innovation culture (β = 0.182, p < 0.001) were associated with more frequent use of DAs for breast cancer screening. Greater barriers to innovation were associated with less frequent use of DAs (β = -0.142, p < 0.001). Counter to our initial hypotheses, a greater number of PCPs per 10,000 residents was associated with a decrease in DA use (β = -0.620, p < 0.01), higher aggregate HCC scores were associated with an increase in DA use (β = 21.528, p < 0.001), and the percent of females over the age of 65 was not significantly associated with frequency of DA use (Table 3, Model 1).

Table 3. Multi-Level Regression Models Predicting Breast Cancer Decision Aid (DA) Use.

Variable	Model 1 Linear Specification		Model 2 Ordinal Specification	
	β	95% C.I.	β	95% C.I.
Size				
3 Physicians (ref)				
4-7 Physicians	0.708	-2.590 – 4.006	0.180	-0.101 – 0.460
8-12 Physicians	-0.783	-5.023 – 3.458	0.124	-0.234 – 0.482
13-19 Physicians	-1.052	-6.283 – 4.379	0.325	-0.144 – 0.794
20+ Physicians	-5.593*	-10.166 – -1.022	-0.103	-0.489 – 0.283
Ownership				
Independent Practice (ref)				
Large Physician Group	-2.050	-6.723 – 2.623	-0.318	-0.728 – 0.092
Community Health Center	-1.426	-5.940 – 3.089	-0.139	-0.554 – 0.257
Hospital/Healthcare System	-4.415*	-7.752 – -1.078	-0.428**	-0.718 – -0.138
Other	2.102	-11.540 – 7.336	0.318	-0.554 – 1.189
Rurality				
Rural (ref)				
Urban	4.307	-0.843 – 9.456	0.437	-0.011 – 0.884
Medicare ACO Participation				
Yes (ref)				
No	1.411	-1.449 – 4.271	0.026	-0.218 – 0.270
Medicaid Scale				
No Medicaid (ref)				
Low Medicaid	-5.340**	-9.333 – -1.347	-0.205	-0.559 – 0.149
High Medicaid	-7.597**	-12.376 – -2.817	-0.443*	-0.862 – -0.025
Training in SDM				
None of the Time (ref)				
Some of the Time	11.947***	8.645 – 15.250	1.214***	0.923 – 1.507
Most of the Time	22.175***	18.388 – 25.963	1.616***	1.244 – 1.988
All of the Time	30.645***	26.245 – 35.044	1.783***	1.324 – 2.241
Advanced HIT Capabilities	0.135***	0.069 – 0.189	0.009**	0.003 – 0.015
Barriers to Innovation Scale	-0.142***	-0.189 – -0.093	-0.009***	-0.013 – -0.005
Culture of Innovation Scale	0.182***	0.128 – 0.264	0.012***	0.006 – 0.018
Specialist Mix	-0.001	-0.034 – 0.033	< 0.000	-0.002 – 0.002
Advanced Practice Clinicians	-0.016	-0.466 – 0.145	-0.015	-0.039 – 0.010
Percent of Females 65+	0.156	-0.269 – 0.581	0.014	-0.023 – 0.051
PCPs per 10,000 Residents	-0.620**	-1.052 – -0.187	-0.048*	-0.084 – -0.012
CMS HCC Score	21.428**	6.773 – 36.082	0.555	-0.712 – 1.823
Median Household Income	< 0.000	-21.812 – 22.178	< 0.000	0.000 – 0.000

Among the covariates, the primary regression results also indicated significant effects of practice size, ownership, Medicaid revenue, and training in shared decision-making on the frequency of DA use. Notably, larger practice size (β = -5.593, p < 0.05) and system ownership (β = -4.415, p < 0.05) were associated with less frequent DA use. Conversely, receiving at least some Medicaid revenue (low: β = -5.340, p < 0.01, high: (β = -7.597, p < 0.01)) was associated with less frequent DA use when compared against physician practices receiving no Medicaid revenue. Having at least some training in shared decision-making was associated with an increase in DA use frequency as compared to practices with no training in shared decision-making (some of the time: β = 11.947, $p < 0.001$, most of the time: β = 22.175, $p < 0.001$, all of the time: β= 30.645, $p < 0.001$). Major fluctuations between the ordinary least squares (OLS) and ordinal logistic specifications of the models were not observed, with the OLS specification offering improved interpretability of the results.

3.4 DISCUSSION

Our study, the first to examine the adoption and use of breast cancer screening DAs among physician practices nationally, found that practices with more advanced HIT functions, stronger innovation cultures, and fewer barriers to adoption of evidence-based practices used the DAs more frequently than practices lacking these capabilities. These results support each of our three initial hypotheses, based on the Strength-Based Innovation Framework,[58] which posits that practices are more likely to embrace innovations that algin with what they are already doing well.

First, physician practices with more advanced HIT functions use DAs more frequently than practices with less advanced HIT functions, supporting hypothesis one. This is consistent with prior evidence that incorporating SDM tools into electronic health records increases the likelihood of successful implementation by allowing for real-time integration into clinical workflows and the ability to generate automatic triggers for use.[70,71] Thus, an important implication of the study findings is that care delivery organizations intending to adopt DAs for breast cancer screening should consider how the DA tool might be integrated into the electronic health record for the purposes of identifying eligible patients, notifying clinicians, and documenting patients' preferences. Alternatively, practices with limited HIT functions might consider non-electronic processes to ensure consistent adoption of DA use for all eligible patients.

Second, physician practices with a stronger culture of innovation and fewer barriers to innovation use DAs more frequently, supporting hypotheses two and three. These findings are consistent with evidence suggesting that organizational cultures that embody and encourage innovation often implement novel interventions more effectively.[72] Therefore, practices that have faced challenges with the implementation of novel evidence-driven tools might consider conducting an internal assessment to identify their specific barriers to innovation, focusing on information dissemination protocols, time availability, financial resources, alignment of physician incentives, and provider training. However, recent evidence indicates that participation in "innovative" primary care reforms is associated with higher burnout, and that an emphasis on fostering a practice culture of psychological safety and organizational learning may promote greater quality improvement capacity compared to engaging in simultaneous reforms.[73] Therefore, practice leaders promoting DAs for breast cancer screening may benefit from monitoring and addressing implementation climate and readiness for organizational change when planning for and implementing DAs (28).[74]

Our latter three hypotheses remained unsupported by our results. It was initially theorized that a higher availability of PCPs in a community would lead to greater time availability to engage in activities such as shared decision-making that are not necessarily reimbursed in a traditional fee-for-service model. However, it is also plausible to consider that physicians facing greater time constraints may be more likely to adopt innovations that have potential for utilization-reduction, as is the case with DAs.[75] Additionally, we hypothesized that providers' preconceptions about their patients' bandwidth for SDM engagement would result in a negative association between patient population complexity (as measured by a community's average HCC score) and DA use. The finding that higher HCC scores were associated with increased DA use may in fact underscore clinicians' appropriate use of DAs for patients who would most benefit from conversations about the risk-benefit trade-off of preventive cancer screenings.

In addition to the main hypothesized relationships, four control variables are associated with more frequent DA use for breast cancer screening. Larger practices and hospitals/healthcare systems used DAs less frequently than smaller practices and independently owned practices. This observation diverges from prior evidence that large health care systems support innovation.[67,76] Recent work has shown that smaller practices have less workforce burnout, which is associated with improvements in quality improvement capabilities.[73] Thus, these practices may have greater "adaptive reserve" to introduce evidence-driven innovation. Large physician practices, facing a rising epidemic of physician burnout,[77] should remain aware of these potential limitations on further innovation. Our results may also depart from previous evidence about the role of systems on innovation adoption. This may be because DAs have unique innovation characteristics: DAs are available in multiple formats (i.e., paper-based vs. electronic) and are not necessarily resource-intensive to obtain or administer to patients. Therefore, when faced with various options for using DAs, smaller independent physician practices without advanced health IT functions but with strong relational orientations with their patients may opt to use paper-based DAs to support shared decision, which is consistent with the Strengths-Based Innovation Framework.[58] This framework also supports the expected finding that practices with training in SDM are more likely to use DAs for breast cancer screening, which is congruent with prior evidence that clinicians trained in DA use are more likely to sustain their implementation in clinical workflows.[78]

Furthermore, practices receiving at least some revenue from Medicaid used DAs less frequently than practices receiving no revenue from Medicaid. This lower frequency of DA use may be a function of lesser need, given that the ideal population for breast cancer screening DAs are older women, and the majority of Medicaid beneficiaries are children and non-elderly adults.[79] It is also plausible that this finding may be explained by the observation that practices not receiving Medicaid reimbursements are typically less resource constrained,[80] and may be able to allocate sufficient resources to innovation implementation, including DA adoption and use.

These study results should be considered in light of some limitations. First, the cross-sectional study design limits assessment of causal relationships. Future field experiments may be able to elucidate causal connections between organizational factors and DA adoption and use. Second, the modest effect sizes of our beta coefficients indicate that omitted variables, such as those relating to actual care team processes (e.g., which care team member is responsible for using the DA tool to engage patients in shared decision-making regarding breast cancer screening) may contribute to the adoption of DAs for breast cancer screening, but were not assessed in the NSHOS physician practice survey. Third, our results may not generalize well to small (<3 physician) practices and federally owned systems (such as Indian Health Services or Veterans Affairs hospitals), as these were also not included in the NSHOS dataset. Fourth, while NSHOS asked about DA adoption and use, the survey instrument did not specifically define what was meant by "eligible patients.'' Respondents may have interpreted DA eligibility criteria differently, e.g., for age-eligible women or for women outside of age eligibility for mammography. Lastly, due to a lack of DA-specific information available in the NSHOS data file, we were not able assess other relevant dimensions of DA implementation, including reach to the target population, efficacy, implementation fidelity, and maintenance over time, to draw from the commonly cited RE-AIM Framework.[81] Future research focused on breast cancer screening DA use should consider these dimensions of implementation and maintenance of DAs.

3.5 CONCLUSION

In conclusion, DAs for breast cancer screening are valuable tools for physicians to engage patients in shared decision-making conversations.[12] However, the data from our national study of physician practices indicate that DAs for breast cancer screening are not consistently used. Practices with limited HIT functions, greater barriers to innovation adoption, and operating within a large or system-owned context may face operational or cultural constraints, which may impact the adoption, reach, implementation, and effectiveness of DAs. Such organizations would benefit from targeted support to improve breast cancer screening DA implementation, to address the overall goal of incorporating patients' personal values and individual risk factors into this important decision about their health care.

CHAPTER 4

MAMMOGRAPY AND DECISION AID USE FOR BREAST CANCER SCREENING IN OLDER WOMEN

4.1 BACKGROUND

Breast cancer is the most common cancer among women in the United States, and constitutes the second leading cause of cancer death among women overall.[82] U.S. Preventive Services Task Force guidelines recommend that eligible women receive biennial mammograms until the age of 74 years,43 although evidence is mixed regarding the importance of screening beyond the age of 70.[44–46] Although mammography can enable early detection of cancer, false-positive results remain a risk. Overdiagnosis occurs when malignancies are detected that would not have resulted in clinical significance; it is estimated that up to 25% of breast cancer cases may be overdiagnosed.[47–49] Decisions about whether to undergo mammography should depend on patients' risks and preferences and include a structured discussion about the risks and benefits of screening.[47,83]

As discussed in the previous chapter of this dissertation, decision aids (DAs) can help clinicians to structure conversations about screening decisions, costs and benefits of various choices,[84] and patients' health goals.[20] Breast cancer screening DAs can increase patient awareness of the risks associated with overdiagnosis.[22,85–87] To date, there is mixed evidence about the association of DAs with mammography use. For example, one systematic review found that DAs have minimal impact on screening decisions,[88] whereas another found that DAs reduce screening intentions.[75] Although DA use is low overall,[89] practices that integrate them into clinic workflows use DAs more consistently.[90] Practices with more advanced health information technology (HIT) may be more likely to use HIT-enabled DAs and patient reminders, which can impact mammography screening rates.

Support for the inclusion of DAs for breast cancer screening, particularly for older women for whom the benefits of population-wide screening is less clear, is predicated in part on the poor performance of risk assessment models to identify patients at high risk of developing breast cancer.[91] There is evidence to suggest that patients at higher risk of developing breast cancer were not being consistently screened at a higher rate than patients at lower risk.[92] Furthermore, decisions about whether a patient should undergo a breast cancer screening seem to vary by sociodemographic characteristics and subspecialty of provider.[93] Patients are often heavily swayed by the recommendations of their providers, with perceived physician enthusiasm for breast cancer screening influencing screening behavior among eligible patients.[92] Taken together, this evidence highlights the importance of including tools such as DAs to elevate the patients' voice by integrating their values and individual risk factors into this important decision about their care. In fact, some experts altogether reject the upper age limit on breast cancer screening guidelines, in favor of individualized evaluations which can be supported through the use of DAs to ensure lack of coercion and a true focus on patient-centered decision-making.[94]

Prior to this analysis, no national evidence existed about whether physician practice adoption of DAs for breast cancer screening or HIT functions are associated with mammography use among older adult women. This analysis fills a critical gap in evidence by analyzing a national sample of physician practices and claims data from eligible, attributed Medicare fee-for-service (FFS) beneficiaries.

4.2 METHODS

DATA

Physician practice responses to the 2017/2018 National Survey of Healthcare Organizations and Systems (NSHOS) were linked to 2017 Medicare FFS beneficiary and claims data using National Provider Identifiers. As mentioned in the previous chapter of this dissertation, NSHOS used a stratified-cluster sampling design to select eligible physician practices and yielded a response rate of 47%, with a total of 2,190 physician practice responses.[65] A total of 881,808 female beneficiaries were attributed to one of 1,773 NSHOS physician practice responses.

ANALYTIC SAMPLE

The analytic sample included female beneficiaries aged 65 −74 years with Part B eligibility and no HMO enrollment in 2017 or 2016. Practices with <100 attributed beneficiaries (n=493) were excluded to ensure the reliable estimation of practice effects on mammography use.[95] Table 1 below provides additional details regarding analytic sample exclusions. The final sample includes 439,684 Medicare FFS beneficiaries attributed to one of 1,236 NSHOS physician practice responses (average beneficiaries per practice = 285, SD = 344).

Table 1. Analytic Sample Exclusions

Exclusion Criteria	**Total (N)**	**Percent (%)**
Beneficiaries Attributed to NSHOS Practices	1,511,938	100%
Exclusion #1: Male	630,130	41.68%
Exclusion #2: Age < 65 or Age ≥ 75	410,353	27.14%
Exclusion #3: Deceased during 2017	4,870	0.32%
Exclusion #4: Evidence of Mastectomy	106	~0%
Exclusion #5: Hospice Use	735	~0%
Exclusion #6: Long-Term Care Use	297	~0%
Exclusion #7 (Practice-Level): < 3 Physicians	3,844	0.25%
Analytic Sample: Total Attributed Beneficiaries	439,684	29.09%
Analytic Sample: Total Physician Practices (Restricted)	1,236	-
Sensitivity Analytic Sample: Total Attributed Beneficiaries	461,603	-
Sensitivity Analytic Sample: Total Physician Practices (Unrestricted)	1,729	-

MEASURE SELECTION

The dependent variable is receipt of screening mammography, as indicated in Medicare FFS claims data from the cohort of eligible beneficiaries in 2017, with a 2-year look-back period of 2016 −2017. The independent variables are (1) a dichotomous measure of physician practice use of DAs for breast cancer screening and (2) a composite measure of advanced HIT functions (range: 0−100). Practice-level control variables include practice size, ownership, specialist-to-primary care physician ratio, and advanced practice clinician count. Patient-level control variables include patient age, race/ethnicity, Hierarchical Condition Category (HCC) risk scores (i.e., comorbidities), dual eligibility for Medicare and Medicaid, high-poverty ZIP code, and median household income. Measures are detailed in Table 2 below.

Table 2. Measure Descriptions.

Variable	Description
Outcome Measure	Data Source: 2017 Medicare Fee-for-Service Claims Data
Mammography Screening	Mammography screening was assessed at the patient-level. Mammography utilization was assessed among female Medicare FFS beneficiaries between the ages of 65-75 years who did not meet the exclusion criteria specified in Table 1. The 2-year lookback period for assessing screening mammography use in claims data includes calendar years 2016 and 2017.
Main Independent Measures	Data Source: 2017/2018 National Survey of Healthcare Organizations and Systems (NSHOS)
Practice Decision Aid (DA) Use	Decision aids (DAs) are tools that aid shared decision-making, which was defined in NSHOS as “informing patients of their options and the benefits or harms of those options, supporting them to compare those options and then make choices that are aligned with their informed goals and values.” Decision aids were defined as providing “objective information on benefits and harms to help patients clarify their goals, values and preferences and make decisions that are consistent with their goals." Respondents reported the extent to which “eligible patients” in their practice received DAs for breast cancer screening “none”, “some”, “most”, or “all” of the time. We defined low DA use to include responses of DA use “none” or “some’ of the time. We defined high DA use to include responses of DA use “all” or “most’ of the time.
Practice Advanced Health Information Technology (HIT) Capabilities	Respondents reported whether their practice’s health information system (including their electronic health record) allowed for five advanced HIT functions: 1) patients’ access to electronic health records, 2) patients’ ability to electronically comment on these records, 3) physicians’ and patients’ ability to communicate with each other via secure email, 4) physicians’ ability to know if patients filled prescriptions, and 5) use of predictive analytics. This index reflects a sum of the number of positive responses. For the predicted probabilities, the advanced HIT scores (range: 0-100) associated with each percentile cut point are: 0th percentile cut point = 0, 25th percentile cut point = 38.1, 50th percentile cutoff = 52.4, 75th percentile cutoff = 66.7, 100th percentile cutoff = 100.
Practice Characteristics	Data Source: 2017/2018 National Survey of Healthcare Organizations and Systems (NSHOS)**
Practice Size	Practice size was calculated based on the total number of practicing physicians at each practice. The measure includes 5 categories of practice size: 3 physicians, 4-7 physicians, 8-12 physicians, 13-19 physicians, and >20 physicians.

Specialty Mix	Specialty mix was calculated as the ratio of specialist physicians to primary care physicians within a practice. The cut-off points for the low, moderate, and high categories are as follows: No = no specialists, Low = 0-33rd percentile, Moderate = 33rd – 66th percentile, High = 66th – 100th percentile.
Advanced Practice Clinicians	This variable is a count of the total number of advanced practice clinicians within a physician practice. Advanced practice clinicians include nurse practitioners, physician assistants, and clinical nurse specialists.
Practice Ownership	Practice ownership was categorized into the following groups: independent, medical group-owned, and system-owned practices.
Beneficiary Characteristics	Data Source: 2017 Medicare Fee for Service Claims Data
Age	Patients' age in years was included from the Medicare Claims dataset.
Race/Ethnicity	Patients' race and ethnicity was included from the Medicare Claims dataset.
Hierarchical Condition Category (HCC) Score[69]	Hierarchical condition category (HCC) coding is a risk-adjustment model used by the Centers for Medicare and Medicaid Services (CMS). Using ICD-10 diagnostic codes, a risk adjustment factor (RAF) score is assigned to each patient to reflect their projected risk for high health care utilization.
Mental Illness Diagnosis[96]	Patients with any current diagnosis of mental illness, excluding autism and mental retardation; beneficiaries with depression, serious mental illness (bipolar disorder, schizophrenia and schizoaffective disorders) and anxiety.
Frail Elder[96]	Frailty was defined as beneficiaries having 2 or more frailty indicators (abnormality of gait, malnutrition, failure to thrive, cachexia, debility, difficulty in walking, fall, muscular wasting and disuse atrophy, muscle weakness, decubitus ulcer of skin, senility without mention of psychosis, Durable Medical Equipment use (cane, walker, bath equipment, and commode).
Dual Eligibility for Medicare & Medicaid	Patients who qualify for both Medicare & Medicaid services.
Resident of High Poverty Zip Code	Patients whose place of residence is in a zip code with high poverty status, defined as 20% or more of residents at or below the poverty level.
Annual Median Household Income	Annual median household in zip code of residence was included.

DATA ANALYSIS

Unadjusted mammography rates were compared for practices with routine DA use vs. practices with no or low DA use. Multivariable generalized linear models were estimated to examine the association of practices' DA use and HIT functions with patient-level receipt of mammography. Complete case analyses were conducted. Model 1 examined the association of practice and patient-level variables with mammography use. Model 2 extended Model 1 and included an interaction term between advanced HIT and DA use. Predicted probabilities of mammography use were calculated to illustrate how use varied by DA use and advanced HIT in adjusted analyses. All statistical analyses were conducted using Stata statistical software.[97]

Sensitivity analyses were conducted using mixed effects generalized linear models using weights and logistics function with a binomial distribution, removing the 100+ beneficiary sample restriction. A secondary sensitivity analysis was conducted focusing on practices' use of DAs for any preference sensitive condition. Collinearity was assessed using variance inflation factor (VIF) estimates, with VIF >2.55 as an indicator of potential collinearity.

4.3 RESULTS

DESCRIPTIVE STATISTICS

Overall, 60.1% of eligible beneficiaries had a mammogram, 37.3% of practices routinely used DAs for breast cancer screening, and practices' advanced HIT functions averaged 0.60 (SD=0.47). In unadjusted analyses, beneficiaries who did not have a mammogram were more likely to be attributed to practices that routinely used DAs than beneficiaries who had a mammogram (37.9% vs 37.0%, $p < 0.001$) (Table 3).

Table 3. Patient and Practice Characteristics, by Practice-Level Mammography Use.

Characteristics	Overall Mean	Beneficiaries without Screening Mammography in the Past 2 Years	Beneficiaries with Screening Mammography in the Past 2 Years	Difference p-value
Patient n (% of analytic sample)	439,684 (100)	171,984 (39.1)	267,700 (60.9)	–
Main predictors				
Practice use of breast cancer screening decision aids (%)	37.3	37.9	37.0	***
Practice advanced HIT functions, mean (SD)	0.600 (0.470)	0.590 (0.480)	0.600 (0.470)	***
Practice Characteristics				
Practice Size				
3-7 Physicians (%)	43.2	43.4	43.1	–
8-12 Physicians (%)	19.1	18.4	19.6	***
13-19 Physicians (%)	8.20	8.50	8.10	***
>19 Physicians (%)	29.4	29.8	29.2	*
Specialty Mixture				
No specialists (%)	26.9	26.5	27.2	**
Low (%)	24.3	26.0	23.2	***
Moderate (%)	23.7	22.9	24.3	***
High (%)	25.0	24.6	25.3	***
Practice Ownership				
Independently owned (%)	39.3	40.9	38.2	***
Medical group owned (%)	13.4	12.8	13.7	***
System owned (%)	47.3	46.3	48.0	***
Total mean advanced practice clinicians, mean (SD)	5.40 (18.1)	5.10 (16.0)	5.60 (19.4)	***
Patient Characteristics				
Age	69.2	68.5	69.7	***
Race/ethnicity				
White (%)	86.3	85.2	87.0	***
Black (%)	7.10	7.70	6.60	***

Asian (%)	1.80	2.20	1.60	***
Latinx (%)	0.700	0.900	0.600	***
Other (%)	4.00	4.00	4.10	–
CMS Hierarchical Condition Category (HCC) score, mean (SD)	0.710 (0.760)	0.790 (0.440)	0.650 (0.00)	***
Dual Medicare/Medicaid eligibility (%)	2.90	4.10	2.10	***
Frail elder (%)	2.80	3.30	2.50	***
Mental illness (%)	21.0	22.6	20.0	***
High-poverty ZIP code (%)	14.8	16.1	13.9	***
Annual median household income, mean (SD)	$61,921 ($42,676)	$60,790 ($42,505)	$62,267 (42,726)	***

Note: Boldface indicates statistical significance (*p<0.05. **p<0.01. ***p<0.001).

REGRESSION RESULTS

In adjusted analyses, routine DA use was not significantly associated with patient-level mammography use (OR = 0.95, p = 0.21) (Table 3, Model 1). Beneficiaries attributed to practices with higher specialist-to-primary care physician ratios (OR = 0.61, p < 0.01) were less likely to have a mammogram, whereas beneficiaries of practices owned by a hospital or health system (OR = 1.18, p < 0.01) and more advanced HIT functions (OR = 1.19, p < 0.05) were more likely to have a mammogram.

Older age (OR = 0.95, p < 0.05), Asian race (OR = 0.78, p < 0.001), more comorbidities (OR = 0.81, p < 0.001), dual Medicare and Medicaid eligibility (OR = 0.60, p < 0.001), and high-poverty ZIP code of residence (OR = 0.91, p < 0.001) were associated with lower odds of mammography use (Table 3, Model 1). Black race (OR = 1.13, p < 0.01) and greater median household income (OR = 1.06, p < 0.001) were associated with higher odds of mammography use.

There was no interaction effect between DA use and HIT (Table 3, Model 2). Predicted probabilities based on Model 2 are presented in Figure 1.

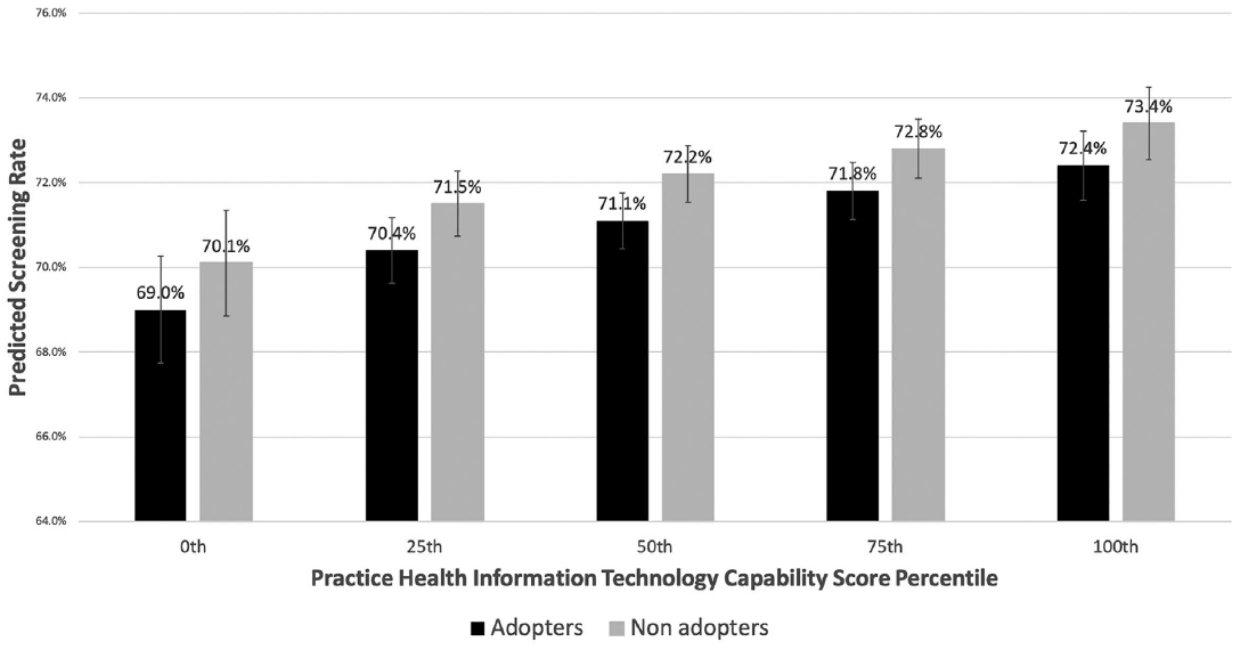
Table 4. Association of Practice Adoption of DAs and Advanced HTT Capabilities With Mammography.

Variables	Model 1: Full model with patient and practice characteristics	Model 2: Full model with DA * HIT interaction
Main predictors		
Practice use of breast cancer screening DAs	0.95 (0.87, 1.03)	0.94 (0.85, 1.03)
Practice advanced HIT functions	**1.19 (1.01, 1.40)***	1.17 (0.970, 1.40)
Practice use of DAs by Practice HIT functions	–	1.05 (0.890, 1.24)
Practice Characteristics		
Practice Size		
3-7 Physicians (ref)	–	–
8-12 Physicians	1.10 (0.95, 1.29)	1.10 (0.95, 1.29)
13-19 Physicians	0.96 (0.83, 1.10)	0.96 (0.84, 1.10)
>19 Physicians	1.06 (0.92, 1.22)	1.06 (0.92, 1.22)
Specialist ratio	**0.61 (0.43, 0.85)****	**0.61 (0.43, 0.86)****

Total advanced practice clinicians	0.95 (0.82, 1.11)	0.95 (0.82, 1.11)
Practice ownership		
Independently owned (ref)	–	
Medical group owned	1.16 (1.00, 1.34)	1.16 (0.99, 1.34)
System owned	**1.18 (1.06, 1.31)****	**1.18 (1.06, 1.31)****
Patient Characteristics		
Age	**0.95 (0.92, 0.99)***	**0.95 (0.92, 0.99)***
Race/ethnicity		
White (ref)	–	
Black	**1.13 (1.04, 1.23)****	**1.13 (1.04, 1.23)****
Asian	**0.78 (0.71, 0.86)*****	**0.78 (0.71, 0.86)*****
Latinx	0.89 (0.76, 1.05)	0.89 (0.76, 1.05)
Other	0.99 (0.92, 1.06)	0.99 (0.92, 1.06)
HCC Score	**0.81 (0.80, 0.82)*****	**0.81 (0.80, 0.82)*****
Dual Medicare/Medicaid	**0.60 (0.56, 0.65)*****	**0.60 (0.56, 0.65)*****
High-poverty ZIP code	**0.91 (0.87, 0.95)*****	**0.91 (0.87, 0.95)*****
Annual median household income	**1.06 (1.04, 1.08)*****	**1.06 (1.04, 1.08)*****
Constant	**2.31 (2.02, 2.63)*****	**2.33 (2.02, 2.69)*****
Total beneficiaries	439,684	439,684
Total physician practices	1,236	1,236

Note: Boldface indicates statistical significance (*p<0.05, **p<0.01, ***p<0.001).
The outcome is patient-level screening mammography use. ORs and 95% CIs are reported.

Figure 1. Mammography Use, by Practice Adoption of Breast Cancer Decision Aids and Advanced HIT Capabilities.



Note: Adopters denote that practice use decision aids for breast cancer screening (use for all or most eligible patients), Nonadopters denote that practice does not use decision aids for breast cancer screening (use for none or some eligible patients). The advanced HIT scores (range: 0–100) associated with each percentile cut point are as follows: 0th percentile cut point=0, 25th percentile cut point=38.1, 50th percentile cut off=52.4, 75th percentile cut off=66.7, and 100th percentile cut off=100.

Results were largely consistent for models that included all practices with attributed beneficiaries, irrespective of volume (Appendix Tables 1 and 2) and when DA use for any preference-sensitive condition was considered (Appendix Table 3)

4.4 DISCUSSION

DAs are encouraged by payers because of their potential to reduce costs and improve quality.[12] The authors hypothesized that advanced HIT would enable DA use and patient reminders for mammography, which could impact mammography rates. Although practice DA use was associated with patient-level mammography use in unadjusted analyses, the DA effect attenuates once advanced HIT and other practice characteristics are considered. The results suggest that HIT and DAs may have countervailing relationships with mammography use among older adult women. HIT-enabled automation of mammography reminders and other advanced HIT functions may support mammography,[89] whereas breast cancer DAs may reduce patients' propensities to be screened through the alignment of their preferences and screening decision. This may be why we found relatively small associations between DA use and advanced HIT functions with mammography use in adjusted analyses that consider both variables simultaneously.

Specialty mixture of physician practices was associated with lower mammography rates, suggesting that having proportionally more specialist physicians may not specifically incentivize breast cancer screening activity. Alternatively, hospital or health system ownership was associated with greater mammography rates, suggesting that the availability of organizational resources may enable greater screening capacity.

This study has some limitations. First, NSHOS assessed breast cancer screening DA use with a single question; DA design, implementation strategies, and patient populations targeted were not assessed. Second, NSHOS does not include small (<3 primary care physicians) or federally owned practices, so the results may not generalize to them. Third, the 47% NSHOS survey response rate may bias results; however, respondent and nonrespondent practices did not substantially differ (Appendix 4). Fourth, racial/ethnic diversity is low because Medicare FFS data were analyzed; inclusion of Medicare Advantage data may improve generalizability. Finally, although mammography was assessed over two years, we could not account for delays or refusals of mammography at the patient level. Future work should include a more robust assessment of patient-level factors associated with DA use and mammography, with an emphasis on understanding how DA use shifts patients differentially toward and away from mammography use to impact overall patterns of use.[98]

4.5 CONCLUSION

U.S. Preventive Services Task Force guidelines recommend breast cancer screening through the age of 74 years, but concerns about overdiagnosis and harm underscore the importance of patient–provider communication regarding risk–benefit trade-offs.[99–101] Despite increasing awareness of breast cancer screening DAs, our results indicate that they likely have not been implemented consistently enough to have an impact on mammography use among older women. More robust organizational support may be needed for physician practices to routinely implement DAs and improve solicitation of patients' preferences and targeting of mammography services.

CHAPTER 5

PATIENT-SHARING CLINICIAN NETWORKS IN FEDERALLY QUALIFIED HEALTH CENTERS BEFORE & DURING THE COVID-19 PANDEMIC

5.1 BACKGROUND

IMPACTS OF THE COVID-19 PANDEMIC ON FEDERALLY QUALIFIED HEATLH CENTERS

The COVID-19 pandemic disrupted care delivery across the entire healthcare continuum.[102,103] It is especially important to investigate how patterns of care delivery may have changed in Federally Qualified Health Centers (FQHCs), as they serve a critical role in the provision of care for low-income patients who may otherwise have limited access to care.[104,105]

FQHCs are community-based primary care clinics funded by the Health Resources and Services Administration (HRSA) to offer comprehensive, culturally competent care to underserved communities.[106] Approximately 1,400 FQHCs exist across the country, providing care to approximately 1 in 11 individuals nationwide.[107] These centers provide medical, dental, behavioral health, and other supportive services, addressing diverse patient needs.[108] Acknowledging their critical importance to the social safety net, approximately $9 billion in federal grant funding was made available to FQHCs to support their operations during this public health crisis.[109] Furthermore, during this time FQHCs received increased revenue for telehealth visits and from Medicaid through continuous coverage provisions,[110] which supported their efforts to provide ongoing medical services on top of COVID-response services. Concerns about the operational implications of rolling back these temporal policy reform remains top-of-mind for many FQHC leaders.[111]

In addition to funding fluctuations, the landscape of care delivery changed considerably for FQHCs during the pandemic. Overall, FQHCs saw a significant decline in visit volume during the pandemic, despite an increase in telehealth utilization and care-seeking for mental health and substance use disorders.[112,113] Many patients deferred non-urgent care, contributing to a reduction in the receipt of many preventive services, such as cancer screenings, tobacco screening and cessation counseling, and depression screening.[114]

During this time, clinicians described the development of novel workflows to expand social needs screening efforts, establish COVID-19 testing and vaccination sites, distribute supplies such as masks, at-home test kits, and oral antiviral pills, implement social distancing strategies in clinic settings, and accommodate in-person home visits and mobile units.[113,115–117] Such efforts likely contributed to the finding that FQHC market penetration was a protective factor against COVID-19 mortality. [118] Throughout the pandemic, the FQHC workforce was also contending with multifaceted stressors (often leading to substantial changes in organizational culture), unexpected challenges such as a lack of needed supplies at the height of the pandemic, and concerns about personal health and safety, all likely contributing to the unprecedented levels of burnout felt among frontline health center staff. [119]

While many of these observed shifts have since returned to pre-pandemic norms, the funding environment remains uncertain, visit volumes remain lower, and the workforce continues to grapple with burnout, staffing shortages, and the sustained implementation of several practice changes (such as telehealth use and expanded social needs screening).[110,111,113,120]

Taken together, the existing literature on the experience of FQHCs during the COVID-19 pandemic highlights that several meaningful changes took place in their day-to-day operations. These changes likely presented both opportunities and impediments to the typical patterns of interpersonal connections among clinicians. It is not yet known the extent to which these changes affected clinical collaboration, or the flow of knowledge in the complex web of clinician interactions in the months following the onset of the pandemic.

CARE COORDINATION FOR FEDERALLY QUALIFIED HEALTH CENTER PATIENTS

The ability to meaningfully interact and transfer information between clinicians is one of the necessary components of well-coordinated care.[29] The successful coordination of clinical services among all clinicians involved in a patients' care is essential for the provision of high-quality, patient-centered care.[26] This is especially true for FQHC patients who often face myriad barriers to accessing high-quality care, greater health-related social needs, and worse health outcomes, yet systematically receive more fragmented care.[121,122]

Furthermore, the communities served by FQHCs often have high rates of chronic health conditions, such as hypertension and diabetes, which increased their vulnerability during the pandemic because their routine care involves close monitoring and medication management services traditionally performed in clinical settings. These patients were not only likely to be at higher risk of COVID-19-related complications,[123] but were also at risk for exacerbations of their existing conditions due to reduced access to care and lower utilization.[124] For these conditions in particular, the combination of regular screening, guidance on lifestyle modifications, and effective medication interventions to control blood pressure, glucose, and cholesterol levels are necessary to limit serious complications including (but not limited to) congestive heart failure, cerebrovascular disease, peripheral artery disease, chronic kidney disease, neuropathy, and retinopathy.[125]

Despite its relevance in improving patient outcomes, the literature regarding care coordination in FQHC settings remains rather limited. Recent studies have largely emphasized the importance of (a) health information technology (HIT) and (b) interprofessional collaboration to improve care coordination and, subsequently, health outcomes for FQHC patients. For example, Jones & Furukawa reported that the adoption and use of electronic health records (EHRs) has grown substantially in recent years,[126] which facilitates improved communication and information sharing among clinicians. Further, integrating nurse care coordinators and clinical pharmacists in FQHCs has been shown to improve patient care and health outcomes.[127,128] These studies highlight the significance of collaboration, often across disciplinary boundaries, in enhancing care coordination in FQHC clinics.

STUDY AIMS AND THEORETICAL ORIENTATION

Patient-sharing clinician networks offer unique structures for understanding the dynamic nature of relationships among the various stakeholders involved in the provision of health services.[129] The sharing of patients between two clinicians, often across organizational or professional silos, frequently involves shared viewing or entering of electronic health record (EHR) data and/or discussing information about individual patients. From such interactions, conclusions can be drawn about the flow of information within network structures. Recent validations studies have demonstrated that a sufficient degree of patient-sharing can serve as a meaningful proxy for understanding patterns of communications among clinicians.[130] The emerging body of work employing patient-sharing clinician network graphs has yet to focus specifically on FQHC settings.

The use of readily available administrative data to understand how patterns of care may have changed among FQHC clinicians caring for patients with chronic conditions is of particular importance to the health care community, as we develop our understanding of the impacts of the pandemic and how disruptions in the future may affect care delivery for vulnerable patients with chronic conditions. Thus, the present work adopts a social network theory lens to address the following questions:

1) How did the constellations of FQHC clinicians caring for individuals with hypertension and diabetes change following the onset of the COVID-19 pandemic, and

2) What clinician-level factors are associated with changes in structural network measures?

As described in the emerging literature, the unprecedented extent of disruption caused by the COVID-19 pandemic led to a complex set of changes to care delivery processes in FQHC settings. While some ties may have been strengthened as clinicians adapted to new methods of care delivery, others may have been weakened due to the resource constraints and shifting patient needs described above. For example, the increase in primary care seeking for respiratory illness coupled with the decrease in preventive care seeking for chronic conditions may lead to fewer shared patients between primary care clinicians and other specialists.

Therefore, our main hypothesis is that patient-sharing clinician networks became less cohesive and more fragmented following the onset of the COVID-19 pandemic. It is also hypothesized that clinicians who adopted telehealth more extensively were less geographically constrained, which may have resulted in stronger network centrality as compared to clinicians who relied upon telehealth visits less frequently.

5.2 METHODS

STUDY CONTEXT

Data for this study are drawn from administrative and EHR data provided by OCHIN. OCHIN is a nonprofit healthcare collaborative that aims to provide its community health center members with knowledge and solutions that promote high-quality and affordable health care for all.[131] Through shared purchasing, the collaborative provides and maintains a comprehensive electronic health information infrastructure for patient data that would be unaffordable for individual members to purchase on their own. Since its inception in 2001, OCHIN has grown to become one of the largest health information networks in the nation, serving nearly 1,000 community health center sites that provide care for a total of six million patients. Due to data availability for the research team, our analytic sample is restricted to data provided by California FQHC members of OCHIN (N=177).

ANALYTIC SAMPLE

These data include encounter-level data for adult patients with hypertension and/or diabetes with both in-person and virtual encounters at FQHCs from January 1, 2019 through December 31, 2020. These data include information from all users of the EHR, including locum tenens as well as other temporary clinicians working in these facilities. A summary of the categorization of clinician types is included in Appendix Table 5.

The dataset was then restricted to encounters that included unique patient and clinician identifiers so that pre- and during-COVID networks could be appropriately constructed, along with matching encounter dates in 2019 and 2020 to control for potential variation in seasonality. Due to the limited encounter data for entries that only included medication dispensing information (i.e., no Clinician ID with which to construct patient-sharing network nodes, nor date to allocate the encounter to a time cohort for comparative analysis), these encounters were removed from the analytic sample. Additional analytic sample restrictions included the removal of facilities with fewer than five associated encounters and facilities that did not have associated encounters during two time periods (before and after the declaration of the COVID-19 pandemic) to avoid duplicative identification of temporary sites (e.g., mobile clinics) that are in fact part of an existing, established facility ID. Additional details regarding the analytic sample exclusions are included in Table 1 below. The final analytic sample included data from 99 facilities, with 965 unique clinicians and 99,830 total encounters across cohorts.

A sensitivity analysis was conducted with an additional sample restriction that limited the dataset to only include patients that were present in both time periods, to assess how observed changes in network configurations may or may not be reflective of changes in care-seeking behavior during the pandemic period.

Table 1. Analytic Sample Exclusions.

Exclusion Criteria	Before Covid (N)	During Covid (N)
Initial Dataset	554,689 Encounters Across Cohorts 67,545 Patients Across Cohorts	
Encounters with Medication Dispensing Information Only	431,316 Encounters Across Cohorts 42,816 Patients Across Cohorts	
Encounters Outside of the March - December (2019 & 2020) Timeframe	70,077 Encounters 33,742 Patients 997 Clinicians	31,457 Encounters 20,892 Patients 890 Clinicians
Facilities with Fewer than Five Encounters	70,016 Encounters 33,714 Patients 961 Clinicians	31,400 Encounters 20,851 Patients 849 Clinicians
Facilities without Activity in Both Cohorts	69,173 Encounters 33,262 Patients 952 Clinicians	30,657 Encounters 20,321 Patients 827 Clinicians
Sensitivity Analysis: Patients without Activity in Both Cohorts	37,609 Encounters 16,290 Patients 832 Clinicians	25,623 Encounters 16,290 Patients 792 Clinicians

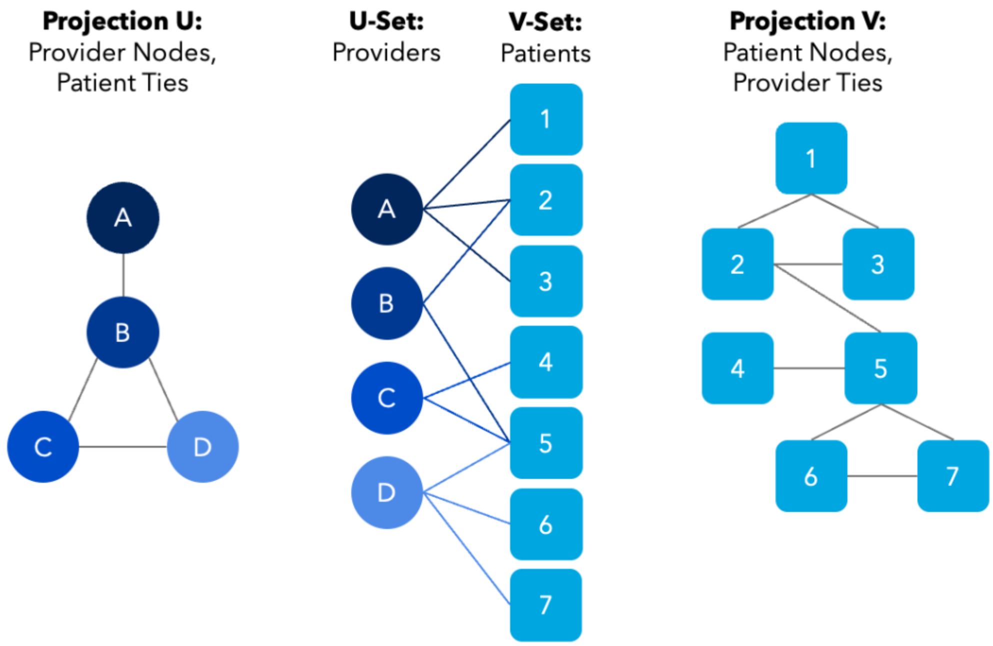
NETWORK CONSTRUCTION

Increasingly in the field of health services research, EHR data are being used to construct networks from which inferences regarding organizational structures and characteristics can be drawn.[129,132] For the present study, undirected unipartite patient-sharing clinician networks were constructed from the bipartite OCHIN EHR dataset prior to COVID-19 (3/17/2019 – 12/31/2019) and following the onset of COVID-19 (3/17/2020 – 12/31/2020).

Bipartite networks contain two sets of nodes (also known as “vertices” in the networks literature), conventionally referred to as “U” and “V” sets. In a bipartite network, nodes in the U-set (in the present data, clinicians) connect directly only to nodes in the V-set (in the present data, patients) and not to themselves. The unipartite network graphs for the current work were generated directly from Projection U, which was therefore obtained by connecting two U-nodes to each other if they linked to the same V-node in the bipartite network.

Thus, in the present network graphs, a tie (also known as an “edge” in the networks literature) was defined between two nodes if they shared at least one patient; ties were then weighted by the number of shared patients. The networks were considered undirected because each tie can be traversed in both directions: in other words, there is no inherent directionality for any given relationship between two clinicians in the present graphs. A visual representation of bipartite-to-unipartite network construction is adapted from Chapter 2 of Network Science (Figure 1).[133]

Figure 1. Visual Representation of Unipartite-to-Bipartite Network Generation



MEASURE SELECTION

First, a commonly reported set of three network-level characteristics (**network diameter**, the **number of connected components**, and the **size of the largest connected component**) were selected to provide an overall assessment and comparison of network size and fragmentation.

Then, specific network measures relevant to the consideration of the effective flow of information between nodes were selected from the social networks literature. Specifically, the present work is grounded in Closure Theory, which argues that dense networks (connected via "strong ties") signal the presence of close connections.[134] Such close contacts are theorized to have the potential to facilitate trust through the accumulation of social capital, which ultimately translates to reliable communication exchange- a necessary function for effective care coordination. Thus, at the network-level, measures of network **density** and **clustering** were constructed to identify how closely connected the entire networks were, and the degree to which clinicians formed tightly knit groups, respectively. At the node-level, **degree centrality** was constructed to understand the number of weighted patient-sharing ties per clinician, **betweenness centrality** was constructed to identify the degree to which individual clinicians may have acted as bridges between separate groups of clinicians, and **clustering coefficients** were constructed to evaluate individual clinicians' participation in tightly knit groups. Finally, PCC (primary care clinician) **dyad formations** were also calculated within each time period, given the unique importance of the PCC's role in care coordination in outpatient settings. The network measures included in this paper, along with their implications, are expanded upon Table 2.

Taken together, these measures collectively provide nuanced insight into the way patient-sharing clinician networks may have become more or less cohesive following the onset of the COVID-19 pandemic.

Table 2. Descriptions of Network Measures.

Measure	Calculation	Implication
Network-Level Calculations		
Network Diameter	$D_{diam} = \max_{i,j} d\,(i,j)$ Where D_{diam} is the network diameter, and $d(i,j)$ is the shortest path length between nodes i and j.	Network diameter represents the longest shortest path between any two clinician nodes in a graph; a larger diameter indicates a more spread-out network.
Connected Components	$N_C =$ The number of connected components in the graph	The number of connected components represents how many distinct subgraphs exist in which each node is connected to one another along paths, and none of the included nodes are connected to additional nodes in the full graph. A larger number of connected components indicates more fragmentation in the network.
Size of Largest Connected Component	$S_{\max} = \max_{i \in \{1,\ldots,C_C\}} \lvert C_i \rvert$ Where $S_{\max}$ represents the size (number of nodes) of the largest connected component, C_C is the total number of connected components, and $\lvert Ci \rvert$ denotes the size of then ith connected component.	The size of the largest connected component represents the number of nodes in the biggest group of interconnected clinicians. A large connected component indicates a cohesive subset of the network where patient sharing is common.
Network Density	$D_{dens} = \frac{2L}{N(N-1)}$ Where D_{dens} is the network density, L is the total number of ties, and N is the total number of nodes in the network.	Network density represents how closely knit the entire network is; higher density indicates a larger proportion of potential patient-sharing connections that are actually realized.
Network Clustering	$C = \frac{3 \times \textit{number of triangles}}{\textit{number of connected triples}}$ Where C is the global network clustering statistic, *triangles* refer to sets of 3 nodes where each node is connected to the other two, forming a closed loop, and *connected triples* consist of a central node that is connected to two others, which may or may not be connected to each other.	Network clustering at the global level represents the degree to which clinicians in the network tend to cluster together; high clustering indicates that clinicians tend to form tightly knit groups.
Node-Level Calculations		
Degree Centrality	$C_D(i) = \frac{\deg(i)}{N-1}$	Degree centrality represents how many direct patient-sharing connections a clinician has.

	Where $C_D(i)$ is the degree centrality of node *i,* deg(*i*) is the degree of node *i,*and *N* is the total number of nodes.	Clinicians with higher degree centrality have more (weighted) ties than those with lower degree centrality.
Betweenness Centrality	$C_B(i) = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}}$ Where $C_B(i)$ is the betweenness centrality score of node *i*, *σst* is the total number of shortest paths from node *s* to node *t*, and *σst*(*i*) is the number of those paths that pass through *i*.	Betweenness centrality represents how often a clinician acts as a bridge within the shortest patient-sharing paths between other clinicians. Higher betweenness centrality indicates a stronger role as a "broker" between two otherwise disparate groups of clinicians.
Clustering Coefficient	$C(i) = \frac{2T(i)}{k_i(k_i - 1)}$ Where *C*(*i*) is the local clustering coefficient of node *i*, *T*(*i*) is the number of triangles through node *i*, and k_i is the degree of node *i*.	Clustering coefficients at the node-level represents how closely a clinician's directly connected neighbors are also connected to each other. High values indicate that a clinician's patient-sharing partners also share patients amongst themselves, suggesting their participation in more tightly-knit groups.
Dyad-Level Calculations		
Dyad Frequencies	$F_{\text{dyad}} = \sum_{\text{all PCC pairs}} \text{ties}_{\text{PCC, Clinician}}$ Where F_{dyad} is the sum of the number of ties between PCCs and other indicated clinician types (i.e., other PCCs, nurses, specialists, etc.)	Dyad frequencies in this context represent the total number of ties formed between pairs of PCCs and the various clinician types represented in the present network graphs (including other PCCs). Higher dyad frequencies indicate a larger presence of PCC connections with various clinician types involved in patients' care.

DATA ANALYSIS

Two approaches to hypothesis testing were employed to compare the network measures across the two time periods. First, to compare the characteristics of whole network-level measures, permutation tests were conducted. A permutation test is a non-parametric statistical method used to test whether an observed difference between two groups is significant or could have occurred by chance. To conduct this test, the observed values were calculated as the difference in the relevant metrics between the two cohorts. Then 1,000 permutations were performed in which both the pre- and during-COVID network graphs were rewired while preserving their degree distribution. For each permuted pairs of graphs, the test statistics were re-calculated, thereby creating a distribution of values. The proportion of permuted differences that were equal to or greater than the observed differences were then calculated to assess for meaningful differences across the two cohorts. Second, for node-level measures, Welch's independent sample t-tests were used to compare network characteristics across the time periods.

Then, multivariable linear regression models estimated the association between each of the three node-level network characteristics and relevant clinician characteristics, with facility fixed effects to control for any unobserved heterogeneity across facilities that might affect the dependent variables. The regression models are described below:

$$Y_i = \beta_0 + \beta_1 \mathrm{ClinicianType}_i + \beta_2 \mathrm{PatientVolume}_i + \beta_3 \mathrm{Age}_\mathrm{i} + \beta_4 \mathrm{Complexity}_\mathrm{i} \\ + \beta_5 \mathrm{Telehealth}_i + \alpha_j \ + \ \epsilon_i$$

Where Y_i refers to the outcome variable (changes in degree centrality, betweenness centrality, or clustering coefficient, represented by subtracting the relevant test statistic in the during-COVID period from that in the pre-COVID period); β_0 refers to the mean of the relevant network measure for all clinicians, $\mathbf{ClinicianType}_i$ refers to a categorical variable indicating the classification of each clinician by role type, $\mathrm{PatientVolume}_i$ refers to the total number of unique patients associated with each clinician, Age_i refers to the average age of the patients seen by each clinician, $\mathbf{Complexity}_\mathrm{i}$ refers to the average Charlson comorbidity score (or HCC score) for each clinician, $\mathbf{Telehealth}_\mathrm{i}$ refers to the percent of each clinicians' encounters that occurred via telehealth appointment (as opposed to an in-person visit), α_j represents the facility fixed effect, and ϵ_i represents the error term.

Overall patient and clinician characteristics were tabulated for each cohort and compared using Welch's t-tests and chi-squared tests to detect the presence of significant differences between the two cohorts.

5.3 RESULTS

DESCRIPTIVE STATISTICS

A detailed comparison of patient and clinician characteristics before and during the COVID-19 pandemic are included in Table 3. Despite an expected and notable decrease in total patient volume from 33,262 pre-COVID to 20,321 during COVID, most of the observed shifts in demographic and clinical compositions suggest minimal differences in patient and clinician characteristics between the two periods.

As anticipated, age increased slightly in mean values between the two cohorts ($t = -6.076$, $p < 0.001$). Similarly, differences in the proportion of patients by sex (χ = 16.972, $p < 0.001$) and by race and ethnicity (χ = 18.088 , $p = 0.012$) between the two periods were statistically significant, but reflect minor variations in the overall composition of the patient population.

The assignment status of patients to primary care providers changed significantly, with a slight reduction in unassigned patients from 1.9% pre-COVID to 1.0% during COVID (χ = 70.241 $p < 0.001$); it is likely that this trend is predominantly influenced by the overall reduction in care-seeking during this time, but it is also possible that this may reflect a slight improvement in care continuity amidst the pandemic. It is also important to note that this change represents a very small fraction of the overall population. Furthermore, other statistically significant findings, such as minor fluctuations in certain comorbidities (e.g., the percentage of patients with type II diabetes shifting from 68.1% to 71.5%) suggest small shifts in patient health profiles that are statistically significant.

Clinician demographics remained largely stable across the two time periods. While the clinician workforce represented in the present network graphs experienced a slight reduction in total volume from 952 to 827, the composition of clinician types did not shift significantly.

Table 3. Patient and Clinician Characteristics Before and During COVID-19.

Patient Characteristics	Before COVID-19 N(%)	During COVID-19 N(%)	Statistical Significance
Total Patients	33,262 (100)	20,321 (100)	--
Age (Mean (SD))	58.69 (12.0)	59.33 (11.7)	t = -6.076, p < 0.001
Charlson Score (Mean (SD))	4.66 (3.3)	4.64 (3.2)	t = 0.827, p = 0.408
Sex			
Female	18,452 (55.5)	11,630 (57.2)	
Male	14,808 (44.5)	8,691 (42.8)	
Other	2 (0.0)	0 (0.0)	χ = 16.972, p < 0.001
Race/Ethnicity			
Hispanic/Latino	18,591 (55.9)	11,520 (56.7)	
White	8,643 (26.0)	5,226 (25.7)	
Asian	2,311 (6.9)	1,463 (7.2)	
Black or African American	1,760 (5.3)	982 (4.8)	
Native Hawaiian/Other Pacific Islander	225 (0.7)	153 (0.8)	
American Indian or Alaskan Native	124 (0.4)	83 (0.4)	
Multiple Races	186 (0.6)	122 (0.6)	
Unknown	1,189 (3.6)	638 (3.1)	χ = 18.088 , p = 0.012
Preferred Language			
English	16,218 (48.8)	9,705 (47.8)	
Spanish	15,863 (47.7)	9,902 (48.7)	
Other	1,181 (3.5)	714 (3.5)	χ = 5.476 , p = 0.065
Homeless Status			
Yes	128 (0.4)	75 (0.4)	χ = 0.046, p = 0.829
Primary Care Provider Assignment Status			
Unassigned	643 (1.9)	203 (1.0)	χ = 70.241 p < 0.001
Insurance Status			
Medicaid	11,504 (34.6)	6,951 (34.2)	
Medicare	9,439 (28.4)	5,722 (28.2)	
Other Public	3,622 (10.9)	2,165 (10.7)	
Private	3,242 (9.7)	2,074 (10.2)	

Uninsured	5,455 (16.4)	3,409 (16.8)	χ = 5.149 p = 0.272
Comorbidities			
Hypertension	25,563 (77.0)	15,610 (76.9)	
Type II Diabetes	22,662 (68.1)	14,518 (71.4)	
Depression	6,950 (20.9)	4,336 (21.4)	
Anxiety/Posttraumatic Stress Disorder	4,911 (14.8)	3,048 (15.0)	
Other Mental Health Condition	4,307 (13.0)	2,631 (13.0)	
Congenital Heart Disease	2,742 (8.3)	1,664 (8.2)	
Substance Abuse	2,544 (7.7)	1,540 (7.6)	
Tobacco Use	2,503 (7.5)	1,533 (7.6)	
Diabetic Retinopathy	2,345 (7.1)	1,587 (7.8)	
Secondary Diabetes	1,726 (5.2)	1,126 (5.5)	
Cardiovascular Disease	1,704 (5.1)	1,040 (5.1)	
Alcohol Use	1,420 (4.3)	806 (4.0)	
Congestive Heart Failure	1,313 (4.0)	759 (3.7)	
Mobility Impairment	346 (1.0)	198 (1.0)	χ = 29.416 p = 0.006
Clinician Characteristics			
Total Clinicians	952 (100)	827 (100)	--
Clinician Types			
Primary Care Physicians	320 (33.6)	263 (31.8)	
Advanced Practice Clinicians	214 (22.5)	182 (22.0)	
Medical Assistants	100 (10.5)	101 (12.2)	
Residents	105 (11.0)	94 (11.4)	
Registered Nurses	54 (5.7)	58 (7.0)	
Specialist Physicians	17 (1.8)	15 (1.8)	
Ancillary Services/Staff	19 (2.0)	13 (1.6)	
Pharmacists	19 (2.0)	16 (1.9)	
Other	89 (9.3)	73 (8.8)	
Missing	15 (1.6)	12 (1.5)	χ = 3.57, p = 0.937

NETWORK COMPARISONS

Significant changes in patient-sharing clinician network configurations following the onset of the COVID-19 pandemic were observed (Figure 2; Table 5). The networks of clinicians practicing in FQHCs suggested that we had a census of the FQHCs. The networks experienced a reduction in both nodes, from 952 to 827, and in weighted patient-sharing ties, from 2,820 to 1,268. Consistent with the reduction in nodes and ties, the overall network diameter decreased from 100 to 70 nodes ($p < 0.001$). The increase in the number of connected components from 132 to 240, while not statistically significant ($p = 0.1812$), indicates a slight increase in the overall fragmentation of the network, with more isolated clusters of clinicians emerging during the pandemic. Similarly, the size of the largest connected component saw a reduction from 218 to

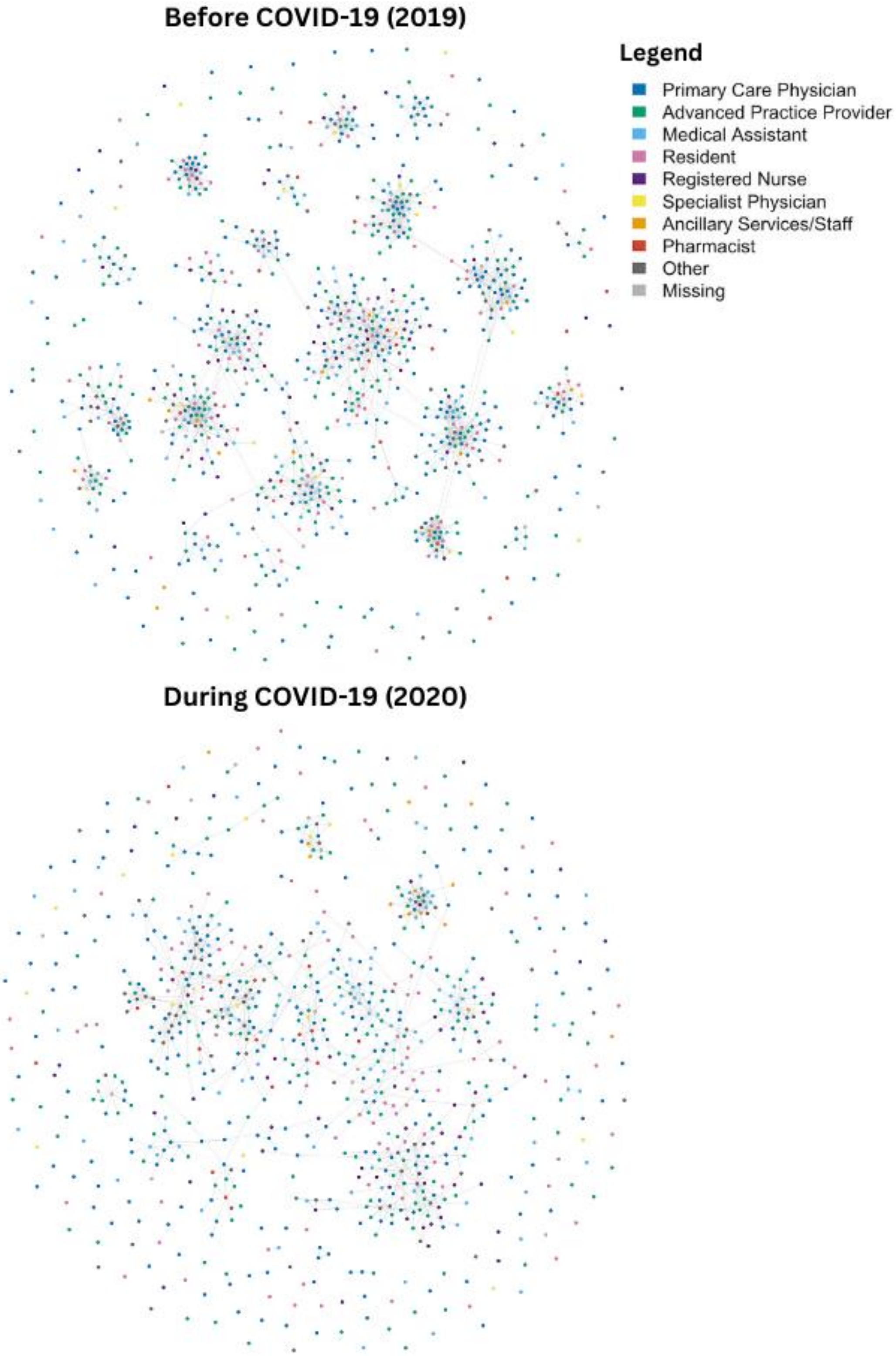
124, indicating that the largest group of interconnected clinicians shrank, although not a statistically significant change.

Significant declines were observed in the whole network measures. Network density decreased from 0.054 to 0.015 ($p < 0.001$), and the global clustering coefficient decreased from 0.418 to 0.310 ($p < 0.05$).

Node-level network measures further illuminate these changing configurations. Average degree centrality fell considerably from 102.525 to 25.495 ($p < 0.001$), reflecting a decrease in the average number of weighted ties per clinician. Similarly, average betweenness centrality decreased from 213.058 to 61.931 ($p < 0.001$), indicating that fewer clinicians served as critical conduits connecting separated groups in the network, and aggregated clustering coefficients fell slightly from 0.591 to 0.520 ($p < 0.05$), indicating that physicians became less likely overall to form tightly knit groups.

The PCP dyad frequencies present a mixed picture of possible collaboration dynamics across the two time periods. For this comparison, advanced practice clinicians were included in the PCP category because they both represent roles that are accountable for ensuring access and quality for a defined panel of patients. Notably, PCC -PCC connections decreased significantly, from 379 to 136 ($p < 0.05$). Additionally, PCC -Specialist and PCC -Nurse ties also declined significantly, indicating decreased collaboration frequencies between these clinician types during the pandemic.

Figure 2. Visual Representations of Patient-Sharing Clinician Network Graphs.



Before COVID-19 (2019)

During COVID-19 (2020)

Table 4. Comparison of Network Characteristics Before and During COVID-19.

Network Metrics	Before COVID-19	During COVID-19	Difference	P-Value
Node and Tie Frequencies				
Nodes (Clinicians)	952	827	125	--
Ties (Weighted Patient-Sharing)	2,820	1,268	1,552	--
Network Characteristics				
Network Diameter	100	70	30	<0.001
Number of Connected Components	132	240	-108	0.181
Size of Largest Connected Component	218	124	94	1
Whole Network Measures				
Density	0.054	0.015	-0.039	<0.001
Clustering	0.418	0.310	-0.108	0.005
Node-Level Network Measures				
Degree Centrality (Mean)	102.525	25.495	77.031	<0.001
Clustering Coefficient (Mean)	0.591	0.520	0.071	0.001
Betweenness Centrality (Mean)	213.058	61.931	151.127	<0.001
PCC Dyad Frequencies				
PCC-PCC	379	136	243	0.002
PCC -Specialist	24	9	15	0.038
PCC -Nurse	46	26	20	0.016
PCC -Medical Assistant	126	80	46	0.892
PCC -Resident	54	22	32	1.000
PCC -Pharmacist	63	23	40	0.380

Note: PCC = Primary Care Clinician.

REGRESSION RESULTS

Degree centrality: Among clinician types, significant decreases in degree centrality were observed for advanced practice clinicians (β = 40.82, $p < 0.05$) and pharmacists (β = 102.78, $p < 0.05$), indicating that serving in this role was associated with a decrease in patient-sharing ties with other clinicians (Table 5). Conversely, an increase in degree centrality was observed for those in ancillary (β = -150.41, $p < 0.05$), and “other” roles (β = -81.81, $p < 0.05$). Patient panel size was associated with a decrease in degree centrality (β = 1.02, $p < 0.001$), whereas average telehealth utilization was associated with an increase in degree centrality (β = -187.34, $p < 0.001$). The overall R-squared value for this model (0.714) indicates that the included covariates explain a significant portion of the variance in degree centrality changes observed during the study period.

Clustering coefficient: The only covariate significantly associated with a change in the clustering coefficient was the specialist role (β = 0.38, $p < 0.05$), indicating that serving in this role was associated with a decrease in the formation of tightly knit groups during the pandemic period

Betweenness centrality: Being a resident was significantly associated with an increase in betweenness centrality (β = -465.51, p < 0.05), reflecting a shift in their role as intermediaries during the pandemic period. Interestingly, having a larger patient panel size was significantly associated with a decrease in betweenness centrality during the pandemic period (β = 1.48, p < 0.001).

Table 5. Multivariable Regression Models Predicting Changes in Node-Level Network Characteristics.

	Δ Degree Centrality			**Δ** Clustering Coefficient			**Δ** Betweenness Centrality		
Covariates	β	SE	p	β	SE	p	β	SE	p
Clinician Type									
PCP	67.84	142.11	0.633	-0.38	0.66	0.566	294.36	389.31	0.450
APP	40.82	20.43	0.046*	0.10	0.07	0.120	-2.80	99.76	0.978
Medical Assistant	-35.04	30.59	0.252	0.16	0.10	0.114	-10.57	158.36	0.947
Residents	-4.14	33.22	0.901	-0.14	0.19	0.472	-465.51	172.03	0.007*
Registered Nurse	36.50	36.99	0.324	0.18	0.18	0.321	-223.01	191.54	0.245
Specialist Physician	-82.74	67.81	0.223	0.39	0.18	0.030*	-188.32	351.11	0.592
Ancillary Staff	-150.41	58.099	0.010*	0.09	0.19	0.619	-54.05	300.82	0.857
Pharmacist	102.78	47.81	0.032*	0.21	0.13	0.100	-193.83	247.55	0.434
Other	-81.81	29.48	0.006*	0.13	0.09	0.153	-122.09	152.65	0.424
Missing	741.60	80.42	<0.001*	0.19	0.19	0.324	-526.46	416.41	0.207
Patient Panel Size	1.02	0.06	<0.001*	0.00	0.00	0.730	1.48	0.30	<0.001*
Patient Age	-1.68	1.64	0.307	0.01	0.01	0.502	-0.71	8.50	0.934
Patient Complexity	-0.10	5.68	0.986	0.02	0.02	0.338	16.73	29.42	0.570
Telehealth	-187.34	66.23	0.005*	0.42	0.25	0.102	13.42	342.89	0.969
R-Squared	0.714			0.319			0.281		
F	<0.001			0.005			<0.001		

Note: APP = Advanced Practice Clinician. All models include facility fixed effects.

Results from the sensitivity analyses are included in Appendix Tables 6 and 7.

5.4 DISCUSSION

The present work fills a critical gap in the care coordination literature, as it expands on the existing knowledge of care coordination for FQHC patients with chronic diseases and lends a novel insight into changes that transpired during the recent public health crisis. Furthermore, to the best of the research team’s knowledge, this is the first study to apply the patient-sharing clinician network methodology in FQHC settings specifically.

In summary, these data illustrate that meaningful changes took place in the structure of patient-sharing networks among FQHC clinicians following the onset of the COVID-19 pandemic. Clinicians were, on average, less interconnected, with fewer patient-sharing ties between them, indicating an overall dispersion of the network structure during the pandemic. The selected network measures together point to an increase in network fragmentation, indicating the emergence of more isolated clusters of clinicians who share patients predominantly within their own group, and who have fewer connections to those clinicians outside of their immediate clusters.

The trend toward fragmentation could also reflect a) a consolidation of patient care within smaller, perhaps more localized groups during a time when travel and increased interpersonal contact was avoided, or b) the impact of reduced patient volumes on network connectivity. While the data clearly indicate an increase in fragmentation, the network did maintain a moderate level of local clustering (0.520) during the pandemic period, suggesting that while the network did become less cohesive overall, many existing clusters of clinicians likely maintained or perhaps even strengthened their patient-sharing ties.

The association between advanced practice clinicians and decreased degree centrality may reflect increased task specialization due to the previously described workflow changes necessitated by the pandemic (i.e., more time spent distributing supplies or administering tests, which may not have been captured in the EHR database), which could result in fewer direct connections with other clinicians if their roles became less generalized during this time. Alternatively, this decrease in degree centrality may reflect conditions in which responsibilities that were previously shared among various clinicians became more streamlined. Interestingly, when the dataset was restricted to patients present in both cohorts, the increase in degree centrality among medical assistants emerged as statistically significant, possibly reflecting an expansion of their roles in which they were seeing more patients or supporting a broader number of care teams to cover staffing shortages. The association between patient volume and decreased degree centrality may be reflective of larger practices streamlining their operations within their organization, or could reflect a trend of larger organizations sharing patients to a lesser degree with clinicians in external organizations due to pandemic-related constraints.

The association between telehealth utilization and increased degree centrality is unsurprising, and possibly reflects a trend in which clinicians who utilized telehealth more regularly became more central in their networks due to their ability to see more patients during remote consultations and follow-ups. Interestingly, this model provided significantly improved model fit (0.714) as compared to the models examining changes in betweenness centrality (0.281) and clustering coefficients (0.319) suggesting that the included covariates explain the decrease in the number of shared patients to a greater degree than they may explain the decrease in the formation of tightly-knit groups or the decrease in clinicians' propensity for serving in brokerage roles between otherwise disconnected clinician groups. It is plausible that the latter two trends may be more likely to be affected by factors not included in the our dataset, such as unobserved variables relating to patients' care-seeking behavior that led to diminished continuity of care (thereby affecting the formation of tightly-knit groups) or changes in resource allocation that could result in certain clinicians being assigned to roles that isolate them from their usual colleagues (thereby limiting their connections to clinicians in separate clusters).

Decreased clustering among specialists is consistent with evidence that indicates that patients would frequently forgo non-urgent care during the pandemic,[112,135] thereby limiting their encounters with specialists. This is consistent with the trend observed in the sensitivity analysis, in which the data were restricted to only include patients present in both cohorts and the decrease in overall network clustering was no longer statistically significant. Controlling for all other covariates, resident physicians were more likely to have increased betweenness centrality scores when compared to their colleagues in other roles. This may be reflective of residents in FQHC settings working at the "top of their license" or otherwise capitalizing on the flexible nature of their roles during this emergency response time, thereby serving in brokerage roles with greater frequency.

Taken together, these study findings may offer starting points for the development of targeted interventions to improve care coordination in FQHCS. First, clinical and administrative leaders might consider strategies to develop more robust and targeted telehealth systems as a means to reconnect fragmented networks. Given the association between telehealth utilization and increased degree centrality, expanding telehealth capabilities could enable clinicians to maintain and even expand their patient-sharing networks remotely. This could be beneficial for the purposes of patient-sharing between PCPs and specialists, for example, but care should be taken to ensure that even in the context of expanded telehealth adoption, patient sharing between PCPs doesn't expand to the point of limiting care continuity. Second, to address the decreased clustering among specialists, FQHCs might create targeted outreach programs that encourage patients to continue necessary specialist care through safe in-person visits or telehealth services. By promoting regular communication and collaboration between PCPs and specialists, FQHCs can continue to provide patient care that remains holistic and integrated, even during times of crisis. Third, the significant roles of medical assistants and residents suggest the potential to enhance care delivery by integrating these professionals into care teams in strategic ways. For instance, FQHC leaders could develop training programs to broaden the scope of tasks performed by medical assistants, ensuring that they can support multiple teams and handle a wider range of patient needs. Or, in times of great disruption to the healthcare system, the "brokerage" role served by residents may be leveraged such that they are assigned tasks that require more nuanced task interdependence (given their potential to link otherwise disconnected clinician groups). Such targeted team-based strategies may help support FQHCs when faced with staffing shortages and may contribute to building a more flexible and responsive workforce.

The present study offers insights into the dynamics of patient sharing among FQHC clinicians; however, several limitations should be considered when interpreting these findings. First, a primary constraint is the reliance on unique facility identifiers which limits the ability to distinguish which FQHCs operate together as part of larger healthcare systems. Additionally, the lack of organizational information about each facility limited the scope of our analysis, but remains an important avenue to explore in future work. However, the presence of unique facility IDs allowed for clustering at the facility level to control for potential unobserved variation in organizational characteristics to the best of our ability. Second, the de-identified nature of the dataset also restricts the ability to link these facilities to the broader regional context, which might offer additional insight into how external factors influenced changes in network configurations. Third, the focus on clinicians operating within FQHCs means that the analysis does not capture the full spectrum of healthcare services, inherently excluding care delivered in hospitals, emergency departments, and other non-FHQC facilities. Fourth, this dataset includes limited information from patient encounters, and does not provide access to clinician notes, messages, or other forms of communication or documentation that could further triangulate the full set of clinicians involved in a patient's care. Furthermore, the definition of a network "tie" employed in this study limits our assessment to a structural view of coordination, and does not allow for a more comprehensive analysis of the elements of relational coordination that may have shifted among FQHC clinicians during the COVID-19 pandemic. This limitation suggests that the actual networks of patient-sharing and collaboration may be even more complex and nuanced, and require further study.

Future research should build on this foundation of evidence by incorporating datasets containing more granular information about patient encounters (e.g., clinical notes or inbox messages) and care team structures, and by employing mixed-methods approaches to clarify clinicians' experiences of care delivery in tandem with EHR-based analyses of network configurations. Such research has the potential to delve deeper into the experiences of the FQHC workforce during this unique time, offer richer insights into the mechanisms behind the observed changes in network configurations, and guide improvements in health care delivery and policy responses in future crises.

5.5 CONCLUSION

This study demonstrates that the COVID-19 pandemic led to a significant restructuring of patient-sharing networks among FQHC clinicians, characterized by increased network fragmentation and isolation of clinician clusters, despite maintaining moderate local clustering. These findings underscore the necessity to adapt care coordination strategies in response to public health crises, and suggests the possibility of developing targeted strategies based on structural network properties to influence collaboration dynamics within community health center settings. Methodologically, our study is among the first to construct patient-sharing clinician network graphs in FQHC settings, and offers suggestions for future research to expand upon the use of this methodology to better understand and potentially tailor interventions based on these network data.

CHAPTER 6

PROVIDER BROKERAGE ACTIVITY AND PATIENT OUTCOMES IN FEDERALLY QUALIFIED HEALTH CENTER SETTINGS

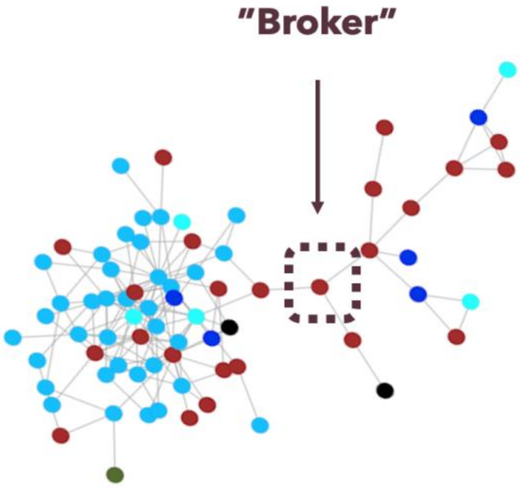
6.1 BACKGROUND

THEORETICAL ORIENTATION TO NETWORK BROKERAGE

The present study builds upon the examination of patient-sharing clinician networks in Federally Qualified Health Centers (FQHCs) presented in Chapter 5, but diverges from the Closure Theory orientation of the prior work. As previously described, Closure Theory posits that the presence of close ties allows for the development of social capital, which can be leveraged to build trust and dependable communication pathways.[134] An alternative perspective within social network theory considers the role of network "brokerage."

The concept of brokerage builds upon formative work in the social networks literature that examines the advantages conferred by the presence of "weak ties," which are connections that bridge otherwise separate groups.[136] Brokers are understood as actors that have the ability to reach across the structural holes that may emerge in network structures (Figure 1).

Figure 1. Visualization of Brokerage Activity: Linking Disparate Groups.



Structural holes appear when two actors are not connected; in network terms, such actors are considered "non-redundant."[137] Brokers are thought to provide unique benefits to networks because they can transmit information from these sources that would not otherwise be connected, and therefore have the ability to facilitate the transfer of novel knowledge and resources. Thus, they may contribute substantially to the effective coordination of efforts across groups of individuals.[137]

However, some network theorists have critiqued Burt's foundational assertions regarding structural holes, suggesting instead that brokers may become bottlenecks in the flow of needed information,[138] or that positive outcomes are more accurately explained by cohesive network structures which facilitate the development of clear normative frameworks that enable effective collaboration.[139] This tension in the theoretical consideration of social networks warrants further empirical investigation.

EMPIRICAL APPLICATION OF BROKERAGE CONSTRUCTS

As discussed in Chapter 5, the patient-sharing clinician graphs in California FQHCs demonstrated substantial fragmentation and clustering within groups. Networks with less overall connectivity inherently exhibit limited redundancy, thereby making them more vulnerable to interruptions in the flow of information or resources.[32] The absence of effective information transfer between clinicians, especially across specialties, is one of the most frequently reported explanations of inefficient care coordination.[29] Given the proposed potential for brokers to facilitate the effective coordination of efforts across groups, coupled with the known relationship between care coordination and patient outcomes, it follows that primary care clinicians' brokerage roles may be associated with improvements in patient outcomes.

In FQHC settings, the importance of understanding the role that network brokerage may play in clinical collaboration is further underscored by the complex and diverse nature of the patients they serve. FQHCs serve patients with significantly higher burdens of disease, who systematically receive more fragmented care.[121,122]

A subset of evidence from hospital settings demonstrates that knowledge sharing is indeed facilitated by brokerage activity, as opposed to strong clustering activity within groups.[140] Another recent study found that primary care provider degree centrality (aka, the number of ties formed by each provider) was associated with higher spending and health care utilization (adjusting for variation in hospital characteristics) while brokerage constructs were associated with lower spending and service utilization.[141] However, the state of the literature is not definitive, with additional studies reporting inconclusive evidence on the association between brokerage and outcome such as ambulatory care sensitive hospitalizations[142] and negative associations between brokerage and health care team performance.[35]

Furthermore, to the best of the researchers' knowledge, brokerage has not been formally investigated in FQHC settings using patient-sharing clinician networks. Among the papers examining the role of brokerage in FQHC settings, authors commonly adopt role-based definitions of 'brokers,' typically emphasizing their engagement in boundary-spanning activities. For instance, it is common for professionals in care navigation roles to be classified as brokers, given their responsibilities that involve linking patients to several clinical services within and perhaps across organizations.[143]

In the context of appropriately implementing the Patient-Centered Medical Home Model (PCMH), which emphasizes comprehensive and well-coordinated patient-centered care across interdisciplinary teams of providers,[144] primary care physicians (PCPs) may play a particularly relevant boundary spanning role for the management of chronic conditions like diabetes and hypertension. For example, PCPs often take responsibility for coordinating care across multiple specialists, such as dieticians, podiatrists, and cardiologists, among others. This responsibility involves ensuring that all relevant healthcare providers are informed of each other's treatment plans and patient responses, thereby facilitating a cohesive approach to care. Additionally, PCPs might bridge information gaps by synthesizing specialist advice into manageable and understandable care plans for patients. Lastly, PCPs may act as advocates within the healthcare system (which is especially important among more fragmented networks), navigating bureaucratic obstacles to access necessary resources like medication, monitoring tools, or education programs for their patients. Thus, it is particularly relevant to examine brokerage through the lens of PCP ties to other clinician types involved in patient care, as PCPs are uniquely responsible for engaging in multifaceted coordination efforts on behalf of their patients.

STUDY AIMS

Thus, aims one and two of the present study are to 1) identify if brokerage differs significantly across clinician types in FQHCs, and 2) identify if brokerage among primary care clinicians is associated with improvements in clinical outcome measures routinely managed by primary care clinicians and collected by FQHCS (i.e., hemoglobin A1C levels among diabetic patients, and systolic and diastolic blood pressure levels among hypertensive patients).

Despite positive trends for these measures in FQHCs in the years preceding the COVID-19 pandemic, significant declines were observed in blood pressure control in patients with hypertension and blood glucose control in patients with diabetes in the year 2020,[145] which are likely functions of the pandemic impacts on FQHCs and systematic barriers disproportionately affecting the patients the serve, along with reduced care-seeking during this time due to social distancing and other factors.[112,121,122] It is plausible that the specific restructuring efforts that FQHCs engaged in during the pandemic may have particularly benefited those clinicians in brokerage positions, by facilitating information sharing and collaboration and thereby possibly mitigating these negative trends in chronic disease management. Thus, aim three of the present study is to examine if the relationship between brokerage and patient outcomes may have changed over time.

6.2 METHODS

STUDY CONTEXT

The present study draws upon the same dataset that is described in Chapter 5: administrative and electronic health record (EHR) data provided by OCHIN. This dataset includes encounter-level data for adult patients with hypertension and/or diabetes from California-based community health centers with OCHIN's network.

ANALYTIC SAMPLE

The analytic sample for the present study draws upon the same exclusion criteria described in the previous chapter (see Chapter 5, Table 1: Analytic Sample Exclusions). In summary, we removed medication-dispensing-only visits due to their insufficient datapoints necessary to construct patient-sharing clinician network graphs (i.e., unique provider identifiers), and visits associated with a) facilities with fewer than five total encounters and b) facilities without activity in both time periods, to avoid potential duplicative identification of temporary sites (such as mobile or school-based clinic settings).

For the present study, the analytic sample was further restricted to only include unique provider identifiers that were present in both pre- and during-COVID timeframes, to allow for the appropriate comparison of clinician-level trends before and during the COVID-19 pandemic. The final analytic sample incudes data from 103,344 encounters, 38,298 patients, and 664 clinicians.

MEASURE SELECTION

Independent Variables: The primary network measurement of interest in the present study is betweenness centrality**.** Betweenness centrality is a commonly utilized measure to identify brokers among recent network analyses across academic disciplines, but particularly in hospital and health promotion settings.[138] Betweenness centrality measures the number of "shortest paths" between nodes that pass through a focal node. In other words, this metric offers an empirical way to calculate the degree to which an individual may be responsible for transmitting, or brokering, novel information between otherwise disparate groups.[146] For the purposes of the descriptive analyses, the distribution of betweenness centrality was dichotomized into "non-brokerage" and "brokerage" groups based on whether the score equaled 0 or was greater than 0, respectively. The regression analyses maintain the continuous nature of this variable specification. For the purposes of comparison, the primary regression analyses also include degree centrality, which is widely considered to be the most basic network centrality measure. It reflects the sum of the total number of direct ties a node has with others in a network, reflecting a clinician's overall level of connectedness to other clinicians in the network.[146]

Dependent Variables: The primary outcome variables in the present study include glycated hemoglobin (A1c), systolic blood pressure, and diastolic blood pressure values. These variables are relevant because they serve as indicators of chronic disease management, particularly for patients with hypertension and diabetes, and they are predominantly managed by primary care clinicians. These measures are incorporated in the Healthcare Effectiveness Data and Information Set (HEDIS),[147] and are frequently used in various incentive programs due to their widely acknowledged acceptance as standardized performance measures. A1c reflects long-term glucose control in diabetic patients, while systolic and diastolic blood pressure outcomes are essential measures of blood pressure control in patients with hypertension.[148,149] Each of these measures were aggregated at the clinician level, to provide an overall summary of each clinician's chronic disease management outcomes.

Covariates: The models also include the following potential patient covariates, aggregated at the clinician level by calculating the means for each clinician: patient complexity (reflecting clinicians' patients' hierarchical condition category (HCC) scores),[69] patient age (reflecting clinicians' average patient age), panel size (reflecting the average number of patients seen by each clinician in our dataset), percent of female patients seen by each clinician, percent of patients whose preferred language was not English, percent of patients below 138% of the federal poverty line

(FPL), percent of patients experiencing housing insecurity, and percent of patients who did not have health insurance. Additionally, unique facility identifiers were used to construct facility-level fixed effects to account for potential variation among organizational resources and settings for which more specific covariates were not available.

DATA ANALYSIS

To address aim one, betweenness centrality scores were compared across the various clinician types present in our dataset. Preliminary tests were conducted to assess the distribution of the betweenness centrality scores and to determine the appropriateness of our statistical methods. QQ plots indicated deviations from normality (Appendix Figure 1), which was confirmed by the Shapiro-Wilk test for normality (Appendix Table 9). Homogeneity of variances was then assessed using Levine's test (Appendix Table 10), which demonstrated heterogeneity in variances across the groups (F = 2.2516, df = 654, p = 0.01753), suggesting that the assumptions for a standard parametric ANOVA were violated.

Given the non-normal distributions and the heterogeneity of variances, the non-parametric Kruskal-Wallis rank sum test was employed to compare the betweenness centrality sores across clinician roles.

Then, to address aim two, the data were restricted to clinicians serving in primary care roles (specifically, primary care physicians and advanced practice clinicians). Fixed-effect regression models were used to quantify the relationship between relevant network characteristics and the outcome measure of interest, controlling for potential confounders among each clinician's patient panel. The applied regression models are described below:

$$Y_i = \beta_0 + \theta Z_i + \alpha \text{Facility}_j \ + \ \epsilon_i$$

Where Y_i refers to the outcome variable (A1c, systolic, or diastolic blood pressure); $\boldsymbol{\beta_0}$ refers to the mean network characteristic for each model (betweenness centrality or degree centrality), $\boldsymbol{Z_i}$ refers to the set of aggregated patient covariates (patient complexity, patient age, panel size, percent of patients that identify as female, percent of patients reporting a language other than English as their preferred language, percent of patient below 138% of the federal poverty line, percent of patients experiencing housing insecurity, and precent of patients who were uninsured when seeking care), Facility_j represents the facility fixed effect, and $\boldsymbol{\epsilon_i}$ refers to the error term.

To address the trends over time in aim three, a variable representing each month represented in the data was added to the analytic file. Then, an interaction term between betweenness centrality and time was added to the initial models to examine how the association between network brokerage and patient outcomes changed over time. Provider fixed effects were included in this model.

Aggregated clinician characteristics were tabulated for brokers and non-brokers, and compared using Welch's t-tests to detect the presence of significant differences between the two groups.

6.3 RESULTS

DESCRIPTIVE STATISTICS

A detailed comparison of aggregated clinician characteristics among brokers (betweenness centrality > 0) and non-brokers (betweenness centrality = 0) is included in Table 1. The distribution of clinicians between the two groups indicates a higher representation of brokers (78.2%) compared to non-brokers (21.8%), which is likely reflective of the conservative dichotomization of this variable at a betweenness centrality score of 0.

Brokers exhibited significantly higher degree centrality scores (mean = 462.362) than non-brokers (mean = 214.083), indicating that individuals who were classified as brokers tended to have more connections overall than those who were not classified as brokers ($p < 0.001$). The number of patients seen by brokers was significantly higher (mean = 96.819 patients) as compared to non-brokers (mean = 44.303, $p < 0.001$).

Patient characteristics aggregated at the clinician level predominantly demonstrated subtle and statistically insignificant differences across the two groups. Brokers and non-brokers appeared to manage patient panels with nearly identical complexity and age, with means of 5.164 vs. 5.093 and 57.285 vs. 57.290, respectively. Gender distribution, preferred language, and socio-economic indicators such as poverty status and housing insecurity similarly showed minimal differences across the groups.

Without controlling for potential confounders, the patient outcomes reported in this study showed no significant variation across the patient panels managed by brokers and non-brokers. Across both categories, aggregated A1c levels remained within the “controlled” threshold of <8%, and blood pressure measures remained within the “controlled” threshold of <140/90 mm Hg, per the National Committee for Quality Assurance (NCQA) guidelines.[150]

Table 1. Clinician Characteristics Among Brokers and Non-Brokers.

Clinician Characteristics	Non-Brokers (Mean)	Brokers (Mean)	95% Confidence Interval
Total Clinicians (N(%))	145 (21.8%)	519 (78.2%)	--
Network Characteristics			
Betweenness Centrality	0.000	590.265	--
Degree Centrality	214.083	462.362	-357.012 – -139.546***
Aggregated Patient Characteristics			
Patient Complexity	5.093	5.164	-0.496 – 0.355
Patient Age	57.290	57.285	-1.129 – 1.139
Panel Size	44.303	96.819	-70.249 – -34.782***
% Female	54.733	54.325	-4.372 – 5.186
% Non-English as a Preferred Language	45.867	47.362	-7.867 – 4.876
% <138% Federal Poverty Line	85.512	83.722	-2.228 – 5.807

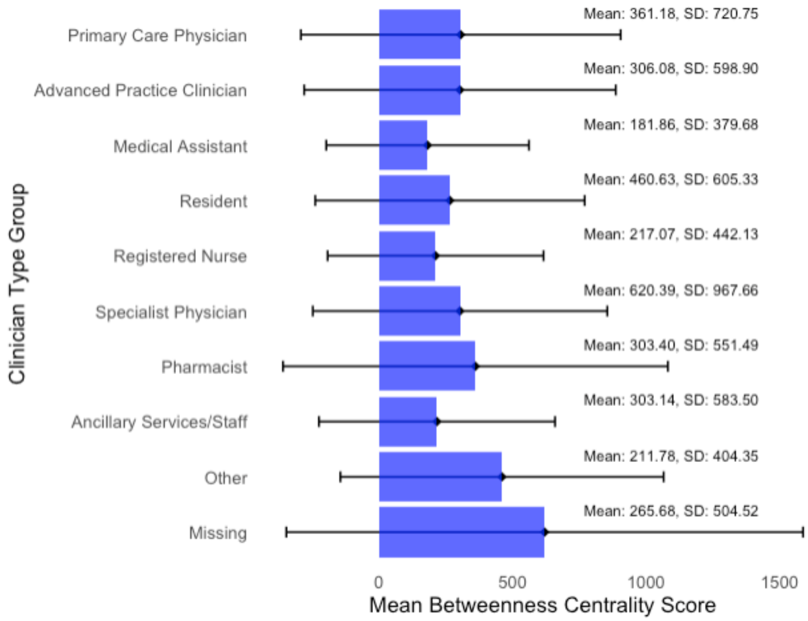
% Housing Insecure	1.736	0.695	-0.692 – 2.773
% Uninsured	22.054	19.994	-2.076 – 6.196
Aggregated Patient Outcomes			
A1c	7.660	7.578	-0.103 – 0.268
Systolic Blood Pressure	133.847	132.136	-0.093 – 3.515
Diastolic Blood Pressure	76.966	77.347	-1.43 – 0.668

*** $p < 0.001$

BROKERAGE ACROSS CLINICIAN TYPES

To compare betweenness centrality scores across clinician types, the Kruskal-Wallis test yielded a chi-squared value of 16.019 with 9 degrees of freedom, resulting in a p-value of 0.066. This indicates that there was no statistically significant difference in the median scores of betweenness centrality across the different clinician categories at the conventional alpha level of 0.05 (Figure 2). A detailed description of each of the clinician groups is included in Appendix Table 5.

Figure 2. Betweenness Centrality Scores by Clinician Type.



MAIN REGRESSION RESULTS

Among primary care clinicians, a significant relationship between brokerage and A1c levels was observed, with a decrease in A1c associated with higher betweenness centrality among clinicians ($\beta = -5.2E-05$, $p < 0.05$), controlling for relevant covariates. In contrast, degree centrality was not significantly related to A1c outcomes (Table 1a). Network characteristics were not significantly associated with either systolic or diastolic blood pressure outcomes (Tables 2a, b).

Various covariates were also associated with A1c levels. In both models, patient age was negatively correlated with A1c, signifying that older average patient age was associated with improved diabetes control ($p < 0.01$). In the betweenness centrality model, larger panel size was associated with an increase in A1c outcomes ($p < 0.01$). In both models, a higher percentage of patients whose preferred language was not English was associated with higher A1c levels ($p < 0.001$), and housing insecurity was associated with higher A1c ($p < 0.001$). The model for betweenness centrality (adjusted R-squared = 0.463) suggests that these variables, along with facility fixed effects, explain a significant portion of the variance in A1c levels.

Several patient covariates were also associated with blood pressure management. A higher percentage of female patients was associated with lower systolic blood pressure outcomes ($p < 0.001$), a higher percentage of patients below 138% of the federal poverty line was associated with higher systolic blood pressure outcomes ($p < 0.05$), and a higher percentage of patients experiencing housing insecurity ($p <0.001$) and a lack of health insurance were associated with slightly lower systolic blood pressure outcomes ($p < 0.001$) (Table 2b). For the diastolic blood pressure models, lower average patient age was associated with higher diastolic blood pressure outcomes ($p < 0.001$), a higher percentage of female patients was associated with lower diastolic blood pressure outcomes ($p < 0.01$), and a higher percentage of patients whose preferred language was not English was associated with lower diastolic blood pressure outcomes ($p < 0.05$) (Table 2c).

Table 2a. Primary Care Clinician Network Characteristics and A1c Measurement.

Covariates	Degree Centrality Model			Betweenness Centrality Model		
	β	SE	p	β	SE	p
Network Characteristic	6.1E-06	1.1E-04	9.5E-01	-5.2E-05	2.1E-05	1.2E-02*
Patient Complexity	3.3E-02	2.4E-02	1.7E-01	3.2E-02	2.3E-02	1.8E-01
Patient Age	-2.5E-02	8.1E-03	2.6E-03**	-2.4E-02	7.9E-03	2.6E-03**
Panel Size	5.9E-04	6.4E-04	3.5E-01	9.5E-04	4.3E-04	2.9E-02*
% Female	-2.3E-03	2.0E-03	2.5E-01	-2.5E-03	1.9E-03	2.0E-01
% Non-English as Preferred Language	9.3E-03	2.3E-03	8.1E-05***	9.5E-03	2.3E-03	3.5E-05***
% <138% Federal Poverty Line	4.1E-03	3.4E-03	2.3E-01	4.2E-03	3.4E-03	2.2E-01
% Housing Insecure	-3.3E-02	6.3E-03	2.5E-07***	-3.4E-02	6.2E-03	1.3E-07***
% Uninsured	4.6E-03	3.1E-03	1.4E-01	4.8E-03	3.1E-03	1.2E-01
R-Squared	0.452			0.463		
F	<0.001			<0.001		

* p<0.05, **p<0.01, ***p<0.001. Models account for facility fixed effects

Table 2b. Primary Care Clinician Network Characteristics and Systolic Blood Pressure Management.

Covariates	Degree Centrality Model			Betweenness Centrality Model		
	β	SE	p	β	SE	p
Network Characteristic	-1.4E-05	8.9E-04	9.9E-01	9.0E-05	1.7E-04	6.0E-01

Patient Complexity	-8.5E-01	2.0E-01	2.1E-05***	-8.5E-01	2.0E-01	2.1E-05***
Patient Age	2.8E-01	6.9E-02	8.1E-05***	2.7E-01	6.8E-02	6.6E-05***
Panel Size	-3.4E-03	5.3E-03	5.2E-01	-4.0E-03	3.6E-03	2.7E-01
% Female	-6.2E-02	1.6E-02	1.9E-04***	-6.2E-02	1.6E-02	2.1E-04***
% Non-English as Preferred Language	-7.6E-03	1.9E-02	7.0E-01	-8.0E-03	1.9E-02	6.8E-01
% <138% Federal Poverty Line	5.9E-02	2.8E-02	3.8E-02*	5.9E-02	2.8E-02	3.7E-02*
% Housing Insecure	-2.1E-01	5.2E-02	7.8E-05***	-2.1E-01	5.2E-02	8.2E-05***
% Uninsured	-1.1E-01	2.6E-02	1.8E-05***	-1.1E-01	2.6E-02	1.7E-05***
R-Squared	0.489			0.489		
F	<0.001			<0.001		

* p<0.05, **p<0.01, ***p<0.001. Models account for facility fixed effects

Table 2c. Primary Care Clinician Network Characteristics and Diastolic Blood Pressure Management.

Covariates	Degree Centrality Model			Betweenness Centrality Model		
	β	SE	p	β	SE	p
Network Characteristic	1.3E-05	4.9E-04	9.8E-01	4.3E-05	9.5E-05	6.5E-01
Patient Complexity	-1.3E-01	1.1E-01	2.4E-01	-1.3E-01	1.1E-01	2.4E-01
Patient Age	-1.3E-01	3.8E-02	7.9E-04***	-1.3E-01	3.7E-02	6.0E-04***
Panel Size	-2.9E-03	2.9E-03	3.2E-01	-3.1E-03	2.0E-03	1.2E-01
% Female	-3.6E-02	9.1E-03	9.9E-05***	-3.6E-02	9.0E-03	1.1E-04***
% Non-English as Preferred Language	-2.1E-02	1.1E-02	5.0E-02*	-2.1E-02	1.1E-02	4.5E-02*
% <138% Federal Poverty Line	1.2E-02	1.6E-02	4.5E-01	1.2E-02	1.6E-02	4.5E-01
% Housing Insecure	-1.7E-02	2.9E-02	5.5E-01	-1.7E-02	2.9E-02	5.6E-01
% Uninsured	-2.1E-02	1.4E-02	1.5E-01	-2.1E-02	1.4E-02	1.4E-01
R-Squared	0.507			0.508		
F	<0.001			<0.001		

*p<0.05, *** p<0.001. Models account for facility fixed effects.

VIF values among all models ranged from 1.046 to 2.616, indicating minimal concern for potential collinearity among the included covariates based on the recommendation of VIF < 2.0 for overall models. (72)

PANDEMIC TIMELINE COMPARISONS

To address trends over time, additional regression analyses were conducted to examine the interaction between betweenness centrality and time.

Notably, betweenness centrality was significantly associated with A1c (β = -2.48e-04 p < .001), systolic blood pressure (β = 2.56e-03, p < .001), and diastolic blood pressure (β = -8.95e-04, p < .001) in the models that included the time covariates, though the effect sizes were still relatively small. However, the interaction terms between betweenness centrality and time were not significant in any of the models, indicating that these associations did not meaningfully vary across the timespan included in our dataset (Tables 3a-c).

Table 3a. Betweenness Centrality and A1c Levels Over Time.

Covariates	A1c		
	β	SE	p
Betweenness Centrality	-2.48e-04	1.43E-17	<2e-16***
Time	-4.55e-03	2.01e-15	<2e-16 ***
Betweenness Centrality*Time	-1.32e-20	2.02e-19	0.948
Patient Complexity	3.12e-0	5.81e-14	<2e-16 ***
Patient Age	8.21e-02	1.056e-14	<2e-16 ***
Panel Size	9.28e-03	3.90e-15	<2e-16 ***
% Female	5.94e-02	1.38e-14	<2e-16 ***
% Non-English as Preferred Language	2.43e-02	3.35e-15	<2e-16 ***
% <138% Federal Poverty Line	-4.81e-02	7.73e-15	<2e-16 ***
% Housing Insecure	1.31e-01	2.98e-14	<2e-16 ***
% Uninsured	-4.55e-03	2.01e-15	<2e-16 ***

*p<0.05, ** p<0.01, *** p<0.001. Models account for clinician fixed effects

Table 3b. Betweenness Centrality and Systolic Blood Pressure Over Time.

Covariates	Systolic Blood Pressure		
	β	SE	p
Betweenness Centrality	-2.56e-03	1.00e-15	<2e-16 ***
Time	-2.56e-17	3.80e-14	<2e-16 ***
Betweenness Centrality*Time	-1.26e-18	1.42e-17	0.930
Patient Complexity	1.16e+01	4.09e-12	<2e-16 ***
Patient Age	2.90e-01	7.43e-13	<2e-16 ***
Panel Size	5.57e-01	2.75e-13	<2e-16 ***
% Female	2.45e+00	9.69e-13	<2e-16 ***
% Non-English as Preferred Language	-1.15e-01	5.44e-13	<2e-16 ***
% <138% Federal Poverty Line	-1.38e+00	5.44e-13	<2e-16 ***
% Housing Insecure	5.05e+00	2.10e-12	<2e-16 ***
% Uninsured	-1.62e-01	1.42e-13	<2e-16 ***

*p<0.05, ** p<0.01, *** p<0.001. Models account for clinician fixed effects

Table 3c. Betweenness Centrality and Diastolic Blood Pressure Over Time.

Covariates	Diastolic Blood Pressure		
	β	SE	p
Betweenness Centrality	-8.95e-04	6.65e-17	<23-16***
Time	-4.73e-15	2.52e-15	0.061
Betweenness Centrality*Time	2.12e-19	9.43e-19	0.822
Patient Complexity	3.23e+00	2.71e-13	<2e-16 ***
Patient Age	-6.10e-02	4.92e-14	<2e-16 ***
Panel Size	1.30e-01	1.82e-14	<2e-16 ***
% Female	4.83e-01	6.41e-14	<2e-16 ***
% Non-English as Preferred Language	-2.42e-02	1.56e-14	<2e-16 ***
% <138% Federal Poverty Line	-1.76e-01	3.60e-14	<2e-16 ***

% Housing Insecure	1.24e+00	1.39e-13	<2e-16 ***
% Uninsured	-5.53e-02	9.37e-15	<2e-16 ***

*p<0.05, ** p<0.01, *** p<0.001. Models account for clinician fixed effects

6.4 DISCUSSION

The present study extends the previous chapter's examination of patient-sharing clinician networks within FQHCs by focusing on the role of network brokerage and its relationship to clinical outcomes. This research addresses a pertinent gap in our field's current understanding of brokerage and boundary-spanning roles: it remains unclear under which conditions brokers may facilitate or impede the flow of needed information across groups. From an organizational perspective, this is a critical process to understand fully because effective team performance involves task interdependencies[151] that inherently rely on effective information transfer between individuals, which has critical implications for care coordination efforts. Furthermore, this work provides a novel contribution to the literature by exploring the relationship between primary care clinician brokerage, as defined by the betweenness centrality metric constructed from patient-sharing clinician network graphs in FQHC settings.

In summary, measures of brokerage activity did not vary meaningfully across the clinician roles included in our data. This may reflect an overall network structure in which few "holes" in communication exist for clinicians to span. It is plausible that our findings reflect the existence of high relational coordination between members of PCMH care teams and the broader care neighborhood. Relational coordination theory posits that well-coordinated communication and relationships characterized by shared goals, shared knowledge, and mutual respect can lead to improved efficiency and quality of care.[152] In the FQHC context, relational coordination may manifest as clinicians engaging in informal conversations to share best practices, or in interdependent tasks required for successful patient care (e.g., health education efforts, follow-up calls, etc.) that may not be captured as formal encounters in an EHR. Therefore, future work should expand upon our definition of patient-sharing as "ties" to capture additional forms of collaboration between providers. The inclusion of this information could provide more specific and nuanced insight into which individuals emerge as brokers that span structural holes.

Overall, the present findings highlight that higher betweenness centrality among primary care clinicians is associated with slightly improved A1c control (i.e., lower A1c levels) among their patients. This supports the notion that brokers may indeed facilitate information and resource flow across network gaps and therefore enhance chronic disease management efforts. However, our study found no significant relationship between brokerage and blood pressure outcome in our primary models, suggesting that the benefits of brokerage may be condition-specific or otherwise influenced by other unmeasured confounders. While the adjusted R-squared values suggest reasonably strong model fit, the small beta coefficients indicate that the covariates in our models may only explain a small improvement in clinical outcomes.

Following our primary analysis, a sub-analysis was conducted to examine how the relationship between brokerage and clinical outcomes may have changed over the timeframe represented in our data, which spans the onset of COVID-19. While the effects of the pandemic were realized among all communities, historically marginalized groups such as those served by FQHCs, experienced disproportionately adverse effects,[112,121,145] so understanding how their care was impacted is particularly important as we consider potential lasting effects of the pandemic among FQHCs and the potential for future crises to disrupt the normal cadence of care delivery. When the models were revised to include time and the interaction between betweenness centrality and time, betweenness centrality remained significant across all models, but the time covariate were not statistically significant, suggesting that any possible advantages conferred by brokerage did not appreciate or diminish over the COVID-19 timeframe. Future research could further elucidate the observed trends by employing more robust causal inference techniques on panel data that spans the COVID-19 timeframe, such as interrupted time-series models, to interrogate the effect of this exogenous shock.

Health services researchers are increasingly employing large administrative datasets to construct patient-sharing clinician networks to generate inferences about constellations of clinical care. Several systematic reviews have called for moving beyond a descriptive network approach, toward the identification of optimal network structures and/or measures that may be targeted for intervention design.[153,154] Such interventions may involve improving existing interdisciplinary care team structures, fostering collaboration across different care domains, or incentivizing providers to actively reach across structural holes to better serve their patient panels and improve overall care quality. Scholars have identified how these network approaches differ from traditional approaches leveraging the role of opinion leaders or quality improvement champions in the development of novel evidence-based interventions and may provide fresh insights into improvement efforts.[138] One recent example of a network-driven ideology for targeting improvement efforts involved the implementation of a leadership training program designed to facilitate the creation of interdisciplinary ties among pediatricians in a large urban academic medical center; the study confirmed the effect of homophily among clinician connections, and found that the intervention meaningfully reduced network fragmentation, showing promise for similar interventions in the future.[155]

The following limitations should be considered alongside the interpretation of this study's findings. First, patient-sharing clinician networks were constructed to identify the presence of clinician ties. While prior work has established the use of this method as a meaningful proxy for identifying communication between two clinicians, the presence of additional data to triangulate our identification of clinician ties could strengthen our interpretations of the data. For example, reviewing inbox messages sent between providers within EHR systems, or interviewing clinicians about which aspects of relational coordination are most prevalent across their teams could provide nuanced insight into the nature of the patient-sharing ties we identify through a structural approach. Second, the present dataset is limited in its ability to identify regional contexts, FQHC system affiliation, or team structures within practice sites. Thus, care should be taken when generalizing the findings beyond the present context, and future work will explore the identification of network "cliques" (or groups of clinicians in which everyone is connected directly to everyone else),[156] as this may be a particularly salient structural method for analyzing team composition. Third, the sub-analysis in aim three was intended to provide an exploratory analysis of how the relationship between brokerage and clinical outcomes may have differed over time, but causation about the impact of the pandemic cannot be inferred from this approach. Future work could borrow from the econometrics literature and employ causal inference techniques on administrative panel data to further elucidate change in these trends, but doing so is beyond the scope of this manuscript.

6.5 CONCLUSION

The study underscores the importance of network brokerage in improving diabetes outcomes within FQHCs, highlighting the potential for targeted network interventions to enhance chronic disease management. While brokerage was not significantly associated with blood pressure outcomes, its role in diabetes management suggests that clinician network structures may be significantly correlated with certain health outcomes. Future research should explore the mechanisms through which clinicians' brokerage efforts may uniquely influence various health conditions, and extend these insights to additional care delivery settings to inform health policy and practice optimization efforts.

CHAPTER 7

CONCLUSION

This dissertation examined various dimensions of patient-centered care in the United States health care system, informed in part by the Institute of Medicine's landmark report advocating for dramatic medical practice reforms. Emphasizing both patient-provider and provider-provider relationships, this body of work investigated patient engagement efforts in outpatient care settings and patterns of provider interactions in community health centers, as well as how these dynamics relate to patient outcomes.

The first and second papers dove into the role of decision aids (DAs) for breast cancer screening, drawing upon survey data from a nationally representative sample of physician practices in the United Sates. Current guidelines recommend that women participate in breast cancer screenings until the age of 74. Decision aids (DAs) are one patient engagement tool that providers may use to structure conversations about screening decisions, the associated risks, and patients' individual health goals. To date there is limited evidence that exists about (a) the organizational and community factors that are associated with increased use of DAs for breast cancer screening, and mixed evidence about (b) the association of DA use with actual mammography uptake. The findings from our analyses indicated that while technological advancements and having fewer barriers to innovation adoption were associated with more frequent use of DAs for breast cancer screening, system-owned and large (20+ physician) practices were less likely to implement them. Furthermore, greater technological capacity was associated with increased mammography use, but practices' frequency of DA use was not. Taken together, it is evident that more resources may be needed for decision aids to be routinely implemented, to improve solicitation of patient preferences and appropriate targeting of mammography services.

The third paper employed social network analysis to understand how patterns of care changed in Federally Qualified Health Center (FQHC) settings during the COVID-19 pandemic. The pandemic caused widespread disruption across multiple sectors and limited many people's ability to seek regular and preventive care services. Medically underserved populations, who often seek care at FQHCs, have been particularly impacted by this harmful trend. Patient-sharing clinician networks were constructed from electronic health record data across FQHCs in California. Both network density and network clustering decreased significantly during the pandemic period, suggesting that there were fewer connections and less tightly-knit groupings of clinicians in the COVID period as compared to the pre-COVID period. Notably, telehealth adoption was associated with clinicians' increased degree centrality. These clinician-specific trends likely reflect shifts in their respective roles and responsibilities during the pandemic, as well as changes in patients' care-seeking and referral patterns.

The fourth paper considered these network characteristics and applied a theoretical lens to interrogate how these changes may have been associated with variations in patient outcomes. Specifically, we identified individual clinicians that bridged structural holes that naturally emerged in the network graphs. Our findings suggest a modest but statistically significant association between brokerage capacity and A1c levels among diabetic patients, a condition that is primarily addressed in outpatient settings. No statistically significant findings emerged for the relationship between brokerage and blood pressure control in our primary models. Further research is warranted to examine the specific mechanisms that may explain this trend for diabetes management, and how these associations may vary by patient characteristics. Findings from this analysis have the potential to inform policy and managerial decisions regarding care coordination efforts within and across community health centers. Furthermore, this work has critical implications for future disruptions that may plague our most vulnerable populations and our burned-out health care workforce.

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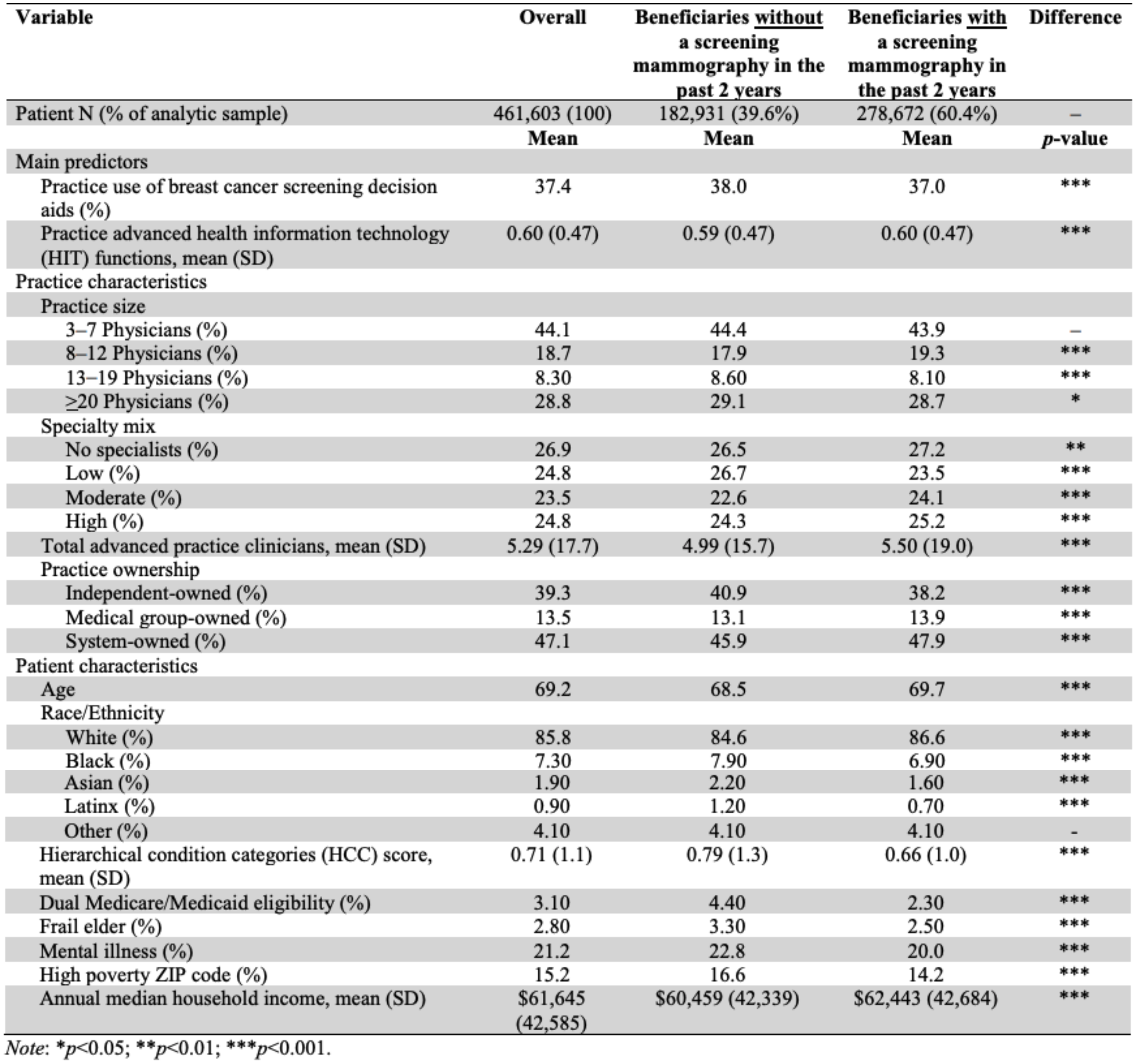
APPENDICES

CHAPTER FOUR APPENDICES

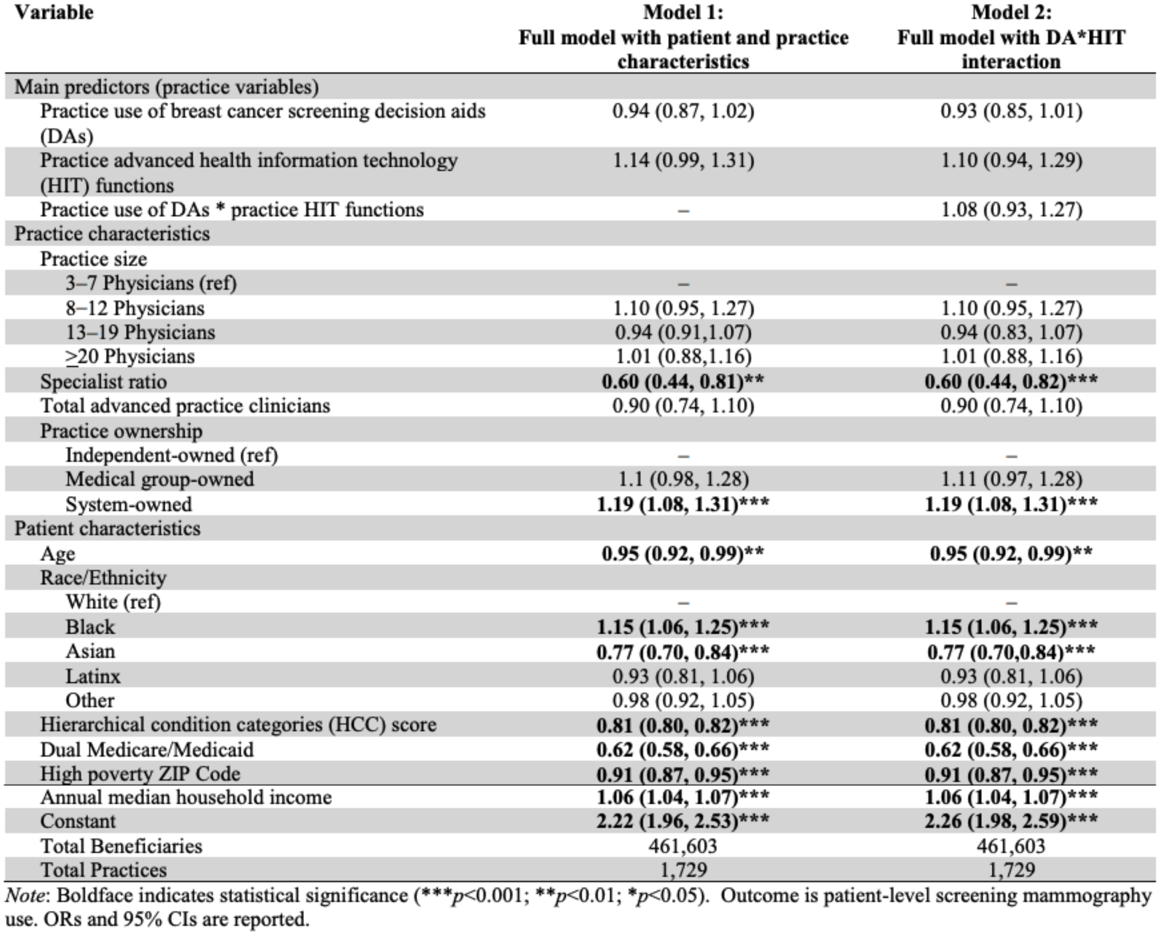
Appendix Table 1. Descriptive Statistics: Patient and Practice Characteristics With Unrestricted Sample, by Mammography Use.



Variable	**Overall**	**Beneficiaries without a screening mammography in the past 2 years**	**Beneficiaries with a screening mammography in the past 2 years**	**Difference**
Patient N (% of analytic sample)	461,603 (100)	182,931 (39.6%)	278,672 (60.4%)	–
	Mean	**Mean**	**Mean**	***p*-value**
Main predictors				
Practice use of breast cancer screening decision aids (%)	37.4	38.0	37.0	***
Practice advanced health information technology (HIT) functions, mean (SD)	0.60 (0.47)	0.59 (0.47)	0.60 (0.47)	***
Practice characteristics				
Practice size				
3–7 Physicians (%)	44.1	44.4	43.9	–
8–12 Physicians (%)	18.7	17.9	19.3	***
13–19 Physicians (%)	8.30	8.60	8.10	***
≥20 Physicians (%)	28.8	29.1	28.7	*
Specialty mix				
No specialists (%)	26.9	26.5	27.2	**
Low (%)	24.8	26.7	23.5	***
Moderate (%)	23.5	22.6	24.1	***
High (%)	24.8	24.3	25.2	***
Total advanced practice clinicians, mean (SD)	5.29 (17.7)	4.99 (15.7)	5.50 (19.0)	***
Practice ownership				
Independent-owned (%)	39.3	40.9	38.2	***
Medical group-owned (%)	13.5	13.1	13.9	***
System-owned (%)	47.1	45.9	47.9	***
Patient characteristics				
Age	69.2	68.5	69.7	***
Race/Ethnicity				
White (%)	85.8	84.6	86.6	***
Black (%)	7.30	7.90	6.90	***
Asian (%)	1.90	2.20	1.60	***
Latinx (%)	0.90	1.20	0.70	***
Other (%)	4.10	4.10	4.10	-
Hierarchical condition categories (HCC) score, mean (SD)	0.71 (1.1)	0.79 (1.3)	0.66 (1.0)	***
Dual Medicare/Medicaid eligibility (%)	3.10	4.40	2.30	***
Frail elder (%)	2.80	3.30	2.50	***
Mental illness (%)	21.2	22.8	20.0	***
High poverty ZIP code (%)	15.2	16.6	14.2	***
Annual median household income, mean (SD)	$61,645 (42,585)	$60,459 (42,339)	$62,443 (42,684)	***

Note: *$p<0.05$; **$p<0.01$; ***$p<0.001$.

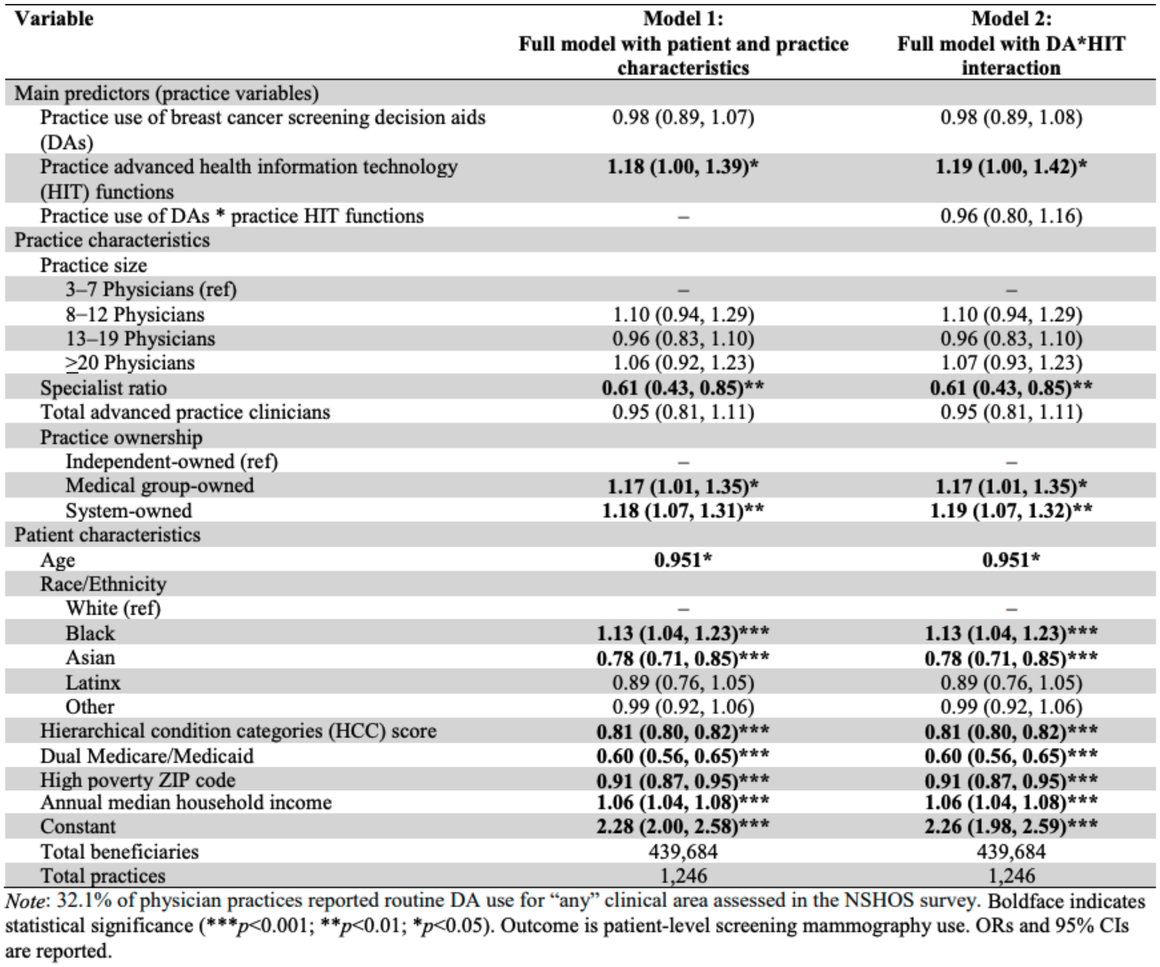
Appendix Table 2. Sensitivity Analysis: Regression Results With No Practice Restriction for Beneficiary Volume.



Variable	Model 1: Full model with patient and practice characteristics	Model 2: Full model with DA*HIT interaction
Main predictors (practice variables)		
Practice use of breast cancer screening decision aids (DAs)	0.94 (0.87, 1.02)	0.93 (0.85, 1.01)
Practice advanced health information technology (HIT) functions	1.14 (0.99, 1.31)	1.10 (0.94, 1.29)
Practice use of DAs * practice HIT functions	–	1.08 (0.93, 1.27)
Practice characteristics		
Practice size		
3–7 Physicians (ref)	–	–
8–12 Physicians	1.10 (0.95, 1.27)	1.10 (0.95, 1.27)
13–19 Physicians	0.94 (0.91,1.07)	0.94 (0.83, 1.07)
≥20 Physicians	1.01 (0.88,1.16)	1.01 (0.88, 1.16)
Specialist ratio	**0.60 (0.44, 0.81)****	**0.60 (0.44, 0.82)*****
Total advanced practice clinicians	0.90 (0.74, 1.10)	0.90 (0.74, 1.10)
Practice ownership		
Independent-owned (ref)	–	–
Medical group-owned	1.1 (0.98, 1.28)	1.11 (0.97, 1.28)
System-owned	**1.19 (1.08, 1.31)*****	**1.19 (1.08, 1.31)*****
Patient characteristics		
Age	**0.95 (0.92, 0.99)****	**0.95 (0.92, 0.99)****
Race/Ethnicity		
White (ref)	–	–
Black	**1.15 (1.06, 1.25)*****	**1.15 (1.06, 1.25)*****
Asian	**0.77 (0.70, 0.84)*****	**0.77 (0.70,0.84)*****
Latinx	0.93 (0.81, 1.06)	0.93 (0.81, 1.06)
Other	0.98 (0.92, 1.05)	0.98 (0.92, 1.05)
Hierarchical condition categories (HCC) score	**0.81 (0.80, 0.82)*****	**0.81 (0.80, 0.82)*****
Dual Medicare/Medicaid	**0.62 (0.58, 0.66)*****	**0.62 (0.58, 0.66)*****
High poverty ZIP Code	**0.91 (0.87, 0.95)*****	**0.91 (0.87, 0.95)*****
Annual median household income	**1.06 (1.04, 1.07)*****	**1.06 (1.04, 1.07)*****
Constant	**2.22 (1.96, 2.53)*****	**2.26 (1.98, 2.59)*****
Total Beneficiaries	461,603	461,603
Total Practices	1,729	1,729

Note: Boldface indicates statistical significance (***p<0.001; **p<0.01; *p<0.05). Outcome is patient-level screening mammography use. ORs and 95% CIs are reported.

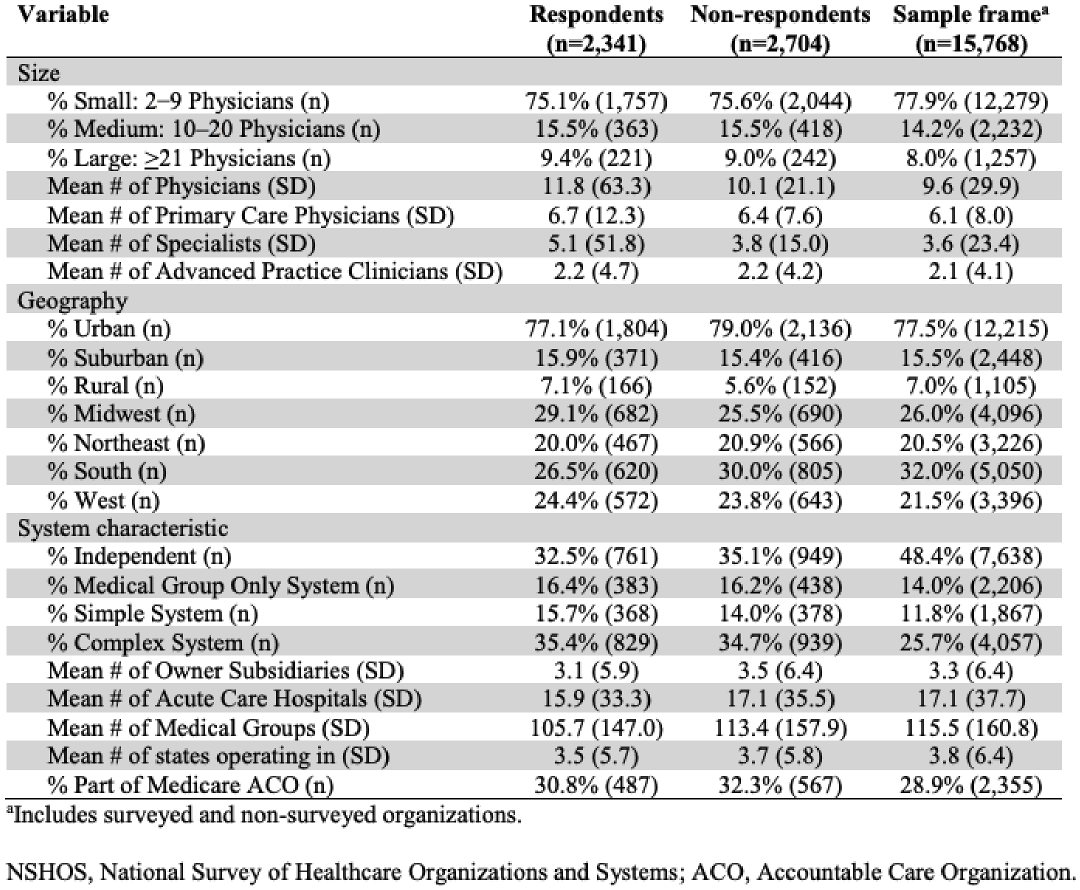
Appendix Table 3. Sensitivity Analysis: Routine Use of Decision Aids for Any Preference-Sensitive Condition.



Variable	Model 1: Full model with patient and practice characteristics	Model 2: Full model with DA*HIT interaction
Main predictors (practice variables)		
Practice use of breast cancer screening decision aids (DAs)	0.98 (0.89, 1.07)	0.98 (0.89, 1.08)
Practice advanced health information technology (HIT) functions	**1.18 (1.00, 1.39)***	**1.19 (1.00, 1.42)***
Practice use of DAs * practice HIT functions	–	0.96 (0.80, 1.16)
Practice characteristics		
Practice size		
3–7 Physicians (ref)	–	–
8–12 Physicians	1.10 (0.94, 1.29)	1.10 (0.94, 1.29)
13–19 Physicians	0.96 (0.83, 1.10)	0.96 (0.83, 1.10)
≥20 Physicians	1.06 (0.92, 1.23)	1.07 (0.93, 1.23)
Specialist ratio	**0.61 (0.43, 0.85)****	**0.61 (0.43, 0.85)****
Total advanced practice clinicians	0.95 (0.81, 1.11)	0.95 (0.81, 1.11)
Practice ownership		
Independent-owned (ref)	–	–
Medical group-owned	**1.17 (1.01, 1.35)***	**1.17 (1.01, 1.35)***
System-owned	**1.18 (1.07, 1.31)****	**1.19 (1.07, 1.32)****
Patient characteristics		
Age	**0.951***	**0.951***
Race/Ethnicity		
White (ref)	–	–
Black	**1.13 (1.04, 1.23)*****	**1.13 (1.04, 1.23)*****
Asian	**0.78 (0.71, 0.85)*****	**0.78 (0.71, 0.85)*****
Latinx	0.89 (0.76, 1.05)	0.89 (0.76, 1.05)
Other	0.99 (0.92, 1.06)	0.99 (0.92, 1.06)
Hierarchical condition categories (HCC) score	**0.81 (0.80, 0.82)*****	**0.81 (0.80, 0.82)*****
Dual Medicare/Medicaid	**0.60 (0.56, 0.65)*****	**0.60 (0.56, 0.65)*****
High poverty ZIP code	**0.91 (0.87, 0.95)*****	**0.91 (0.87, 0.95)*****
Annual median household income	**1.06 (1.04, 1.08)*****	**1.06 (1.04, 1.08)*****
Constant	**2.28 (2.00, 2.58)*****	**2.26 (1.98, 2.59)*****
Total beneficiaries	439,684	439,684
Total practices	1,246	1,246

Note: 32.1% of physician practices reported routine DA use for "any" clinical area assessed in the NSHOS survey. Boldface indicates statistical significance (***p<0.001; **p<0.01; *p<0.05). Outcome is patient-level screening mammography use. ORs and 95% CIs are reported.

Appendix Table 4. NSHOS Practice Survey Respondents vs Nonrespondents.[65]



Variable	Respondents (n=2,341)	Non-respondents (n=2,704)	Sample frame[a] (n=15,768)
Size			
% Small: 2–9 Physicians (n)	75.1% (1,757)	75.6% (2,044)	77.9% (12,279)
% Medium: 10–20 Physicians (n)	15.5% (363)	15.5% (418)	14.2% (2,232)
% Large: >21 Physicians (n)	9.4% (221)	9.0% (242)	8.0% (1,257)
Mean # of Physicians (SD)	11.8 (63.3)	10.1 (21.1)	9.6 (29.9)
Mean # of Primary Care Physicians (SD)	6.7 (12.3)	6.4 (7.6)	6.1 (8.0)
Mean # of Specialists (SD)	5.1 (51.8)	3.8 (15.0)	3.6 (23.4)
Mean # of Advanced Practice Clinicians (SD)	2.2 (4.7)	2.2 (4.2)	2.1 (4.1)
Geography			
% Urban (n)	77.1% (1,804)	79.0% (2,136)	77.5% (12,215)
% Suburban (n)	15.9% (371)	15.4% (416)	15.5% (2,448)
% Rural (n)	7.1% (166)	5.6% (152)	7.0% (1,105)
% Midwest (n)	29.1% (682)	25.5% (690)	26.0% (4,096)
% Northeast (n)	20.0% (467)	20.9% (566)	20.5% (3,226)
% South (n)	26.5% (620)	30.0% (805)	32.0% (5,050)
% West (n)	24.4% (572)	23.8% (643)	21.5% (3,396)
System characteristic			
% Independent (n)	32.5% (761)	35.1% (949)	48.4% (7,638)
% Medical Group Only System (n)	16.4% (383)	16.2% (438)	14.0% (2,206)
% Simple System (n)	15.7% (368)	14.0% (378)	11.8% (1,867)
% Complex System (n)	35.4% (829)	34.7% (939)	25.7% (4,057)
Mean # of Owner Subsidiaries (SD)	3.1 (5.9)	3.5 (6.4)	3.3 (6.4)
Mean # of Acute Care Hospitals (SD)	15.9 (33.3)	17.1 (35.5)	17.1 (37.7)
Mean # of Medical Groups (SD)	105.7 (147.0)	113.4 (157.9)	115.5 (160.8)
Mean # of states operating in (SD)	3.5 (5.7)	3.7 (5.8)	3.8 (6.4)
% Part of Medicare ACO (n)	30.8% (487)	32.3% (567)	28.9% (2,355)

[a]Includes surveyed and non-surveyed organizations.

NSHOS, National Survey of Healthcare Organizations and Systems; ACO, Accountable Care Organization.

CHAPTER FIVE APPENDICES

Appendix Table 5. Categorization of Clinician Types.

Clinician Type Category (N)	Clinician Type Raw Data (N)
Primary Care Physician (371)	Physician (355) Osteopath (16)
Advanced Practice Clinician (259)	Nurse Practitioner (168) Physician Assistant (86) Certified Nurse Midwife (3) Midwife (1) Psychiatric Nurse Practitioner (1)
Medical Assistant (150)	Medical Assistant (132) Certified Medical Assistant (16) Certified Clinical Medical Assistant (2)
Resident (136)	Resident (136)
Registered Nurse (86)	Registered Nurse (84) Public Health Nurse (1) Case Manager (1)
Specialist Physician (22)	Podiatrist (10) Psychiatrist (6) Obstetrician (3) Radiologist (2) Physiatry (1)
Ancillary Services/Staff (21)	Health Educator (9) Nutritionist (4) Phlebotomist (4) Dialysis (2) Interpreter Only (1) Patient Care Team Assistant (1)
Pharmacist (21)	Pharmacist (20) Pharmacy Student (1)
Other (110)	Lab Technician (66) Licensed Vocational Nurse (26) Resource (16) Non-Billing (1) Other (1)
Missing (19)	Missing (19)

Note: The study team reached consensus on the most accurate categorization of clinical roles, and ultimately collapsed the raw data into the final clinician type categories which were used in the main statistical and sensitivity analyses.

Appendix Table 6. Sensitivity Analysis: Comparison of Network Characteristics Before and During COVID-19, with Sample Restricted to Patients Present in Both Cohorts.

Network Metrics	Before COVID-19	During COVID-19	Difference	P-Value
Node and Tie Frequencies				
Nodes (Clinicians)	832	792	40	--
Ties (Weighted Patient-Sharing)	2,209	1,287	922	--
Network Characteristics				
Network Diameter	114	64	50	<0.001
Number of Connected Components	97	228	-131	0.441
Size of Largest Connected Component	137	120	17	1.000
Whole Network Measures				
Density	0.045	0.016	0.029	<0.001
Clustering	0.395	0.307	0.087	0.392
Node-Level Network Measures				
Degree Centrality (Mean)	74.606	24.934	49.671	<0.001
Clustering Coefficient (Mean)	0.565	0.518	0.048	0.036
Betweenness Centrality (Mean)	112.360	58.312	54.041	<0.001
PCC Dyad Frequencies				
PCC- PCC	289	120	160	0.023
PCC -Specialist	27	7	20	0.008
PCC -Nurse	32	25	7	0.310
PCC -Medical Assistant	101	75	26	0.968
PCC -Resident	35	17	36	1.000
PCC -Pharmacist	51	23	28	0.508

Note: PCC = Primary Care Clinician.

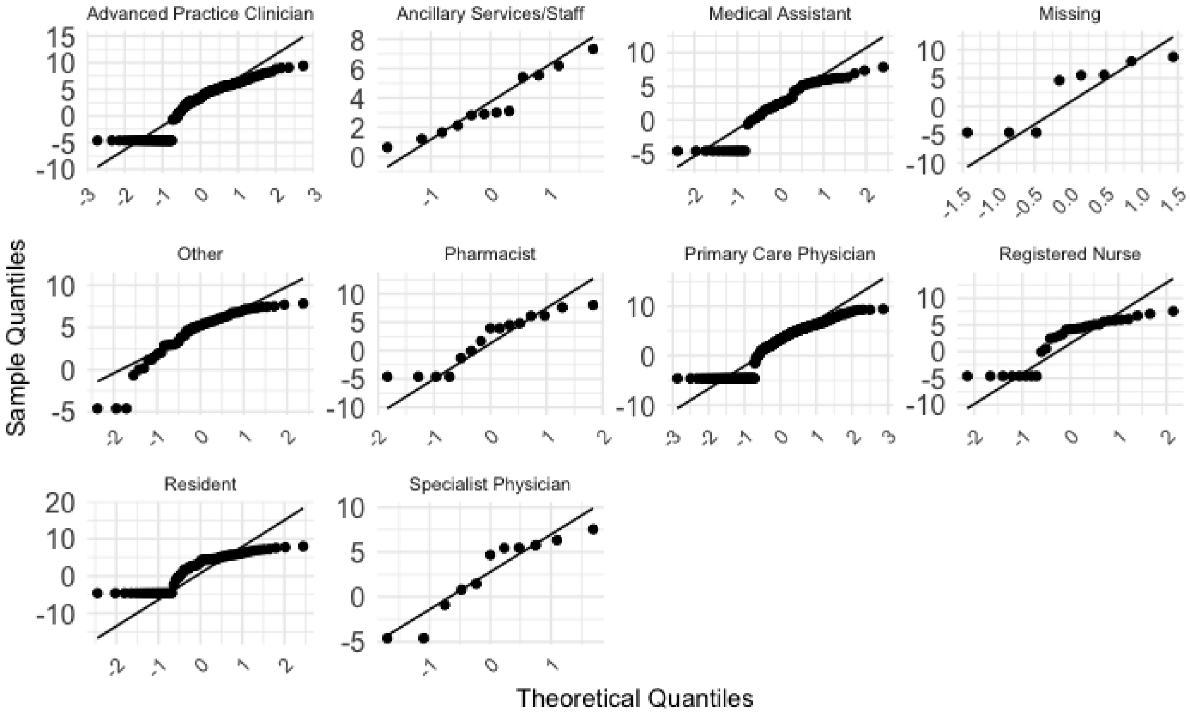
Appendix Table 7. Sensitivity Analysis: Multivariable Regression Models Predicting Changes in Node-Level Network Characteristics, with Sample Restricted to Patients Present in Both Cohorts.

	Δ Degree Centrality			**Δ Clustering Coefficient**			**Δ Betweenness Centrality**		
Covariates	β	SE	p	β	SE	p	β	SE	p
Clinician Type									
PCP	96.34	95.31	0.313	-2.55E-05	6.68E-01	1.000	518.29	348.28	0.137
APP	15.07	13.36	0.260	5.32E-02	6.76E-02	0.432	-35.03	48.81	0.473
MA	-43.58	21.29	0.041*	6.31E-02	1.00E-01	0.531	22.07	77.80	0.777
Residents	-9.07	25.12	0.718	1.45E-01	1.86E-01	0.436	-173.97	91.78	0.059
RN	4.43	28.43	0.876	1.06E-01	2.25E-01	0.637	35.76	103.89	0.731
Specialist	-86.74	50.87	0.089	3.25E-01	1.87E-01	0.083	159.81	185.88	0.390
Ancillary Staff	-91.22	40.92	0.027*	1.26E-01	1.90E-01	0.507	-42.77	149.53	0.775
Pharmacist	58.68	31.39	0.062*	1.28E-01	1.32E-01	0.334	-79.96	114.71	0.486
Other	-42.64	19.42	0.029*	5.27E-02	9.74E-02	0.589	-233.85	70.96	0.001*
Missing	324.01	51.59	<0.001*	7.21E-02	2.13E-01	0.735	-168.61	188.51	0.372
Patient Volume	0.88	0.061	<0.001*	2.44E-04	2.56E-04	0.342	1.44	0.22	<0.001*
Patient Age	-1.66	1.14	0.146	1.52E-03	9.60E-03	0.875	-7.02	4.17	0.093
PHCC	0.99	3.54	0.780	1.42E-02	2.13E-02	0.507	7.19	12.95	0.579
Telehealth	-125.45	47.44	0.009*	2.08E-01	2.64E-01	0.431	-21.35	173.35	0.902
R-Squared	0.608			0.304			0.175		
F	<0.001			0.031			0.440		

Note: APP = Advanced Practice Clinician. All models include facility fixed effects.

CHAPTER SIX APPENDICES

Appendix Table 8. QQ Plots for Betweenness Scores.



Appendix Table 9. Shapiro-Wilk Test for Normality.

Group	W	p-value
Primary Care Physician	0.8822231	8.628433e-13
Advanced Practice Clinician	0.8718607	2.344871e-10
Ancillary Services/Staff	0.9262469	3.420224e-01
Resident	0.8417443	3.707339e-07
Pharmacist	0.8778505	4.407312e-02
Other	0.8527787	5.894600e-06
Registered Nurse	0.8115509	8.508912e-05
Specialist Physician	0.8754984	9.117701e-02
Missing	0.7940127	2.468951e-02
Medical Assistant	0.8806469	2.782587e-05

Appendix Table 10. Levene’s Test for Homogeneity of Variances.

Group	DF	F-Value	P-Value
Group	9 654	2.2516	0.01753