Heterogeneous Treatment Effects of the Patient Aligned Care Team Initiative on Service Utilization in the Veterans Health Administration

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Abstract

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Payers across the nation have been testing new models of care delivery like the patient-centered medical home (PCMH) to improve quality of care and reduce costs. PCMHs use team-based, patient-centered care to reduce costs by shifting utilization from high-cost services like emergency departments and hospitals to primary care settings. Literature on the effectiveness of PCMHs is mixed but fails to account for treatment effect heterogeneity. Applying unique clinical and methodological innovations, we estimated heterogenous treatment effects among one of the nation's largest PCMH initiatives, the Veterans Health Administration's Patient Aligned Care Team (PACT) initiative. We found little evidence of heterogeneous treatment effects by patient characteristics such as risk status, demographics, and social stability and clinic-level measures of access up to six years into PACT. Continuing to expand this knowledge base is critical to better target interventions, particularly in resource-constrained environments.

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DEDICATION

To Lucy

Chapter 1. INTRODUCTION

1.1 PRIMARY CARE: A CHIEF PRIORITY IN THE U.S.

The U.S. spends more on health care and has worse health outcomes than other developed nations.[1,2] The U.S. has among the highest rates of hospitalizations from preventable causes and the highest rate of premature death from conditions that are considered preventable with timely access to primary care, such as diabetes and hypertensive disease.

One driver of higher costs and lower quality has been the U.S.'s reliance on more hospital-based care and less primary care. Between 2002 and 2015, the U.S. experienced a 12% increase in emergency department (ED) use and a 32% reduction in the rate of acute care visits to primary care practices.[3] Studies suggest, however, that about one-third of ED visits could be addressed in a primary care or retail setting, and one study predicted $4.4 billion in savings if non-urgent ED visits were cared for in non-hospital settings.[4,5] Overreliance on EDs and hospitals not only leads to high costs, but also undesirable patient experiences including unnecessary or duplicative testing and treatment and high out-of-pocket costs.[5,6] In contrast, greater use of primary care has been associated with fewer hospitalizations, fewer ED visits, lower mortality, and lower costs.[7–12]

Deemed "too important to fail" in 2009[13], improving access to primary care has become a key strategy to improving health care quality, costs, and outcomes in the U.S. Good primary care provides patients with timely and appropriate care, promotes longitudinal relationships between patients and providers, and manages patients' conditions and care needs.[4] Timely access to primary care provides patients with a place to receive non-urgent care and also reduces the likelihood of complications that can lead to ED visits and hospital stays. As such, improving access to primary care is a key institutional priority for the U.S. Department of Health and Human Services and the Veterans Health Administration.[14–16]

1.2 THE PATIENT-CENTERED MEDICAL HOME

The patient-centered medical home (PCMH) has become a popular approach among health care payers and providers for improving primary care. The PCMH defines a strategy to structure primary care that puts patients at the forefront of care to optimize outcomes and reduce costs.[17,18] The PCMH strategy emphasizes longitudinal and episodic care management of chronic conditions; use of health information technology to identify, measure, and track population health; patient and caregiver engagement; and enhanced access to care.[17–19]

Through PCMH, primary care practices restructure care delivery to utilize multi-disciplinary teams of physicians, nurses, and administrative staff to manage and coordinate care across the medical and social support neighborhood. Practices hire new staff and train existing staff in expanded roles, invest in health information technology and patient registries, and expand access options by creating and promoting secure messaging portals and longer office hours.[18,20] Transitioning to the medical home model is time intensive, challenging, and expensive, taking on average between 9 and 12 months and costing between \$100,000 and \$517,000 per full-time equivalent physician.[17,18,20–22] Today, more than 13,000 primary care practices are a recognized PCMH by the National Committee for Quality Assurance, and more than 100 payers have supported practices' transitions through financial incentives or coaching.[17]

1.3 Primary care and the Veterans Health Administration

In the chapters that follow, we take a closer look at the PCMH within the Veterans Health Administration (VHA). Being one of the largest integrated health care systems in the U.S., the VHA provides a unique opportunity to estimate the effect of a PCMH among a large and diverse population. In 2017, more than 8 million veterans are enrolled in the VHA, representing about 40% of all veterans.[23–25] All individuals that served in the active military, naval, or air service that did not receive a dishonorable discharge are eligible to enroll in VHA health care.[26] The VHA provides care at 1,255 health care facilities in urban and rural settings, including 170 Medical Centers and 1,074 outpatient clinics.[27] VHA enrollees are subject to modest copays for outpatient care ranging from $15 for primary care services to $50 for specialty care, although, more than 70% of VHA enrollees are exempt from paying copays.[28]

Veterans served by the VHA have more chronic physical and mental illness, are more socioeconomically vulnerable, are mostly male, and are less racially and ethnically diverse than the general population.[25,29,30] VHA is also the largest provider of health care services for homeless veterans.[31] VHA-enrolled veterans are also different in some ways from the wider Veteran population. For example, in 2017 the unemployment rate among VHA enrollees was 9.2% compared to 3.7% for all veterans and 4.4% for civilians.[23] Many VHA-enrolled veterans are dually-enrolled with Medicare (51%) or private coverage (28%) and use non-VHA services for their health care needs.[23,32]

Primary care is the foundation of VHA health care and is generally the VHA-enrolled veterans' first point of contact with the health system. In April 2010, the VHA launched their PCMH model, the Patient Aligned Care Team (PACT) initiative in all primary care clinics nationwide.[24,25,33,34] PACT built off already strong primary care foundations set by the VHA in the 1990s. Prior to PACT, the VHA implemented several PCMH elements including comprehensive electronic medical records, population management tools, quality improvement programs, and behavioral health integration.[25,35] Through PACT, the VHA focused on increasing and reorganizing primary care staff to prioritize (1) team-based care, (2) patient access, and (3) care management and coordination.[25,35] The VHA seeks to improve the care and health outcomes for all VA enrollees via PACT.

Upon enrolling in the VHA, a patient is assigned to a primary care team (i.e., a Patient Aligned Care Team) that is charged with coordinating and managing that patient's care, serving as a gatekeeper to specialty care and other services. Each primary care team consists of one primary care provider (medical doctor [MD] or nurse practitioner [NP]), one registered nurse care manager, one licensed practical nurse or medical assistant, and one administrative clerk.[25] Teams are additionally connected to integrated behavioral health, pharmacy, and social work services. Together, a care team is responsible for a panel of 900 to 1200 primary care patients.

1.4 Evidence on the effectiveness of the PCMH to alter utilization

Despite its widespread adoption, the literature on the effectiveness of the PCMH to shift utilization from high-cost settings like EDs and hospitals toward primary care settings is mixed. A meta-analysis of 17 peer-reviewed studies of PCMH initiatives concluded no effect of PCMH on total or potentially avoidable ED use, hospitalizations for any reason, or hospitalizations for ambulatory care-sensitive conditions (ACSC).[36] In contrast, a study of primary care clinics in the VHA found that greater adoption of medical home features were associated with fewer ACSC hospitalizations, but again, had no effect on ED use.[37]

Early results from the VHA's PACT initiative have shown modest effects on some measures of high-cost service utilization.[32] During the first two years of implementation, PACT was associated with a 1.7% decrease in ACSC hospitalizations, but had no effects on other types of hospitalizations, ED visits, or urgent care clinic visits. Moreover, longitudinal changes in PACT implementation two to five years after implementation were not associated with changes in ED visits, ACSC or all-cause hoapitalizations.[38]

1.5 Heterogeneous treatment effects in the PCMH

These average effects, however, may be obscuring differential effects in specific subpopulations. For example, chronically ill patients like those with comorbidities may disproportionally benefit from enhanced team-based access to care, care management and coordination. Thus, PCMH models may have larger effects on the subpopulation of patients with comorbidities, but these effects would go unnoticed in population-level estimates. The health services literature suggests that several patient characteristics may lead to different experiences with PCMH and thus heterogeneous treatment effects. For example, patients with longer travel distances and disabilities[39,40] as well as those characterized by different races, [41,42] age and gender,[43,44] risk-status,[45] marital status,[46] and income[47] have been shown to face additional obstacles to accessing primary care. Emerging research is also demonstrating the relevance of social stability on health care use. Markers of social instability, such as frequent changes of residence and history of hospital discharge against medical advice (AMA) have been strongly associated with 30-day hospital readmissions, and are predictive of patients' high-risk status.[48,49] Housing instability and homelessness have specifically been linked to higher hospitalizations and barriers to accessing care.[50,51] To better understand the potential effect of care delivery programs, we must look beyond the average effects and examine how demographic and social characteristics differentially affect patients' outcomes in specific contexts.

Studies on heterogeneous treatment effects of PCMHs are beginning to emerge and have demonstrated that there are subgroups of the primary care population that have benefited while others have not.[28,52] A study of the PACT initiative its first three years found that among patients 65 years or older, PACT was associated with larger increases in primary care visits for high-comorbid patients relative to low-comorbid patients.[28] David et al. (2015) found that adoption of a PCMH across 280 primary care practices in Pennsylvania was associated with lower ED use among chronically ill patients, but not among patients without chronic illness.[7] However, the current literature has not examined whether the PCMH differentially affects patients with other characteristics like race, travel distance, marital status, and social instability characteristics like homelessness.

1.6 DISSERTATION AIMS

In this dissertation we seek to estimate the extent to which the PACT initiative differentially affected patients based on their demographic, social, and economic characteristics. By identifying for whom primary care initiatives like PACT benefit and isolating the size of differential benefits, delivery systems and payers can more efficiently allocate their resources to target patients most likely to benefit from PCMH. This approach will maximize health and economic benefits without mitigating care for those unlikely to benefit from practice transformation. Using advanced analytic methods, we investigate the following specific aims:

AIM 1: Estimate whether the effect of PACT on avoidable, high-cost utilization differs between individuals with more or fewer comorbidities. We apply interrupted time series regressions to examine associations between PACT and the number of all-cause and preventable ED visits, and hospitalizations for ambulatory care-sensitive conditions. We hypothesize that

PACT will reduce high-cost utilization, but at a greater rate among patients with more comorbidities compared to those with fewer comorbidities.

AIM 2: Measure the effects of greater access through PACT on ED and hospital use, using a unique multidimensional composite measure of access and a new instrumental variables estimator to measure heterogeneous treatment effects among specific subpopulations. We estimate the effect of access to primary care—a key tenant of PACT[14]—on measures of total and potentially preventable ED and hospital use using an instrumental variables approach, and apply a unique estimator to measure heterogeneous effects across individual characteristics including comorbidity status, socioeconomic status, and travel distances. We hypothesize that (1) delays in timely access to care could lead patients to seek care at the ED rather than primary care and (2) certain VHA subpopulations may disproportionately benefit from PACT access leading to markedly fewer ED visits and hospitalizations.[7]

AIM 3: Test for differential treatment effects of the PACT Intensive Management (PIM) Program on acute care use using model-based recursive partitioning. In 2014, the VHA launched a demonstration to test whether augmenting primary care (via PACT) with intensive management for high-risk patients improved outcomes and reduced costs. An early study of the PIM program—a five clinic pilot for intensive management programs within PACT—found few statistically significant effects on service utilization.[53] We employ model-based recursive partitioning to identify subgroups of patients whose utilization was differentially affected by PIM. Recursive partitioning allows us to model complex interactions between patient characteristics not possible using standard regression techniques.

The proposed research is important to various stakeholders, including payers, health care delivery systems, and practices who are considering the PCMH model as an approach to improve quality without increasing costs.[54,55] By finding heterogeneous treatment effects, we can identify the populations for whom PCMH models are benefiting and inform stakeholders on how they can optimize the allocation of their resources to maximize benefits and contain costs without reducing the quality of care for others. If we conclude that the VHA's PCMH model did not affect certain veteran subpopulations differently than others, our research would suggest that more work is needed to determine how best to alter patients' use of care in high-cost settings without reducing quality and increasing costs.

1.7 Roadmap

The rest of this dissertation is organized as follows. Chapters 2 through 4 present the study design, analytic methods, and findings from Aims 1, 2, and 3, respectively. Each of these three chapters have accompanying appendices with additional details and data tables. Finally, Chapter 5 summarizes the findings, policy implications, and future directions implicated from this dissertation.

Chapter 2. PATIENT CENTERED MEDICAL HOME IMPLEMENTATION IN THE VETERANS HEALTH ADMINISTRATION AND POTENTIALLY AVOIDAVLE, HIGH-COST SERVICE UTILIZATION: DOES COMORBIDITY MATTER?

2.1 INTRODUCTION

In 2010, the Veteran's Health Administration (VHA)—one of the largest integrated health care systems in the United States—launched the Patient Aligned Care Team (PACT) initiative in all primary care clinics nationwide.[24,25,33] PACT is a patient-centered medical home (PCMH) model that built off strong primary care foundations set by the VHA in the 1990s. Prior to PACT, the VHA implemented several PCMH elements including comprehensive electronic medical records, population management tools, quality improvement programs, and behavioral health integration.[25,35] Thus, PACT increased and reorganized primary care staff to prioritize (1) team-based care, (2) patient access, and (3) care management and coordination.[25,35] Through PACT, the VHA sought to improve the care and health outcomes for all veterans.

Early results from the VHA's PACT initiative have shown modest effects on some measures of high-cost service utilization.[32] During the first two years of implementation, among patients aged 65 and older, PACT was associated with a 0.2% decrease in hospitalizations for ambulatory care-sensitive conditions (ACSC), but had no effects on other types of hospitalizations, emergency department (ED) visits, or urgent care clinic visits. Moreover, longitudinal changes in PACT implementation two to five years after implementation were not associated with changes in ED visits, ACSC or all-cause hoapitalizations.[38] These average effects, however, may be obscuring differential effects in specific populations. Chronically ill patients like those with comorbidities may disproportionally benefit from enhanced team-based access to care, care management and coordination—PACT's key components.

Studies on differential effects of PCMH by comorbidity burden are beginning to emerge, but findings are inconsistent. Notably, a study of the PACT initiative through 2013 found that among patients 65 years or older, PACT was associated with larger increases in primary care visits for high-comorbid patients relative to low-comorbid patients through the first three years after PACT began.[28] David et al. (2015) found that adoption of a PCMH across 280 primary care practices in Pennsylvania was associated with lower ED use among chronically ill patients, but not among patients without chronic illness.[7] Other studies, however, found no effects of PCMH on patients with comorbidities. A meta-analysis of the early PCMH literature concluded no effect of PCMH on total or potentially avoidable ED use and ACSC hospitalizations or other measures of health care use among the higher-morbidity population.[36] More recently, Grove et al. 2020 found a positive association between PCMH and outpatient health care use but no association on ED use and inpatient admissions among Medicaid beneficiaries with comorbid mental and physical illness.[56]

We hypothesize that PACT would reduce potentially avoidable high-cost service use six years after implementation and PACT may differentially effect patients based on their comorbidity burden. Elements of team-based care, enhanced access, care management, and care coordination are likely to be more impactful on patients with more comorbidities because these patients often have greater continuous care needs than healthier patients.[45] In principle, enhanced access to providers and care through expanded staffing, same-day visits, and alternatives to traditional office visits could increase patients' ability to receive timely and appropriate care from the primary care setting, and shift some care away from EDs and hospitals. We focus on ED visits, preventable ED visits, and ACSC hospitalizations because they include types of services that are hypothesized to be avoidable with adequate primary care and proactive disease management.[57–59]

In this study, we estimated the effect of PACT on total and potentially preventable ED visits and ACSC hospitalizations on veterans aged 65 and older and examined whether effects differed by level of patient comorbidity. The findings from this study are important to payers, health care delivery systems, and practices who continue to test primary care redesign to improve quality without increasing costs.[54,55] By understanding the extent to which PCMH models impact subpopulations of patients, stakeholders can continue to strengthen primary care to maximize benefits for populations most likely to benefit without mitigating care for the rest of the population.

2.2 METHODS

2.2.1 *Study design*

We conducted a retrospective national cohort study of patients 65 years or older who received primary care from the VHA at any time between October 2002 and December 2016. We applied an interrupted time series (ITS) study design to estimate the association of PACT with total ED visits, preventable ED visits, and ACSC hospitalizations. Because PACT was implemented simultaneously across all VHA clinics in April 2010, there is no comparison group of VHA clinics that did not receive PACT.[25,35] Therefore, we used ITS regression models to derive long-run time trends in our outcomes and to identify whether deviations in utilization trends resulted from PACT implementation. We then examined whether the association of PACT with our outcomes differed between patients with and without high comorbidity burden.

2.2.2 *Data and study sample*

Data for this study come from the VHA Corporate Data Warehouse (CDW), a national repository that contains administrative and clinical data on all patient encounters within the VHA. We used the VHA's Primary Care Management Module (PCMM), a database within CDW that contains information on patient assignment to primary care providers and care teams. CDW data were linked to Medicare fee-for-service (FFS) claims, to measure utilization outside of the VHA. We used data from the Veterans Administration Site Tracking System (VAST) to obtain information on the physical locations of VHA facilities. Finally, we used data from the Health Resources & Services Administration's (HRSA) Area Health Resources File to obtain characteristics of the patients' residential county.

We identified 9,816,691 veterans receiving primary care from VHA at any time between October 2002 and December 2016. For each of the 9.8 million patients, we identified which quarters they had an active relationship with a VHA primary care provider. We then extracted a 5% random sample of active patient-quarters. We included only patients 65 years or older so we could capture all encounters within VHA or in Medicare FFS. We excluded Medicare Advantage enrollees because we did not have claims for them. The final sample consisted of a repeated cross-sectional sample of 5.2 million patient-quarter observations, representing 2.8 million unique patients in 1,012 VHA primary care clinics nationally.

2.2.3 *Measures*

Patient comorbidity measure. We measured patient comorbidity burden using the Gagne comorbidity score.[60] The Gagne measure is a weighted composite of conditions from the Charlson and Elixhauser comorbidity measures and ranges from -2 to 24. The Gagne score has been validated in the Medicare population and shown to have better performance in predicting 30-day mortality compared to the individual component measures.[60] Following the literature, we categorized patients with a Gagne score ≥ 2 as having high comorbidity burden and those < 2 as patients with low comorbidity.[28]

Outcome measures. We estimated the effect of PACT on three measures of high-cost service utilization: total ED visits, preventable ED visits, and hospitalizations for ambulatory care-sensitive conditions (ACSCs).

- *Total ED visits* were measured for each veteran in each quarter and were identified in VHA administrative data and Medicare outpatient claims. Following Liu et al. 2018, we identified ED visits using the 15 Healthcare Common Procedure Coding System (HCPCS) codes associated with the Berenson-Eggers Type of Service (BETOS) code M3-emergency room visit, and VHA encounter stop codes (for ED visits in the VHA) and place of service codes (for ED visits outside of the VHA) that indicate the type of facility that provided the care.[61]
- *Preventable ED visits* were measured for each patient in each quarter using the New York University (NYU) ED Algorithm (EDA)—a valid and reliable measure of potentially avoidable ED visits[58,62,63,64]—and the patch to the algorithm developed by Johnson 2015.[59] Following the algorithm, we used primary ED discharge diagnosis codes to assign probabilities that each ED visit fell into four categories: (1) non-emergent, (2) emergent/primary care treatable, (3) emergent-ED care needed-preventable/avoidable, and (4) emergent-ED care needed-not preventable/avoidable. We then calculated the sum of the probabilities of an ED visit being (1) non-emergent or (2) emergent/primary care treatable across all visits in a given quarter for a given patient following the literature.[65] This gave us a weighted patient-level count of preventable ED visits in each quarter.

- *ACSC hospitalizations* were measured using hospital inpatient diagnosis codes and followed the Agency for Healthcare Research and Quality specifications.[66] ACSC hospitalizations are considered potentially preventable by good primary care. For example, early intervention and disease management can prevent complications or more severe disease that leads to hospitalization. We measured ACSC hospitalizations as those for which an individual was admitted with a diagnosis of one of these conditions: bacterial pneumonia; dehydration; urinary tract infection; perforated appendix; congestive heart failure; hypertension; asthma; chronic obstructive pulmonary disease (COPD); diabetes related short-term complications, long-term complications, uncontrolled diabetes, and lower extremity amputation among patients with diabetes.[57]

For each of the three types of service use, we measured the outcomes as the number of ED visits, preventable ED visits or ACSC hospitalizations for each patient in a given quarter and as a binary indicator for whether the patient had any of that utilization type in the quarter.

Covariates. We constructed several measures to control for patient and local area characteristics that could affect service utilization. We measured each patient's age, gender, race (white, Black, or other), marital status, and whether they were eligible for copayment-exempt VHA care for the given quarter using VHA administrative data. We calculated the distance from the patients' residence ZIP code to the ZIP code of the nearest VHA clinic using the Haversine-based geodesic distance.[67]

Using VHA and Medicare FFS inpatient and outpatient claims data, for each patient in each quarter, we identified whether the patient had each of the 20 comorbidities in the Gagne measure, and counted total ED visits and total hospitalizations in the 4 quarters before the given quarter.

For each patient, we also measured the unemployment rate of their residence county to account for changes in outcomes influenced by economic conditions, and the number of hospital beds to control for variations in the health care services environment.[30]

2.2.4 *Statistical analysis*

We estimated the ITS models using repeated cross-sectional data fit on negative binomial regressions for count outcomes to account for right skewness in the distribution of the outcomes and logistic models for binary outcomes. The unit of analysis was 5.2 million patient-quarters. We included a total of 56 quarters in our models for total and preventable ED visits and 51 quarters for ACSC hospitalizations. There were 29 quarters in the pre-period (January 2003 through March 2010) and 27 and 22 quarters in the post period for the two ED visit outcomes (April 2010 through December 2016) and ACSC hospitalizations (April 2010 through September 2015), respectively. PACT was implemented in April 2010; the first quarter of the post period was calendar-year quarter 2 of 2010 (Q2-2010).

Each model included three components to capture potential deviations in outcome trends at the time of PACT implementation: (1) an indicator for post-PACT implementation, (2) a time trend term, (3) an interaction between the post-PACT indicator and the time-trend term. We determined the best-fitting time trend using fractional polynomials.[68] The best fitting time trend was a reciprocal function (1/t) for ED and preventable ED visits and a linear function for ACSC hospitalizations.

To model potential differences by comorbidity status, we included an indicator for high-comorbidity status that we interacted with the post-PACT implementation indicator and time trend. Additionally, each model included variables to adjust for patient and local area characteristics.

Finally, we included clinic fixed effects to control for time invariant characteristics of the clinic, and indicators for the calendar-year quarter to account for seasonality in service use.

To calculate changes in outcomes attributable to PACT implementation, we calculated the difference in the predicted visits or probabilities holding all covariates at their sample mean using the method of recycled predictions.[69] Predicted outcomes were calculated for each quarter post-PACT and separately by comorbidity status. In each quarter after PACT was implemented, we then calculated the difference in the PACT effect between patients with and without high-comorbidity burden. All models used heteroskedastic robust standard errors, and the delta method to calculate standard errors for the predictions.[70] All statistical analyses were performed using Stata version 15.0 (Stata Corp., College Station, TX). We present results as visit rates, defined as the number of visits per 1,000 patients per quarter. We considered effects to be statistically significant at the 5% significance level.

2.2.5 *Sensitivity analysis*

We conducted three sensitivity analyses to test the robustness of our findings to different specifications of comorbidity burden, time, and exposure. First, to test the robustness of our findings to multiple definitions of comorbidity burden, we conducted sensitivity analyses that used the Elixhauser comorbidity measure instead of the Gagne measure.[71] The Elixhauser measure includes more conditions than the Gagne measure (30 versus 20) and equally weights each condition (the Gagne score weights conditions based on its predictability of one-year mortality). Like the Gagne score, the Elixhauser score has been validated among Medicare beneficiaries.[72] We considered patients with Elixhauser scores ≥ 4 to have high-comorbidity burden.[28]

Second, we stratified patients by whether they had 3 or more primary care visits with VHA providers in the previous year to account for patients' exposure to PACT. The extent to which PACT can impact patients outcomes is conditional on patients' exposure to VHA primary care.

Finally, in August 2014, the VHA introduced the Veterans Choice Program (VCP). The program enabled eligible veterans to receive care from providers outside of the VHA and for that care to be reimbursed by the VHA. About two years into the program, roughly 17% of all users of the VHA was through the VCP.[73] The VCP was a policy change that could alter patients' exposure to PACT as well as their utilization, therefore we repeated the analyses using data through 2013 only, before the VCP. The best fitting time trend for each of the three outcomes was a reciprocal function (1/t), comparable to the primary analysis with the exception of ACSC admissions that used a linear time trend in the primary analysis.

2.3 RESULTS

2.3.1 *Descriptive statistics*

In the quarter before PACT implementation, patients 65 years or older were on average 76 years old, mostly male (98%), white (89%), married (64%), and exempt from VHA copayments (64%) (Table 2.1). Sixteen percent of these patients were considered to have high-comorbidity burden (Gagne score ≥ 2). Compared to low-comorbid patients, high-comorbid patients were more likely to be Black, not married, exempt from VHA copayments, and have had an ED visit or hospital stay in the prior year. High-comorbid patients were also more likely than low-comorbid patients to have health conditions including renal failure, congestive heart failure, cardiac arrhythmias, and chronic pulmonary disease. Notably, about two-thirds of both low-comorbid and high-comorbid patients had hypertension.

Table 2.1. Characteristics of VHA Patients aged 65+ in the quarter before PACT implementation (calendar-year quarter 1 2010) by comorbidity status

		Comorbidity burden[a,b]	
	All patients	Low	High
Number of patients (%)	88,569 (100.0)	74,015 (83.6)	14,554 (16.4)
Male (%)	98.1	98.0	98.4
Race (%)			
White	89.4	89.9	86.9
Black	8.7	8.2	11.0
Other	1.9	1.9	2.1
Marital Status (%)			
Never married	4.3	4.1	5.0
Married	64.0	65.0	58.7
Separated or divorced	16.6	15.9	20.1
Widowed	11.6	10.8	15.9
Missing	3.5	4.1	0.3
Exempt from VHA copayments (%)			
Non-exempt	36.4	38.7	24.8
Exempt due to service	37.2	35.9	43.6
Exempt due to income	26.4	25.4	31.6
Gagne score (mean/sd)	0.4 (1.5)	-0.1 (0.7)	3.2 (1.6)
Age (mean/sd)	76.4 (7.9)	76.1 (7.8)	77.8 (7.9)
Miles to nearest VHA clinic (%)			
<5	36.1	35.7	38.4
5 to <10	22.6	22.7	21.9
10 to <20	21.1	21.1	20.6
20 to <40	16.7	16.9	15.9
40 or more	3.5	3.6	3.1
Comorbidities in the prior year (%)[c]			
Congestive heart failure	6.4	1.0	33.6
Cardiac arrhythmias	12.7	7.9	37.2
Peripheral Vascular Disorder	7.1	4.2	21.6
Chronic Pulmonary Disease	14.8	10.1	38.4
Complicated Diabetes	6.3	3.9	18.6
Renal Failure	7.9	2.3	36.4
Weight Loss	1.7	0.3	9.1
Fluid/Electrolyte Disorder	3.6	1.4	15.0
Deficiency anemias	2.6	1.3	9.0

Alcohol Abuse	2.8	1.9	7.7
Psychosis	1.9	1.1	6.2
Dementia	1.5	0.4	7.2
Any tumor	12.1	8.8	28.6
Hypertension	64.4	63.6	68.7
ED visit in prior year	34.0	29.8	55.3
Hospital visit in prior year	21.8	17.5	43.3
Hospital beds per 1,000 population (mean/sd)	3.3 (2.6)	3.3 (2.6)	3.4 (2.7)
Unemployment rate (mean/sd)	9.8 (2.7)	9.8 (2.7)	9.8 (2.7)

[a] High-comorbidity patients were defined as those with a Gagne risk score ≥ 2.
[b] Differences between patients with high-comorbidity burden and all other patients were statistically significant at the 5% level for all variables except other race and unemployment rate.
[C] These conditions represent a subset of the conditions included as covariates in the regression models. In the regression models we included each of the 20 conditions included in the Gagne Index.

2.3.2 *PACT implementation and total ED visits*

Between Q1-2003 and Q1-2010, the quarter before PACT was implemented, unadjusted average quarterly total outpatient ED visits increased from a rate of 262 visits to a rate of 297 visits. (We present results as visit rates, defined as the number of visits per 1,000 patients per quarter.) Between Q1-2010 and Q4-2016, six and half years after PACT was first implemented, unadjusted average quarterly ED visits increased further to a rate of 308 visits (Figure 2.1).

Based on the ITS models, PACT was associated with an increase in the rate of ED visits for each quarter after PACT started for both comorbidity groups (Figure 2.1 and Appendix Table 2.3). Among high-comorbid patients, PACT was associated with an average increase of 12.8 ED visits per 1,000 patients between the period before PACT and Q2-2010 (the first quarter of PACT's implementation) ($p<0.01$) and increased to a rate of 20.2 ED visits in Q4-2016 ($p<0.01$). Among low-comorbid patients, PACT was associated with an average increase of 11.4 ED visits per 1,000 patients in Q2-2010 ($p<0.01$), increasing to an average rate of 25.6 ED visits in Q4-2016 ($p<0.01$).

There were no statistically significant differences in the association of PACT on total ED visits between high-comorbid and low-comorbid patients in any quarter (p>0.05) (Figure 2.1 and Appendix Table 2.3).

PACT was associated with small, less than 0.5 percentage point increases in the probability of having an ED visit for both groups of patients throughout the study period (Appendix Table 2.6). There were statistically significant differences in the effect of PACT on the probability of having an ED visit between the two comorbidity groups beginning in Q1-2013, 3 years after PACT implementation. In Q1-2013, PACT was associated with a 0.2 percentage point and 0.4 percentage point increase in the probability of having an ED visit for high-comorbid and low-comorbid patients, respectively (difference=-0.19, p=0.036). Differences in the effect of PACT on high-comorbid and low-comorbid patients continued to widen through the rest of the post period to a relative reduction of -0.3 percentage points between high-comorbid and low-comorbid patients in Q4-2016 (p<0.01) (Appendix Table 2.6).

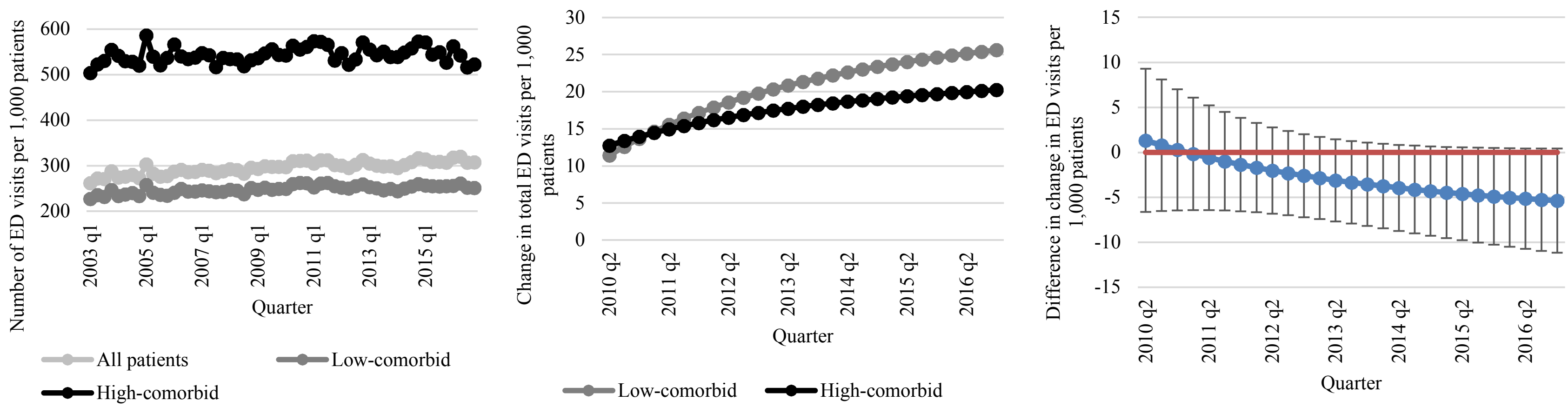

Figure 2.1. The unadjusted average number of ED visits, the regression-adjusted effect of PACT on ED visits and the difference between low- and high-comorbid patients

Three figures showing the (left) unadjusted average number of ED visits per 1,000 patients per quarter, (middle) regression-adjusted average change in the number of ED visits per 1,000 patients per quarter, by comorbidity status, and (right) regression-adjusted difference in the effect of PACT on ED visits between patients with high- and low-comorbidity burden with 95% confidence interval

Notes:
High-comorbidity patients were defined as those with a Gagne risk score ≥ 2.
ED = emergency department; PACT = Patient-Aligned Care Team initiative.

2.3.3 *PACT implementation and potentially preventable ED visits*

Between Q1-2003 and Q1-2010, unadjusted average quarterly preventable ED visits increased from a rate of 100 visits per 1,000 patients to a rate of 107 visits. Between Q1-2010 (the quarter before PACT implementation) and Q4-2016, unadjusted average quarterly preventable ED visits decreased to a rate of 97.6 visits (Figure 2.2).

Based on the ITS models, among high-comorbid patients, PACT was associated with an average increase of 8.1 preventable ED visits per 1,000 patients between the period before PACT and Q2-2010 (the first quarter of PACT's implementation) ($p<0.01$). Over time, increases in preventable ED visits attributable to PACT attenuated. By Q1-2014 (nearly four years after PACT began), there were no associated effects of PACT on preventable ED visits among high-comorbid patients (Figure 2.2 and Appendix Table 2.4). Among low-comorbid patients, by the first quarter of PACT (Q2-2010), PACT was associated with an average increase of 7.2 preventable ED visits per 1,000 patients ($p<0.01$). Despite lessening over time, by the end of the study period (Q4-2016), PACT continued to be associated with more preventable ED visits among low-comorbid patients, with an estimated effect size of 1.9 more preventable ED visits per 1,000 patients ($p<0.01$) attributable to PACT.

Differences between comorbidity groups in the association of PACT with preventable ED visits were statistically significant beginning in Q3-2016 (about 6.5 years after PACT implementation). In Q3-2016 and Q4-2016, PACT was associated with 2.2 and 2.3 fewer preventable ED visits per 1,000 patients for high-comorbid patients relative to low-comorbid patients, respectively ($p=0.049$, $p=0.048$) (Figure 2.2 and Appendix Table 2.4).

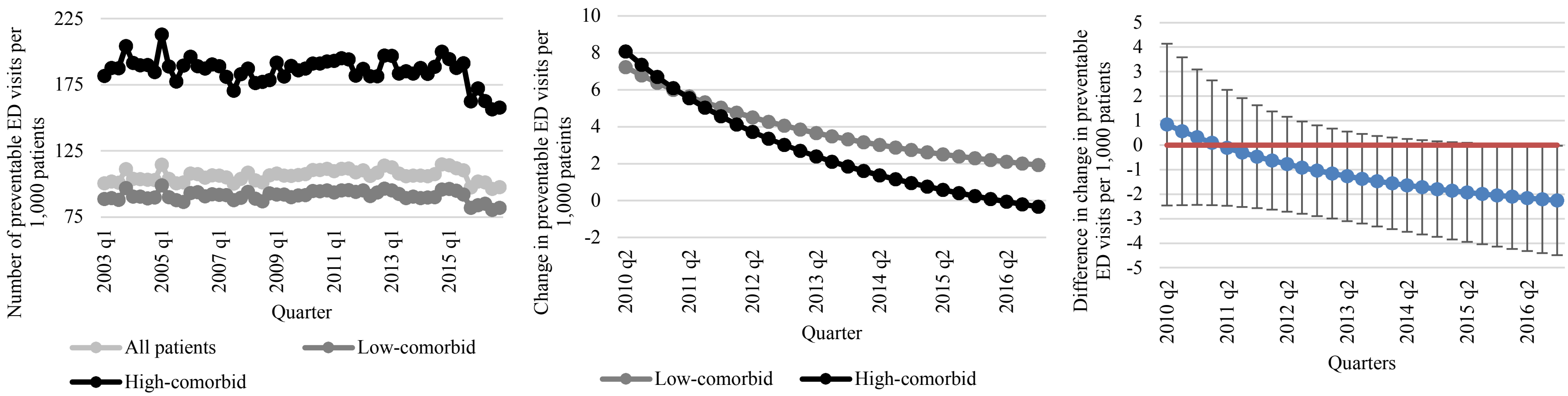

Figure 2.2. The unadjusted average number of preventable ED visits, the regression-adjusted effect of PACT on preventable ED visits and the difference between low- and high-comorbid patients

Three figures showing the (left) unadjusted average number of preventable ED visits per 1,000 patients per quarter, (middle) regression-adjusted average change in the number of preventable ED visits per 1,000 patients per quarter, by comorbidity status, and (right) regression-adjusted difference in the effect of PACT on preventable ED visits between patients with high- and low-comorbidity burden with 95% confidence interval.

Notes:
High-comorbidity patients were defined as those with a Gagne risk score ≥ 2.
ED = emergency department; PACT = Patient-Aligned Care Team initiative.

Turning to the probability of having a preventable ED visit, PACT was associated with small, between 0.2 and 0.6 percentage point, increases for both groups of patients over time, with associated increases lessening over time (Appendix Table 2.7). Differences between comorbidity groups in the association of PACT on the probability of having a preventable ED visit were not statistically significant through the post PACT period.

2.3.4 *PACT implementation and ACSC hospitalizations*

Between Q1-2003 and Q1-2010, unadjusted average quarterly ACSC hospitalizations decreased from 23.7 stays per 1,000 patients to 22.2 stays per 1,000 patients. Between Q1-2010 and Q3-2015, unadjusted average quarterly ACSC hospitalizations decreased further to a rate of 12.8 stays (Figure 2.3).

Based on the ITS models, PACT was not associated with statistically significant changes in ACSC hospitalizations among high-comorbid patients throughout the post period (Figure 2.3 and Appendix Table 2.5). Among low-comorbid patients, PACT was associated with statistically significant increases in ACSC hospitalizations through the first 1.5 years of PACT implementation (from Q2-2010 through Q3-2011). The magnitude of the associated effect of PACT was 0.81 ACSC hospitalizations per 1,000 patients in Q2-2010 ($p=0.035$) and lessening to a rate of 0.68 ACSC hospitalizations by Q3-2011 ($p=0.049$). Between Q4-2011 and Q3-2015 (the end of the study period), the estimates remained positive, but continued to lessen and were not statistically significant.

Differences between comorbidity groups in the association of PACT with ACSC hospitalizations were not statistically significant throughout the post period ($p>0.05$) (Figure 2.3 and Appendix Table 2.5).

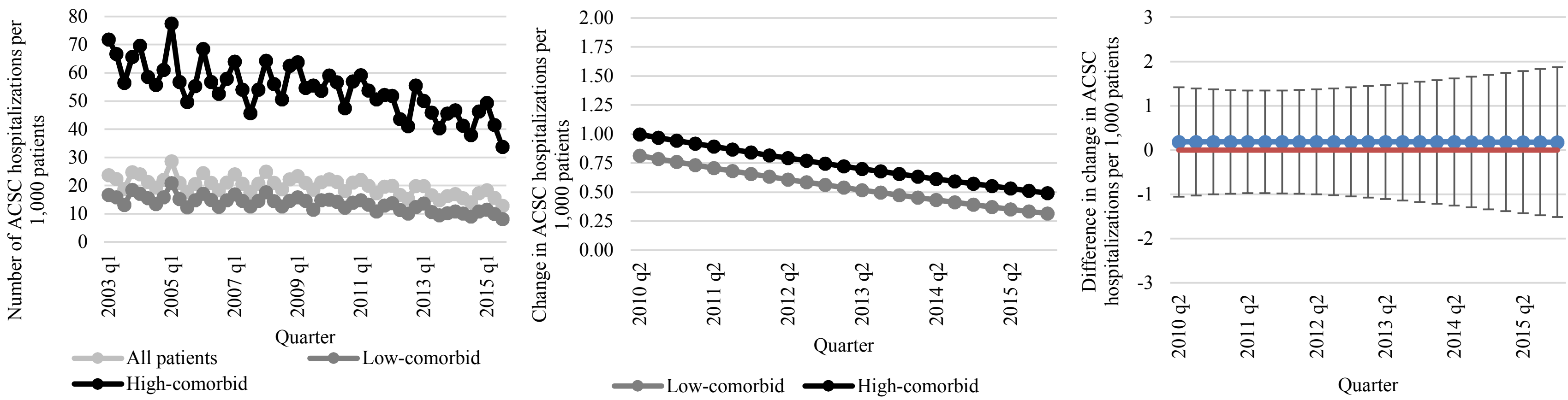

Figure 2.3. The unadjusted average number of ACSC hospitalizations, the regression-adjusted effect of PACT on ACSC hospitalizations and the difference between low- and high-comorbid patients.

Three figures showing the (left) unadjusted average number of ACSC hospitalizations per 1,000 patients per quarter, (middle) regression-adjusted average change in the number of ACSC hospitalizations per 1,000 patients per quarter, by comorbidity status, and (right) regression-adjusted difference in the effect of PACT on ACSC hospitalizations between patients with high- and low-comorbidity burden with 95% confidence interval

Notes:
High-comorbidity patients were defined as those with a Gagne risk score ≥ 2.
ACSC=ambulatory care-sensitive conditions; PACT = Patient-Aligned Care Team initiative.

Turning to the probability of having an ACSC hospitalization, among the high-comorbid group, PACT was associated with a 0.08 percentage point increase in the probability of having an ACSC hospitalization in each of the first five quarters after PACT implementation ($p<0.05$, Appendix Table 2.8). Beginning in Q4-2011, the association of PACT was not statistically significant. Among the low-comorbid group, the association of PACT on the probability of having an ACSC hospitalization was not statistically significant ($p>0.05$) in any quarter. Differences between comorbidity groups in the association of PACT on the probability of having an ACSC hospitalization were not statistically significant throughout the post-PACT period.

2.3.5 *Sensitivity analysis*

Results from the three sensitivity analyses were mostly similar to the primary analysis. Notably, *among patients with 3 or more VHA primary care visits in the previous year*, PACT was associated with statistically significant increases of 8.7 and 9.8 preventable ED visits per 1,000 patients in Q2-2010 (the first quarter after PACT) for low-comorbid and high-comorbid patients, respectively ($p<0.01$). Over time, the impact of PACT diminished to an associated increase of 4.1 preventable ED visits per 1,000 patients for low-comorbid patients ($p=0.01$) and a not statistically significant decrease of 0.5 preventable ED visits per 1,000 high-comorbid patients in Q4-2016 ($p=0.786$). PACT was associated with fewer preventable ED visits for high-comorbid patients relative to low-comorbid patients beginning one year after PACT began, but differences were not statistically significant until 6.5 years after PACT in Q3-2016 (4.5 fewer preventable ED visits for high-comorbid patients relative to low-comorbid patients, $p=0.050$) (Appendix 2.10).

Among patients with fewer than 3 VHA primary care visits in the previous year, PACT was associated with an increase of 6.3 and 8.3 preventable ED visits per 1,000 patients in Q2-2010 for low-comorbid and high-comorbid patients, respectively ($p<0.01$). Over time the impact of PACT lessened to an associated increase of 3.1 preventable ED visits per 1,000 patients for low-comorbid patients ($p<0.01$) and a not statistically significant increase of 1.7 preventable ED visits per 1,000 high-comorbid patients ($p=0.190$) in Q4-2016. There were no differential associations of PACT on preventable ED visits by patients' comorbidity status.

Despite mostly comparable results between the main analysis and the sensitivity analyses, the association of PACT on ACSC hospitalizations may be dependent on the length of the follow-up period. When restricting the post-period to April 2010 through December 2013 (and not using the full follow-up period through September 2015), among low-comorbid patients, PACT was associated with an average decrease of 0.59 ACSC hospitalizations per 1,000 patients one year after PACT implementation ($p=0.047$) and decreasing further to 2.5 ACSC hospitalizations per 1,000 patients by Q4-2013 ($p<0.01$) (Appendix Table 2.11). Among high-comorbid patients, PACT was associated with an average decrease of 0.81 ACSC hospitalizations per 1,000 patients two years after PACT implementation ($p=0.032$) and decreasing further to an associated reduction of 1.75 ACSC hospitalizations per 1,000 patients by Q4-2013 ($p<0.01$). This is in contrast to the primary analysis that found no association of PACT with ACSC hospitalizations on low-comorbid or high-comorbid patients. However, similar to the primary analysis, differences in the association of PACT between comorbidity groups were not statistically significant

2.4 DISCUSSION

In this study, we estimated the extent to which the VHA's PCMH initiative—PACT—affected the utilization of high-cost services among older veterans, and whether the associated effect of PACT differed by patients' comorbidity burden. We hypothesized that PACT's team-based care approach to enhancing access, care management, and care coordination would reduce patients' use of EDs and hospitalizations for ambulatory care-sensitive conditions, and that impacts would be larger for patients with greater comorbidity burden.

However, we found that PACT was associated with an increase in total and preventable ED visits for patients with and without high-comorbidity burden. PACT did not affect hospitalizations for ACSC conditions for either group, although these findings varied by the length of the post-period. Furthermore, there was little statistical evidence that PACT had differential effects on patients' outcomes by comorbidity status, though the direction of differences were as hypothesized. PACT was associated with smaller increases in total and preventable ED visits for patients with high-comorbidity burden compared to those with low-comorbidity burden beginning about one year after PACT implementation. Differences were not statistically significant in any quarter, however, for ED visits, and not until six years after PACT implementation for potentially preventable ED visits.

Findings were robust to sensitivity analyses that (1) defined comorbidity burden using the Elixhauser comorbidity measure and (2) stratified the analysis by patients' utilization of VHA primary care. Notably, when excluding observations from 2014-2016 to account for the VHA's Choice Program, we found that PACT was associated with a reduction in ACSC hospitalizations among low- and high-comorbid patients whereas the primary analysis found no effect of PACT on ACSC hospitalizations for either group. It is unclear why we found this contradictory effect for ACSC hospitalizations.

Overall, the study's findings generally support the larger PCMH literature that continues to find mixed evidence of the effect of PCMHs on high-cost service utilization among the total primary care population as well as the subpopulation of patients with comorbidities.[32,74,83,84,75–82]

These findings also support the mixed evidence within the PACT literature. While early studies by Hebert et al. 2014 and Nelson et at. 2014 found that PACT was associated with small reductions in ACSC hospitalizations, these studies only estimated VHA utilization and did not include utilization outside of the VHA.[32,35] Similar to our study, Reddy et al. 2020 estimated total utilization (within and outside of the VHA) and found no association between longitudinal change in PACT implementation and our measures of high-cost service use.[38]

There are several explanations for why we did not find evidence to support our hypothesis that PACT would reduce total and preventable ED visits and ACSC hospitalizations. For example, measurable effects of PACT might only exist among the subset of clinics that implemented PACT well. An early study of the VHA's PACT initiative found that only the most advanced PACT clinics experienced a lower rate of ED visits for all patients and fewer ACSC hospitalizations for patients aged 65 years or older compared to the least advanced PACT clinics (the study did not examine ED visits on only the older populations).[35] Implementing PACT effectively relied on clinics' ability to reach the target staffing ratio and to reshape staffing models around team-based care to provide enhanced access, care management, and care coordination. However, clinics' success in restricting care delivery was variable[25] and could suggest the presence of other, underlying structural, cultural, or economic barriers that could also limit a clinic's ability to alter patients' utilization.

We would also find null effects of PACT if the PCMH components do not adequately address the barriers patients face to augment behaviors or shift utilization. For example, PCMH focuses on enhancing access to the care team and same-day access to care. However, the effect of these specific changes might be limited by more fundamental barriers to access. Indeed, VHA patients who reported other barriers to access that PACT did not target directly, such as getting an appointment when they were available, waiting too long in the doctor's office, or that they did not have transportation, were more likely to visit the ED than those that did not report these barriers.[85]

Alternatively, PACT's emphases on enhanced access could increase engagement and induce more health care use. First, to the extent that easier access allows individuals who were previously disengaged with the health care system to become engaged in seeking care, we could find that enhanced access increases their use of outpatient and acute care services.[86] Second, PACTs introduction of a secure messaging portal and focus on increasing telephone visits could lead to more ED visits. Each of these mechanisms has been shown to increase utilization. A study of adults with diabetes in Group Health, found that secure messaging and telephone encounters led to more in-person office visits.[87] Future research should examine whether increasing non-traditional access to care affects other types of service use including ED visits and hospitalizations.

There are also several explanations for why we did not find that PACT differentially affected high-cost service use of high-comorbid patients relative to low-comorbid patients. First, PACT is focused on altering care for the broad primary care population, and not specifically on high-risk patients' preventive care.[88] Second, high-risk patients have more complex care needs that could impede physicians' ability to reduce acute care use. Even programs that specifically target high-risk patients have resulted in null or increasing effects on hospitalizations and ED visits.[53,89]

Finally, Green et al. (2018) suggest that outcomes such as total ED visits, preventable ED visits, and ACSC hospitalizations may not be specific enough to the PCMH activities to find measurable impacts.[90] In particular, they found substantially larger PCMH impacts on measures of ED use for PCMH-targeted conditions relative to total ED visits. Therefore, we may not have the specificity in our outcomes needed to find effects of PACT.

Our findings have implications for the health care delivery system as it continues to test and evaluate the PCMH and other primary care delivery transformation. Our research suggests that enhanced access, care management, and coordination, as implemented in PACT, might not meet the underlying needs of the older adult patient population sufficiently to reduce acute care utilization. Furthermore, there may be unexpected consequences of strengthening primary care, such as increased ED visits or hospitalizations that, in some cases, represent better care.

Despite the small and limited effects of PCMH in the literature, studies should continue to investigate the extent to which PCMH can impact patients. Future studies should examine the effect of access and other components of PCMH models to understand the extent to which specific care delivery changes impact specific patient populations and specific outcomes. Component-specific effects might be masked by the general effects of PCMHs in the current literature. For example, specific care management services are more likely to be used by patients with greater health care needs such as those with comorbidities, and thus we could hypothesize that care management services specifically have differing effects on certain patient outcomes. With more knowledge of the potential impacts of PCMH and its specific components, stakeholders can continue to strengthen primary care to maximize benefits for populations most likely to benefit without mitigating care for the rest of the population.

2.4.1 *Limitations*

This study has several limitations. First, the ITS study design requires a clear differentiation of the pre- and post-periods, and while the VHA introduced PACT to all clinics in April 2010, clinics adopted intervention components at different rates and to varying degrees.[29,35] Moreover, our lack of a comparison group of patients that were not exposed to the PACT model might be limiting our ability to observe PACT effects. Much of the PCMH literature uses a difference-in-differences regression approach to compare changes in outcomes between patients exposed to PCMH with a group of similar patients that were not exposed to PCMH. Despite the unique characteristics of the VHA clinics and patient population that restricted our ability to construct a comparison group of clinics or patients, not having a non-exposed comparison group poses a substantial limitation to this study.

Second, given our 14 year study period, our analysis is subject to biases from concurrent policy and delivery system changes that could also affect our outcomes. Notably, when we accounted for the Veterans Choice Program, we found that PACT was associated with a reduction in ACSC hospitalizations for patients of both comorbidity statuses compared to the primary analysis that found null or increasing PACT effects. It is unclear why we found this contradictory effect for ACSC hospitalizations. However, it highlights the need to understand how policy initiatives may interact with each other.

Third, despite its widespread use, the emergency department algorithm employed in this analysis to identify preventable ED visits, may not be sufficiently sensitive to changes in ED utilization to be useful for assessing the effects of interventions like PACT.[91,92] Additionally, the algorithm's use of principal diagnosis codes ignores the presence of other diagnoses that might require emergency care or hospital admission.[91,93]

Fourth, our study population is limited to patients age 65 or older that are enrolled in VHA or are dually-enrolled in Medicare FFS that are receiving primary care from VHA. While earlier studies suggested the PACT was associated with a reductions in some service use, they only accounted for utilization within the VHA.[35] Thus, restricting our sample to older veterans allowed for more comprehensive measurement of utilization both within and outside of VHA. The tradeoff is a potential limitation in generalizability to younger or non-VHA populations. Prior research, however has demonstrated substantial overlap in characteristics between VHA enrollees and Medicare FFS beneficiaries.[94]

Fifth, patients might have a different provider of care besides their VHA provider that could influence their use of high-cost services and dilute PACT effects. In 2014, about 35% of Medicare-enrolled veterans' primary care visits were at the VHA, indicating a substantial proportion of primary care is received outside of the VHA.[61] Our sensitivity analysis that stratified by VHA primary care use showed that, among patients with a history of more VHA primary care visits, PACT was associated with fewer preventable ED visits among high-comorbid patients relative to low-comorbid patients, but that there were no differential effects among patients with fewer VHA primary care visits.

2.4.2 *Conclusions*

Despite these limitations, our study utilizes a large sample size and a long post-period to inform primary care practices, health care systems, and policy makers on the potential of one of the nation's largest PCMH models to augment the utilization of high-cost services among older U.S. adults. Our findings suggest that although PACT did not decrease the use of high-cost services during the six years after implementation began, and in fact, PACT was associated with increased utilization through much of the study period, differential effects by patient comorbidity burden were beginning to emerge. Future studies should continue to examine the potential effects of PCMH models to alter patient outcomes. By understanding the ability of PCMH models to improve patient outcomes for different subpopulations, we can help inform directions of future care transformation programs, particularly in resource-constrained environments.

2.5 APPENDIX

2.5.1 *Appendix tables*

Table 2.2. Appendix Table: Number of ED visits, preventable ED visits, ACSC hospitalizations per 1,000 patients per quarter, unadjusted

	ED visits			Preventable ED visits			ACSC hospitalizations		
CYQTR	All patients	Low-comorbid	High-comorbid	All patients	Low-comorbid	High-comorbid	All patients	Low-comorbid	High-comorbid
2003 q1	262.1	227.1	503.6	100.3	88.5	181.7	23.7	16.7	71.8
2003 q2	272.5	236.1	522.8	101.8	89.3	187.8	22.3	15.9	66.7
2003 q3	271.0	232.2	530.7	101.0	88.0	187.6	18.8	13.2	56.5
2003 q4	288.3	247.2	555.2	111.3	96.9	204.3	24.7	18.4	65.6
2004 q1	274.7	234.1	541.6	103.8	90.5	191.6	24.0	17.1	69.6
2004 q2	276.6	237.3	529.8	103.7	90.3	189.8	21.3	15.5	58.6
2004 q3	280.5	240.3	528.4	103.2	89.1	189.9	19.3	13.4	55.7
2004 q4	273.3	233.9	520.5	102.8	89.8	184.7	22.0	15.8	61.1
2005 q1	303.1	258.0	586.2	114.5	98.9	213.0	28.6	20.8	77.5
2005 q2	283.0	241.4	539.7	103.8	90.0	188.9	21.0	15.2	56.7
2005 q3	276.6	236.2	521.2	100.3	87.6	177.5	17.6	12.3	49.6
2005 q4	277.8	234.6	536.9	101.1	86.4	189.5	20.6	14.8	55.3
2006 q1	287.7	241.3	566.7	107.7	93.0	196.2	24.4	17.1	68.4
2006 q2	291.1	249.3	540.4	107.4	93.7	189.1	21.0	14.9	56.8
2006 q3	286.1	243.5	534.5	104.8	90.6	187.3	18.4	12.5	52.6
2006 q4	286.9	243.9	538.0	106.6	92.2	190.4	21.1	14.8	57.9
2007 q1	291.5	246.1	547.9	106.3	91.6	189.0	24.0	16.9	64.0
2007 q2	289.7	244.3	542.9	105.0	91.4	180.9	20.6	14.6	54.1
2007 q3	284.2	242.4	517.1	100.3	87.7	170.6	17.7	12.7	45.7
2007 q4	288.2	243.2	537.0	103.8	89.5	182.9	20.6	14.6	54.0
2008 q1	292.6	247.8	534.5	108.6	94.0	187.3	24.9	17.6	64.3
2008 q2	290.9	245.8	534.0	102.6	88.9	176.2	21.0	14.5	56.0
2008 q3	283.0	238.0	519.1	101.2	86.7	177.3	18.7	12.6	50.6
2008 q4	296.1	251.6	531.7	106.4	92.8	178.7	22.2	14.6	62.5
2009 q1	293.7	247.7	536.8	107.8	91.9	191.8	23.4	15.8	63.8
2009 q2	299.4	252.0	547.2	106.3	91.9	181.3	21.0	14.6	54.7
2009 q3	297.8	247.9	556.1	106.0	89.9	189.4	18.6	11.5	55.5
2009 q4	297.6	249.8	543.5	106.7	91.3	186.0	21.2	14.8	53.7
2010 q1	297.6	249.4	542.7	107.3	91.5	187.4	22.2	15.0	59.0
2010 q2	310.7	260.3	564.3	110.6	94.7	191.1	21.3	14.3	56.6
2010 q3	311.3	262.8	555.3	110.5	94.4	191.2	18.0	12.2	47.4
2010 q4	312.0	262.3	561.1	111.3	95.1	192.6	21.1	14.0	56.9
2011 q1	305.1	253.1	573.6	109.6	93.5	193.1	22.0	14.8	59.2
2011 q2	312.3	261.2	572.4	111.5	95.0	195.1	19.9	13.2	53.7
2011 q3	312.6	262.4	566.1	111.6	95.2	194.1	17.4	10.8	50.6
2011 q4	302.1	255.3	531.5	108.8	93.9	181.9	19.6	13.0	52.2
2012 q1	300.7	252.3	547.8	110.2	95.1	187.1	20.0	13.7	51.9
2012 q2	295.6	250.1	522.2	106.0	90.8	181.5	16.7	11.3	43.6
2012 q3	302.6	255.3	533.8	108.4	93.5	181.4	15.3	10.1	41.0
2012 q4	313.0	259.2	571.4	113.8	96.4	197.0	19.8	12.4	55.5
2013 q1	305.0	253.5	555.6	112.4	95.1	197.0	19.8	13.6	50.1
2013 q2	300.5	250.9	543.1	107.8	92.3	183.4	16.6	10.6	45.9
2013 q3	298.8	246.3	551.0	105.9	89.4	185.2	14.8	9.5	40.3
2013 q4	299.2	249.4	538.9	106.4	90.3	183.5	16.3	10.2	45.5
2014 q1	295.4	244.4	539.5	106.2	89.2	187.7	17.0	10.8	46.7
2014 q2	301.7	250.3	548.8	105.8	89.7	183.3	15.5	10.2	41.2
2014 q3	308.2	254.7	558.1	107.3	89.9	188.6	14.1	9.0	37.9
2014 q4	316.8	260.1	572.9	114.7	95.8	200.0	17.3	10.9	46.3
2015 q1	314.1	257.1	570.9	114.1	96.2	194.4	18.3	11.4	49.3
2015 q2	308.4	255.2	544.4	111.9	94.8	187.7	15.7	9.9	41.5
2015 q3	309.2	254.7	549.9	110.3	91.9	191.4	12.8	8.1	33.7
2015 q4	307.1	255.5	526.5	97.3	81.9	162.5	n.a.	n.a.	n.a.
2016 q1	318.3	256.3	562.7	101.8	83.9	172.3	n.a.	n.a.	n.a.
2016 q2	319.9	261.3	542.5	101.1	84.9	162.6	n.a.	n.a.	n.a.
2016 q3	307.4	252.2	516.5	96.2	80.3	156.3	n.a.	n.a.	n.a.
2016 q4	307.9	251.6	523.1	97.6	81.9	157.8	n.a.	n.a.	n.a.

ED = emergency department; ACSC = ambulatory care-sensitive conditions; q=calendar-year quarter.

Table 2.3. Appendix Table: ITS model results for total ED visits

	PACT effect					
CYQTR	Low-comorbid	p-value	High-comorbid	p-value	Differential effect	p-value
2010 q2	11.4	0.000	12.8	0.001	1.3	0.745
2010 q3	12.6	0.000	13.4	0.000	0.8	0.834
2010 q4	13.7	0.000	13.9	0.000	0.3	0.934
2011 q1	14.6	0.000	14.5	0.000	-0.2	0.956
2011 q2	15.5	0.000	14.9	0.000	-0.6	0.839
2011 q3	16.4	0.000	15.4	0.000	-1.0	0.721
2011 q4	17.2	0.000	15.8	0.000	-1.4	0.606
2012 q1	17.9	0.000	16.2	0.000	-1.7	0.500
2012 q2	18.6	0.000	16.5	0.000	-2.0	0.408
2012 q3	19.2	0.000	16.9	0.000	-2.3	0.330
2012 q4	19.8	0.000	17.2	0.000	-2.6	0.268
2013 q1	20.3	0.000	17.5	0.000	-2.9	0.219
2013 q2	20.8	0.000	17.7	0.000	-3.1	0.182
2013 q3	21.3	0.000	18.0	0.000	-3.3	0.154
2013 q4	21.8	0.000	18.2	0.000	-3.6	0.133
2014 q1	22.2	0.000	18.5	0.000	-3.8	0.117
2014 q2	22.6	0.000	18.7	0.000	-4.0	0.105
2014 q3	23.0	0.000	18.9	0.000	-4.1	0.096
2014 q4	23.4	0.000	19.1	0.000	-4.3	0.089
2015 q1	23.7	0.000	19.2	0.000	-4.5	0.084
2015 q2	24.0	0.000	19.4	0.000	-4.6	0.080
2015 q3	24.3	0.000	19.6	0.000	-4.8	0.076
2015 q4	24.6	0.000	19.7	0.000	-4.9	0.074
2016 q1	24.9	0.000	19.8	0.000	-5.0	0.072
2016 q2	25.1	0.000	20.0	0.000	-5.2	0.070
2016 q3	25.4	0.000	20.1	0.000	-5.3	0.069
2016 q4	25.6	0.000	20.2	0.000	-5.4	0.068

ITS = interrupted time series regression model; ED = emergency department; PACT = Patient Aligned Care Team initiative; CYQTR = calendar-year quarter

Table 2.4. Appendix Table: ITS model for preventable ED visits

	PACT effect					
CYQTR	Low-comorbid	p-value	High-comorbid	p-value	Differential effect	p-value
2010 q2	7.2	0.000	8.1	0.000	0.8	0.619
2010 q3	6.8	0.000	7.4	0.000	0.6	0.712
2010 q4	6.4	0.000	6.7	0.000	0.3	0.819
2011 q1	6.0	0.000	6.1	0.000	0.1	0.941
2011 q2	5.6	0.000	5.5	0.000	-0.1	0.928
2011 q3	5.3	0.000	5.0	0.000	-0.3	0.793
2011 q4	5.0	0.000	4.6	0.000	-0.5	0.661
2012 q1	4.8	0.000	4.1	0.000	-0.6	0.538
2012 q2	4.5	0.000	3.7	0.000	-0.8	0.430
2012 q3	4.3	0.000	3.4	0.000	-0.9	0.341
2012 q4	4.1	0.000	3.0	0.000	-1.0	0.270
2013 q1	3.9	0.000	2.7	0.001	-1.2	0.215
2013 q2	3.7	0.000	2.4	0.003	-1.3	0.173
2013 q3	3.5	0.000	2.1	0.010	-1.4	0.142
2013 q4	3.3	0.000	1.8	0.025	-1.5	0.119
2014 q1	3.2	0.000	1.6	0.054	-1.6	0.102
2014 q2	3.0	0.000	1.4	0.103	-1.6	0.089
2014 q3	2.9	0.000	1.2	0.177	-1.7	0.079
2014 q4	2.7	0.000	1.0	0.274	-1.8	0.072
2015 q1	2.6	0.000	0.8	0.391	-1.9	0.066
2015 q2	2.5	0.000	0.6	0.521	-1.9	0.061
2015 q3	2.4	0.000	0.4	0.657	-2.0	0.058
2015 q4	2.3	0.000	0.2	0.793	-2.0	0.055
2016 q1	2.2	0.000	0.1	0.924	-2.1	0.052
2016 q2	2.1	0.000	-0.1	0.955	-2.2	0.051
2016 q3	2.0	0.001	-0.2	0.844	-2.2	0.049
2016 q4	1.9	0.002	-0.3	0.746	-2.3	0.048

ITS = interrupted time series regression model; ED = emergency department; PACT = Patient Aligned Care Team initiative; CYQTR = calendar-year quarter

Table 2.5. Appendix Table: ITS model for ACSC hospitalizations

	PACT effect					
CYQTR	Low-comorbid	p-value	High-comorbid	p-value	Differential effect	p-value
2010 q2	0.81	0.035	1.00	0.055	0.18	0.772
2010 q3	0.79	0.035	0.97	0.056	0.18	0.767
2010 q4	0.76	0.036	0.94	0.057	0.18	0.762
2011 q1	0.73	0.039	0.92	0.061	0.18	0.758
2011 q2	0.71	0.043	0.89	0.066	0.18	0.756
2011 q3	0.68	0.049	0.87	0.074	0.18	0.756
2011 q4	0.66	0.057	0.84	0.083	0.18	0.756
2012 q1	0.63	0.069	0.82	0.096	0.18	0.758
2012 q2	0.61	0.083	0.79	0.111	0.18	0.761
2012 q3	0.59	0.101	0.77	0.129	0.18	0.765
2012 q4	0.56	0.123	0.75	0.150	0.18	0.770
2013 q1	0.54	0.149	0.72	0.173	0.18	0.775
2013 q2	0.52	0.178	0.70	0.199	0.18	0.781
2013 q3	0.50	0.210	0.68	0.226	0.18	0.786
2013 q4	0.47	0.244	0.66	0.256	0.18	0.792
2014 q1	0.45	0.281	0.63	0.286	0.18	0.799
2014 q2	0.43	0.319	0.61	0.317	0.18	0.805
2014 q3	0.41	0.357	0.59	0.349	0.18	0.810
2014 q4	0.39	0.396	0.57	0.380	0.18	0.816
2015 q1	0.37	0.434	0.55	0.411	0.18	0.822
2015 q2	0.35	0.472	0.53	0.442	0.18	0.827
2015 q3	0.33	0.508	0.51	0.472	0.18	0.832

ITS = interrupted time series regression model; ACSC = ambulatory care-sensitive condition; PACT = Patient Aligned Care Team initiative; CYQTR = calendar-year quarter

Table 2.6. Appendix Table: Probability tables for ED visits

	PACT effect					
CYQTR	Low-comorbid	p-value	High-comorbid	p-value	Differential effect	p-value
2010 q2	0.49	0.000	0.49	0.000	0.00	0.984
2010 q3	0.48	0.000	0.46	0.000	-0.02	0.844
2010 q4	0.48	0.000	0.43	0.000	-0.04	0.701
2011 q1	0.47	0.000	0.41	0.000	-0.06	0.562
2011 q2	0.46	0.000	0.38	0.000	-0.08	0.434
2011 q3	0.46	0.000	0.36	0.000	-0.10	0.323
2011 q4	0.46	0.000	0.34	0.000	-0.12	0.233
2012 q1	0.45	0.000	0.32	0.000	-0.13	0.163
2012 q2	0.45	0.000	0.30	0.000	-0.15	0.112
2012 q3	0.44	0.000	0.28	0.000	-0.16	0.076
2012 q4	0.44	0.000	0.27	0.001	-0.17	0.052
2013 q1	0.43	0.000	0.25	0.002	-0.19	0.036
2013 q2	0.43	0.000	0.23	0.003	-0.20	0.025
2013 q3	0.43	0.000	0.22	0.005	-0.21	0.018
2013 q4	0.42	0.000	0.20	0.010	-0.22	0.013
2014 q1	0.42	0.000	0.19	0.017	-0.23	0.010
2014 q2	0.42	0.000	0.18	0.029	-0.24	0.008
2014 q3	0.42	0.000	0.16	0.046	-0.25	0.007
2014 q4	0.41	0.000	0.15	0.069	-0.26	0.006
2015 q1	0.41	0.000	0.14	0.099	-0.27	0.005
2015 q2	0.41	0.000	0.13	0.137	-0.28	0.004
2015 q3	0.40	0.000	0.12	0.182	-0.29	0.004
2015 q4	0.40	0.000	0.11	0.230	-0.29	0.004
2016 q1	0.40	0.000	0.10	0.289	-0.30	0.004
2016 q2	0.40	0.000	0.09	0.350	-0.31	0.003
2016 q3	0.40	0.000	0.08	0.413	-0.32	0.003
2016 q4	0.39	0.000	0.07	0.478	-0.32	0.003

ITS = interrupted time series regression model; ED = emergency department; PACT = Patient Aligned Care Team initiative; CYQTR = calendar-year quarter

Table 2.7. Appendix Table: Probability tables for preventable ED visits

	PACT effect					
CYQTR	Low-comorbid	p-value	High-comorbid	p-value	Differential effect	p-value
2010 q2	0.63	0.000	0.62	0.000	-0.01	0.947
2010 q3	0.62	0.000	0.60	0.000	-0.02	0.857
2010 q4	0.61	0.000	0.58	0.000	-0.03	0.769
2011 q1	0.61	0.000	0.56	0.000	-0.05	0.684
2011 q2	0.60	0.000	0.54	0.000	-0.06	0.604
2011 q3	0.60	0.000	0.53	0.000	-0.07	0.531
2011 q4	0.59	0.000	0.51	0.000	-0.08	0.465
2012 q1	0.58	0.000	0.49	0.000	-0.09	0.407
2012 q2	0.58	0.000	0.47	0.000	-0.11	0.356
2012 q3	0.57	0.000	0.46	0.000	-0.12	0.312
2012 q4	0.57	0.000	0.44	0.000	-0.13	0.275
2013 q1	0.56	0.000	0.42	0.000	-0.14	0.244
2013 q2	0.56	0.000	0.41	0.000	-0.15	0.217
2013 q3	0.55	0.000	0.39	0.000	-0.16	0.195
2013 q4	0.55	0.000	0.38	0.001	-0.17	0.176
2014 q1	0.54	0.000	0.36	0.001	-0.18	0.160
2014 q2	0.54	0.000	0.35	0.003	-0.19	0.147
2014 q3	0.53	0.000	0.33	0.005	-0.20	0.135
2014 q4	0.53	0.000	0.32	0.009	-0.21	0.126
2015 q1	0.52	0.000	0.30	0.015	-0.22	0.118
2015 q2	0.52	0.000	0.29	0.023	-0.23	0.111
2015 q3	0.51	0.000	0.27	0.035	-0.24	0.105
2015 q4	0.51	0.000	0.26	0.051	-0.25	0.100
2016 q1	0.50	0.000	0.25	0.071	-0.26	0.095
2016 q2	0.50	0.000	0.23	0.096	-0.26	0.091
2016 q3	0.49	0.000	0.22	0.125	-0.27	0.088
2016 q4	0.49	0.000	0.21	0.159	-0.28	0.085

ITS = interrupted time series regression model; ED = emergency department; PACT = Patient Aligned Care Team initiative; CYQTR = calendar-year quarter

Table 2.8. Appendix Table: Probability tables for ACSC hospitalizations

	PACT effect					
CYQTR	Low-comorbid	p-value	High-comorbid	p-value	Differential effect	p-value
2010 q2	0.05	0.091	0.08	0.047	0.03	0.566
2010 q3	0.05	0.097	0.08	0.045	0.03	0.538
2010 q4	0.05	0.106	0.08	0.045	0.03	0.512
2011 q1	0.04	0.119	0.08	0.045	0.03	0.489
2011 q2	0.04	0.136	0.08	0.047	0.03	0.469
2011 q3	0.04	0.158	0.07	0.050	0.04	0.452
2011 q4	0.04	0.185	0.07	0.055	0.04	0.438
2012 q1	0.03	0.218	0.07	0.061	0.04	0.427
2012 q2	0.03	0.257	0.07	0.070	0.04	0.418
2012 q3	0.03	0.301	0.07	0.080	0.04	0.413
2012 q4	0.03	0.350	0.07	0.092	0.04	0.409
2013 q1	0.03	0.402	0.07	0.106	0.04	0.407
2013 q2	0.02	0.456	0.07	0.121	0.04	0.407
2013 q3	0.02	0.511	0.07	0.139	0.04	0.408
2013 q4	0.02	0.567	0.06	0.158	0.05	0.410
2014 q1	0.02	0.621	0.06	0.178	0.05	0.413
2014 q2	0.01	0.674	0.06	0.199	0.05	0.416
2014 q3	0.01	0.725	0.06	0.220	0.05	0.420
2014 q4	0.01	0.773	0.06	0.243	0.05	0.425
2015 q1	0.01	0.818	0.06	0.265	0.05	0.429
2015 q2	0.01	0.860	0.06	0.288	0.05	0.434
2015 q3	0.01	0.900	0.06	0.310	0.05	0.439

ITS = interrupted time series regression model; ACSC = ambulatory care-sensitive condition; PACT = Patient Aligned Care Team initiative; CYQTR = calendar-year quarter

Table 2.9. Appendix Table: ITS model results for total ED visits by patients' potential exposure to PACT

	3 or more VHA primary care visits in previous year						Fewer than 3 VHA primary care visits in previous year					
	PACT effect						PACT effect					
CYQTR	Low-comorbid	p-value	High-comorbid	p-value	Differential effect	p-value	Low-comorbid	p-value	High-comorbid	p-value	Differential effect	p-value
2010 q2	14.5	0.007	15.5	0.018	0.9	0.903	9.8	0.000	11.6	0.014	1.9	0.711
2010 q3	15.2	0.002	15.8	0.008	0.5	0.940	11.3	0.000	12.5	0.004	1.3	0.787
2010 q4	15.9	0.000	16.0	0.003	0.2	0.981	12.6	0.000	13.3	0.001	0.7	0.873
2011 q1	16.5	0.000	16.3	0.001	-0.2	0.975	13.9	0.000	14.0	0.000	0.2	0.969
2011 q2	17.1	0.000	16.5	0.000	-0.5	0.927	15.0	0.000	14.7	0.000	-0.3	0.929
2011 q3	17.6	0.000	16.8	0.000	-0.8	0.877	16.1	0.000	15.3	0.000	-0.8	0.822
2011 q4	18.0	0.000	17.0	0.000	-1.1	0.827	17.1	0.000	15.9	0.000	-1.2	0.716
2012 q1	18.5	0.000	17.2	0.000	-1.3	0.778	18.0	0.000	16.4	0.000	-1.6	0.615
2012 q2	18.9	0.000	17.3	0.000	-1.6	0.731	18.9	0.000	16.9	0.000	-2.0	0.522
2012 q3	19.3	0.000	17.5	0.000	-1.8	0.688	19.7	0.000	17.4	0.000	-2.3	0.441
2012 q4	19.7	0.000	17.6	0.000	-2.0	0.650	20.5	0.000	17.8	0.000	-2.6	0.372
2013 q1	20.0	0.000	17.8	0.000	-2.2	0.617	21.2	0.000	18.3	0.000	-3.0	0.315
2013 q2	20.3	0.000	17.9	0.000	-2.4	0.589	21.9	0.000	18.6	0.000	-3.2	0.270
2013 q3	20.6	0.000	18.0	0.000	-2.6	0.566	22.5	0.000	19.0	0.000	-3.5	0.234
2013 q4	20.9	0.000	18.2	0.000	-2.7	0.548	23.1	0.000	19.3	0.000	-3.8	0.206
2014 q1	21.2	0.000	18.3	0.000	-2.9	0.533	23.6	0.000	19.6	0.000	-4.0	0.184
2014 q2	21.4	0.000	18.4	0.000	-3.0	0.520	24.2	0.000	19.9	0.000	-4.2	0.166
2014 q3	21.6	0.000	18.5	0.000	-3.2	0.511	24.7	0.000	20.2	0.000	-4.4	0.153
2014 q4	21.8	0.000	18.6	0.000	-3.3	0.503	25.1	0.000	20.5	0.000	-4.6	0.142
2015 q1	22.1	0.000	18.7	0.000	-3.4	0.497	25.6	0.000	20.7	0.000	-4.8	0.134
2015 q2	22.3	0.000	18.7	0.000	-3.5	0.492	26.0	0.000	21.0	0.000	-5.0	0.127
2015 q3	22.4	0.000	18.8	0.000	-3.6	0.489	26.4	0.000	21.2	0.000	-5.2	0.121
2015 q4	22.6	0.000	18.9	0.000	-3.7	0.486	26.7	0.000	21.4	0.000	-5.3	0.117
2016 q1	22.8	0.000	19.0	0.000	-3.8	0.484	27.1	0.000	21.6	0.000	-5.5	0.113
2016 q2	22.9	0.000	19.0	0.000	-3.9	0.482	27.4	0.000	21.8	0.000	-5.6	0.110

2016 q3	23.1	0.000	19.1	0.000	-4.0	0.481	27.7	0.000	22.0	0.000	-5.8	0.108
2016 q4	23.2	0.000	19.1	0.000	-4.1	0.480	28.1	0.000	22.2	0.000	-5.9	0.106

ITS = interrupted time series regression model; ED = emergency department; PACT = Patient Aligned Care Team initiative; CYQTR = calendar-year quarter; VHA = Veterans Health Administration

Table 2.10. Appendix Table: ITS model results for preventable ED visits by patients' potential exposure to PACT

	3 or more VHA primary care visits in previous year						Fewer than 3 VHA primary care visits in previous year					
	PACT effect						PACT effect					
CYQTR	Low-comorbid	p-value	High-comorbid	p-value	Differential effect	p-value	Low-comorbid	p-value	High-comorbid	p-value	Differential effect	p-value
2010 q2	8.7	0.000	9.8	0.001	1.2	0.735	6.3	0.000	8.3	0.000	1.9	0.340
2010 q3	8.3	0.000	8.9	0.001	0.7	0.834	6.1	0.000	7.7	0.000	1.6	0.377
2010 q4	7.9	0.000	8.1	0.001	0.2	0.946	5.8	0.000	7.2	0.000	1.4	0.421
2011 q1	7.6	0.000	7.4	0.001	-0.2	0.931	5.6	0.000	6.7	0.000	1.1	0.475
2011 q2	7.3	0.000	6.7	0.001	-0.6	0.802	5.4	0.000	6.3	0.000	0.9	0.539
2011 q3	7.1	0.000	6.1	0.001	-1.0	0.672	5.2	0.000	5.9	0.000	0.7	0.614
2011 q4	6.8	0.000	5.5	0.002	-1.3	0.549	5.0	0.000	5.5	0.000	0.5	0.698
2012 q1	6.6	0.000	5.0	0.003	-1.6	0.439	4.8	0.000	5.2	0.000	0.3	0.790
2012 q2	6.4	0.000	4.5	0.006	-1.9	0.346	4.7	0.000	4.9	0.000	0.2	0.886
2012 q3	6.2	0.000	4.0	0.010	-2.1	0.271	4.5	0.000	4.6	0.000	0.0	0.984
2012 q4	6.0	0.000	3.6	0.019	-2.4	0.214	4.4	0.000	4.3	0.000	-0.1	0.921
2013 q1	5.8	0.000	3.2	0.034	-2.6	0.171	4.3	0.000	4.0	0.000	-0.2	0.832
2013 q2	5.6	0.000	2.8	0.058	-2.8	0.139	4.2	0.000	3.8	0.000	-0.4	0.750
2013 q3	5.5	0.000	2.5	0.096	-3.0	0.116	4.1	0.000	3.6	0.001	-0.5	0.678
2013 q4	5.3	0.000	2.2	0.150	-3.2	0.098	4.0	0.000	3.4	0.001	-0.6	0.615
2014 q1	5.2	0.000	1.9	0.220	-3.3	0.086	3.9	0.000	3.2	0.003	-0.7	0.560
2014 q2	5.1	0.000	1.6	0.305	-3.5	0.077	3.8	0.000	3.0	0.006	-0.8	0.513
2014 q3	4.9	0.000	1.3	0.401	-3.6	0.070	3.7	0.000	2.8	0.010	-0.9	0.473
2014 q4	4.8	0.000	1.1	0.504	-3.8	0.065	3.6	0.000	2.7	0.017	-0.9	0.440
2015 q1	4.7	0.001	0.8	0.610	-3.9	0.061	3.5	0.000	2.5	0.026	-1.0	0.411
2015 q2	4.6	0.001	0.6	0.714	-4.0	0.058	3.5	0.000	2.4	0.039	-1.1	0.386
2015 q3	4.5	0.002	0.4	0.815	-4.1	0.055	3.4	0.000	2.2	0.056	-1.2	0.365
2015 q4	4.4	0.003	0.2	0.909	-4.2	0.054	3.3	0.000	2.1	0.076	-1.2	0.347
2016 q1	4.4	0.004	0.0	0.996	-4.4	0.052	3.3	0.000	2.0	0.100	-1.3	0.331
2016 q2	4.3	0.006	-0.2	0.924	-4.5	0.051	3.2	0.000	1.9	0.127	-1.3	0.317

2016 q3	4.2	0.008	-0.3	0.851	-4.5	0.050	3.2	0.000	1.8	0.158	-1.4	0.305
2016 q4	4.1	0.010	-0.5	0.786	-4.6	0.050	3.1	0.000	1.7	0.190	-1.4	0.295

ITS = interrupted time series regression model; ED = emergency department; PACT = Patient Aligned Care Team initiative; CYQTR = calendar-year quarter; VHA = Veterans Health Administration

Table 2.11. Appendix Table: Effect of PACT on ACSC hospitalizations by comorbidity burden through 2013

	PACT effect					
CYQTR	Low-comorbid	p-value	High-comorbid	p-value	Differential effect	p-value
2010 q2	0.51	0.237	0.97	0.100	0.45	0.518
2010 q3	0.21	0.586	0.70	0.186	0.49	0.438
2010 q4	-0.07	0.839	0.45	0.351	0.52	0.361
2011 q1	-0.34	0.290	0.21	0.635	0.55	0.292
2011 q2	-0.59	0.047	-0.02	0.966	0.57	0.236
2011 q3	-0.83	0.003	-0.23	0.550	0.60	0.194
2011 q4	-1.05	0.000	-0.43	0.248	0.62	0.168
2012 q1	-1.27	0.000	-0.63	0.093	0.64	0.153
2012 q2	-1.47	0.000	-0.81	0.032	0.66	0.149
2012 q3	-1.66	0.000	-0.98	0.011	0.68	0.152
2012 q4	-1.84	0.000	-1.15	0.004	0.69	0.160
2013 q1	-2.02	0.000	-1.31	0.002	0.71	0.171
2013 q2	-2.18	0.000	-1.46	0.001	0.72	0.184
2013 q3	-2.34	0.000	-1.61	0.001	0.73	0.198
2013 q4	-2.49	0.000	-1.75	0.000	0.75	0.213

Notes. This table presents the results of the sensitivity analysis that controlled for the effect of the Veterans Health Choice Program. This analysis models the effect of PACT using a post-period through 2013.
ACSC = ambulatory care-sensitive condition; PACT = Patient Aligned Care Team initiative; CYQTR = calendar-year quarter

Chapter 3. THE RELATIONSHIP BETWEEN PRIMARY CARE ACCESS AND HIGH-COST SERVICE USE IN THE VETERANS HEALTH ADMINISTRATION: A NEW INSTRUMENTAL VARIABLES APPLICATION

3.1 INTRODUCTION

It is no secret that the U.S. spends more on health care and has worse health outcomes than other developed nations.[1,2] The U.S. has among the highest rates of hospitalizations from preventable causes and the highest rates of premature death from conditions that are considered preventable with timely access to care, such as diabetes and hypertensive disease.

One driver of higher costs and lower quality has been the U.S.'s reliance on more hospital-based care and less primary care. Between 2002 and 2015, the U.S. experienced a 12% increase in emergency department (ED) use and a 32% reduction in the rate of acute care visits to primary care practices.[3] Studies suggest, however, that about one-third of ED visits could be addressed in a primary care or retail setting, and one study predicted $4.4 billion in savings if non-urgent ED visits were cared for in non-hospital settings.[4,5] Overreliance on EDs and hospitals not only leads to high costs, but also to undesirable patient experiences including unnecessary or duplicative testing and treatment and high out-of-pocket costs.[5,6]

Improving access to primary care is recognized as a key strategy to improving health care quality, costs, and outcomes. Good primary care provides patients with timely and appropriate care, promotes longitudinal relationships between patients and providers, and manages patients' conditions and care needs.[4] Timely access to primary care provides patients with a place to receive non-urgent care and also reduces the likelihood of complications that lead to ED visits and hospital stays. As such, improving access to primary care is a key institutional priority for the U.S. Department of Health and Human Services and the Veterans' Health Administration.[14–16]

The patient-centered medical home (PCMH) has become a popular approach among health care payers and providers for improving access to primary care. The PCMH defines a strategy to structure primary care that puts patients at the forefront of care to optimize outcomes and reduce costs.[17,18] The PCMH strategy emphasizes longitudinal and episodic care management of chronic conditions; use of health information technology to identify, measure, and track population health; patient and caregiver engagement; enhanced access to care; and a focus on improving quality of care.[17–19] Improving access to primary care is a key tenant of the PCMH strategy. PCMHs are expected to deliver accessible services with shorter wait time for urgent needs through enhanced in-person hours, around-the-clock telephone or electronic access to members of the care team, and alternative methods of communication such as email and telephone.[17,95]

The literature on the effects of access to PCMH on ED visits and hospitalizations is mixed. A meta-analysis of 17 peer-reviewed studies of PCMH initiatives concluded no effect of PCMH on total or potentially avoidable ED use, hospitalizations for any reason, or ACSC hospitalizations.[36] In contrast, a study of primary care clinics in the Veterans Health Administration (VHA) found that greater adoption of medical home features were associated with fewer ACSC hospitalizations.[37] Some studies that have estimated the effect of access to care on ED and hospital use have found that more access was associated with fewer non-emergent and primary care treatable ED visits and lower risk of ACSC hospitalization,[37,96,97] while other studies have found no effects.[98]

Estimating the effect of access to care, however, is challenging. First, "access" is not clearly defined and has been conceptualized and measured differently across the literature.[99] Studies have measured access to primary care based on a single supply-side factor such as availability of insurance,[100] worksite medical offices,[98] primary care providers[65] and same-day appointments.[96] However, these studies miss the role of perceived access to care, such as patients' perception of availability of care,[101] as well as the effect of the combination of factors of access on utilization decisions.

Second, prior literature does not adequately address issues of endogeneity that are inherent in studies of the effect of access on health care utilization.[102,103] For example, patients with greater care needs might selectively choose clinics with extended hours or alternative visits (i.e., greater access). Without accounting for patients' endogenous choices of where to receive care based on unobservable needs or preferences, standard regression approaches could conclude that improved access through extended hours or alternative visits was associated with increased utilization. But in fact, patients' unobservable characteristics or preferences that are associated with increased utilization are driving the positive relationship between greater access and utilization. Thus, the standard regression approaches currently used in the literature are not able to separate patients' endogenous choices and the exogenous changes from improving access to care.

In this study, we address the two prevailing issues in the current literature. First, we apply a unique composite measure of access to care that includes 11 measures of both supply-side access and patients' perceptions of access. In addition to the composite measure, we estimate the effects of access on utilization using the 11 measures individually. Second, we use instrumental variables (IV) to account for the endogeneity present in access and utilization decisions. Recognizing that having an adequate number and quality of primary care providers and staff is paramount to improving access to care via the PCMH models, we captured exogenous variation in access to care by isolating the component attributable to the competitiveness of the local labor market for health care employees. We employ a relatively new extension of local instrumental variable methods that has not been widely deployed across health services research: the person-centered treatment effect instrumental variables (PeT IV) estimator.[104] The PeT IV, which improves upon previous IV estimators to calculate individual-specific treatment effects, allows us to estimate average treatment effects (as opposed to local average treatment effects) and provides a framework to estimate heterogenous treatment effects across subgroups of patients that have been shown to experience additional obstacles to accessing primary care, such as patients' with longer travel distances and disabilities[39,40] or with differential utilization patterns such as race, [41,42] risk-status,[45] marital status,[46] and income.[47]

In this study, we estimate the effect of improving access to primary care within the Veterans Health Administration's PCMH initiative—the Patient Aligned Care Team (PACT) initiative—on total ED and hospital use and ED and hospital use that is potentially preventable or avoidable with timely primary care. VHA is one of the largest integrated health care systems in the U.S., and PACT represents one of the largest PCMH rollouts. This study provides a unique opportunity to rigorously estimate the extent to which improving access to primary care alters patients' use of high-cost services across a large population of diverse patients nationwide. Additionally, by exploring the effects of individual components of access and estimating whether access differentially affects patients based on their risk status, location, socioeconomic status, and other characteristics, this study will provide unique insight into how access to care affects utilization and for which patients it has the largest impacts.

We found that improved access increased the likelihood of having ED visits and potentially preventable ED visits, but did not affect patients' use of hospitals for any reason or for potentially avoidable hospital stays. We found that improved access had larger effects on patients in previously low-access clinics and on patients that lived closer to VHA facilities. Finally, we found that longer wait times, availability of after-hours care, and use of secure messaging are driving factors of the effect of access on utilization of EDs and hospitals.

The rest of this paper is organized as follows. Section 3.2 describes the methods, including a description of the VHA and VHA patient population, study design, data sources, measures, and statistical analysis. Section 3.3 presents the results, and Section 3.4 discusses the results and limitations to the study. Section 3.5 is an accompanying appendix that presents additional details and data tables.

3.2 METHODS

3.2.1 *Setting*

The Veterans Health Administration (VHA) is one of the largest integrated health care systems in the U.S. with more than 8 million enrollees and serving more than 5 million veterans annually in urban and rural settings.[23–25] The VHA provides care at 1,255 health care facilities, including 170 Medical Centers and 1,074 outpatient clinics.[27] All individuals that served in the active military, naval, or air service that did not receive a dishonorable discharge are eligible to enroll in VHA health care.[26] VHA enrollees are subject to modest copays for outpatient care ranging from $15 for primary care services to $50 for specialty care, although, more than 70% of VHA enrollees are exempt from paying copays.[28]

Veterans served by the VHA have more chronic physical and mental illness, are more socioeconomically vulnerable, are mostly male, and are less diverse than the general population.[25,29,30] VHA-enrolled veterans are also different in some ways from the wider veteran population. For example, in 2017 the unemployment rate among VHA enrollees was 9.2%

compared to 3.7% for all veterans and 4.4% for civilians.[23] Notably, many VHA-enrolled veterans are dually-enrolled with Medicare (51%) or private coverage (28%) and use non-VHA services for their health care needs.[23,32]

Primary care is the foundation of VHA health care and is generally the VHA-enrolled veteran's first point of contact with the health system. In April 2010, the VHA launched their PCMH model, the Patient Aligned Care Team (PACT) initiative in all primary care clinics nationwide.[24,25,33,34] Through PACT, the VHA restructured primary care delivery to provide more comprehensive, longitudinal, and patient-centered care.[105] Upon enrolling in the VHA, a patient is assigned to a primary care team (i.e., a Patient Aligned Care Team) that is charged with coordinating and managing that patient's care, serving as a gatekeeper to specialty care and other services. Each primary care team consists of one primary care provider (medical doctor [MD] or nurse practitioner [NP]), one registered nurse care manager, one licensed practical nurse or medical assistant, and one administrative clerk.[25] Teams are additionally connected to integrated behavioral health, pharmacy, and social work services. Together, a care team is responsible for a panel of 900 to 1200 primary care patients.

To enhance patient access to care, PACT focused on increasing the availability of telephone and same-day visits, providing proactive outreach to patients by their care team, and introducing an internet-based secure messaging portal.[25,35] These tools help patients to manage their health and to connect with their care teams virtually. Patient portals have been shown to improve patient-provider communication, quality of care, and contribute to greater self-management.[106]

3.2.2 *Study design*

We conducted a retrospective cohort study of patients 65 years or older who received primary care from the VHA at any time between January 2012 and December 2016. We included only patients 65 years or older to address prior studies indicating many VHA enrollees are dual users of non-VHA care.[61,107,108] By limiting the sample to age 65+ VHA enrollees we are better able to comprehensively measure utilization because the study team were able to link VHA data to Medicare claims. To measure the effect of access on utilization, we used the person-centered treatment (PeT) effect estimator[104]—a unique IV approach measuring causal effects in the presence of treatment effect heterogeneity. The key instrumental variable used to isolate exogenous variation in access to care was health care sector-specific local area employment statistics.

3.2.3 *Data*

Data for this study come from the VHA Corporate Data Warehouse (CDW), a national repository that contains administrative and clinical data and medical claims for all inpatient and outpatient patient encounters within the VHA. We used the VHA's Primary Care Management Module (PCMM), a database within CDW that contains information on patient assignment to primary care providers and care teams. Upon enrollment in the VHA, all patients are assigned to a PACT – a team of primary care providers and administrative staff that help patients use and coordinate health care services within and outside of the VHA. The PCMM indicates when the patient enrolled in VHA, their PACT assignment, changes to the assignment over time (for example, if a patient moved), and the location of the PACT (that is, the clinic identifier and geographic location of where they receive primary care). CDW data were linked to Medicare fee-for-service (FFS) claims, to measure utilization outside of the VHA. Our measure of clinic-level access comes from the VA Office of Primary Care. We used data from the Veterans Administration Site Tracking System (VAST) to obtain information on the physical locations of VHA facilities. Finally, we used data from the Health Resources & Services Administration's (HRSA) Area Health Resources File to obtain characteristics of the patients' residential county.

3.2.4 *Study sample*

To support a wider study of PACT, we identified 9,816,691 veterans that received primary care from VHA at any time between October 2002 and December 2016. For each of the 9.8 million patients, we identified which calendar quarters they had an active relationship with a VHA primary care provider and extracted a 5% random sample of active patient-quarters. We then restricted the time period to January 2012 through December 2016 since our measure of access was first measured in 2012. We included only patients 65 years or older so we could capture patients' utilization of health care services both within and outside the VHA (paid for my Medicare FFS). We additionally excluded Medicare Advantage enrollees because we did not have claims for them. These sample restrictions were important to ensure our utilization measures were not biased by patients altering where they received care as a result of PACT or other, unobservable reasons such as changing preferences. There were 1.9 million patient-quarters representing 1.3 million patients remaining in the sample. Finally, we kept only patient observations from clinics that had clinic-based access scores (described below) in either the lowest or highest quartile. The final sample consisted of a repeated cross-sectional sample of 940,243 patient-quarter observations, representing 733,341 unique patients in 785 VHA primary care clinics nationally.

3.2.5 *Measures*

Outcome measures. We estimated the effect of access on four measures of high-cost service utilization: total ED visits, preventable ED visits, total hospitalizations, and hospitalizations for ambulatory care-sensitive conditions (ACSCs).

- *Total ED visits* were measured for each patient in each quarter and were identified in VHA administrative data and Medicare outpatient claims. Following Liu et al. 2018, we identified ED visits using the 15 Healthcare Common Procedure Coding System (HCPCS) codes associated with the Berenson-Eggers Type of Service (BETOS) code M3-emergency room visit, and VHA encounter stop codes (for ED visits in the VHA) and place of service codes (for ED visits outside of the VHA) that indicate the type of facility that provided the care.[61]
- *Preventable ED visits* were measured for each patient in each quarter using the New York University (NYU) ED Algorithm (EDA)—a valid and reliable measure of potentially avoidable ED visits[58,62,63,64]—and the patch to the algorithm developed by Johnson 2015.[59] The NYU EDA retrospectively assesses the probability that an ED visit was urgent, required ED attention, or was preventable using administrative medical claims data. The patch algorithm provided an update to the classification schema to reflect changes in diagnosis coding between 2001 and 2015 and the industry-wide switch from the ICD-9 classification system to the ICD-10 classification in 2015. Following the algorithm, we used primary ED discharge diagnosis codes to assign probabilities that each ED visit fell into four categories: (1) non-emergent, (2) emergent/primary care treatable, (3) emergent-ED care needed-preventable/avoidable, and (4) emergent-ED care needed-not preventable/avoidable. We then calculated the sum of the probabilities of an ED visit being

(1) non-emergent or (2) emergent/primary care treatable across all visits in a given quarter for a given patient following the literature.[65] This gave us a weighted patient-level count of preventable ED visits in each quarter.

- *Total hospitalizations* were measured for each patient in each quarter and were identified in VHA administrative data and Medicare inpatient claims. The measure of hospitalizations is *all* hospitalizations including medical, surgical, and psychiatric hospitalizations but excludes transfers within a hospital or from another hospital. We identified each unique record as a hospitalization and using admission dates, we counted the number of hospitalizations for each patient in each quarter.
- *ACSC hospitalizations* were measured using hospital inpatient diagnosis codes and followed the Agency for Healthcare Research and Quality specifications.[66] ACSC hospitalizations are considered potentially preventable by high-quality primary care. For example, early intervention and disease management can prevent complications or more severe disease that leads to hospitalization. We measured ACSC hospitalizations as those for which an individual was admitted with a diagnosis of one of these conditions: bacterial pneumonia; dehydration; urinary tract infection; perforated appendix; congestive heart failure; hypertension; asthma; chronic obstructive pulmonary disease (COPD); diabetes related short-term complications, long-term complications, uncontrolled diabetes, and lower extremity amputation among patients with diabetes.[57] Using admission dates, we then counted the number of ACSC hospitalizations for each patient in each quarter.

For each of the four types of service use, we measured the outcomes as the number of visits for each patient in a given quarter and as a binary indicator for whether the patient had any visits in the quarter.

Primary predictor. We measured primary care access at the clinic level using a composite measure of 11 items that was developed by the VA Office of Primary Care to track PACT implementation progress.[35,109] The 11-item composite measure is composed of 6 items from an annual Consumer Assessment of Health Plans-Patient Centered Medical Home (CAHPS-PCMH) survey administered to a random sample of primary care patients from each clinic. The survey includes questions such as "How often did you get an appointment as soon as you needed?" and "When you phoned this provider's office, how often did you get an answer to your medical questions that same day?" Five items were constructed from administrative data that included measures of same-day access and clinics' use of non-face-to-face care (see Appendix Table 3.2 for the 11 items). A composite score for each clinic was calculated using three steps: (1) calculate the average scores for each of the 11 individual components, (2) standardize the average scores using the national average and the standard deviation for all clinics, and (3) calculate the average of the standardized scores for the 11 items.[35] The composite score has been measured annually since 2012.

The 11-item access composite measure has been validated against 48 clinical quality measures for chronic disease management and disease prevention (comparable to the Healthcare Effectiveness Data and Information Set [HEDIS] measures), using medical records abstracted from 422,125 VHA primary care patients from fiscal years 2012 to 2014.[109] The highest-quartile of clinics based on their access measure had significantly better performance than the lowest-quartile clinics for 32 of the 48 quality measures.

For analysis, we dichotomized the 11-item composite access score to denote clinics with access scores in the highest and lowest quartiles.[35,110] Our analysis only uses clinics with access scores in the highest and lowest quartiles to distinctly measure differences in clinic-level access.

For our secondary analysis, we examine how each of the 11 item z-scores were associated with outcomes.

Instrumental variables. PACT mandated clinics reorganize staff into teamlets of one primary care provider, one registered nurse care manager, one licensed practical nurse or medical assistant, and one administrative clerk with a staffing ratio of 3.0 full-time equivalents (FTEs) of primary care support staff per full-time primary care physician.[25] These teamlets were designed to optimize workflow and enhance patient access by enabling members to function at the top of their expertise.[25] For example, RNs are expected to provide patient outreach via in-person and telephone encounters to manage care for patients with chronic conditions, thereby providing more consistent contact with the patient and freeing up physician's time to see other patients or engage in other clinical tasks. MD-led and NP-led teamlets are expected to provide care to a panel of 1200 patients and 900 patients, respectively.[111] Thus, a clinic's ability to provide enhanced access to care is a function of a clinics ability to hire both enough staff and quality staff to build good functioning teamlets for their clinic.

We hypothesized that if the local labor market is competitive, the VHA would have more difficulty hiring quantity and quality staff to build teamlets, hindering access. To estimate local labor market competitiveness, we constructed two measures of relative annual wage growth between health care practitioners (i.e., the types of staff demanded for PACT) and the general labor market. We hypothesized, and later tested that, these measures would satisfy the two assumptions required for instrumental variables: (1) to have strong explanatory power for variation in clinic-level access to care and (2) to not be associated with the outcomes except through their effects on access (i.e., the exclusion restriction). After controlling for general labor market conditions, relative wage growth in the health services sector should not directly affect patients' use of EDs and hospitals, except through its effect on the patient's ability to access providers and care. The patients included in our study, all of which are 65 years old or older, are unlikely to be primary care providers and thus changes in providers' wages should not affect their use of services directly, satisfying the exclusion criteria.

Using annual wage data from the Bureau of Labor Statistics' (BLS) Occupational Employment Statistics (OES),[112] we calculated the relative percentage change in mean hourly wages within a BLS area (most commonly a core-based statistical area [CBSA]) between the general labor market and (1) the OES occupational group "healthcare practitioners and technical occupations" (occupational group 29000) and separately (2) the OES occupational group for medical assistants (occupational group 319092). We could not look at more granular occupational categories such as primary care physicians or registered nurses because these categories were not tracked by the OES in all years or were missing for 5% or more of our geographical areas. Because our unit of analysis is patient-quarter and not an annual measure, we calculated the average annual wage as a weighted average of mean hourly wages between the current and prior year. For example, for Q2-2014 we calculated annual wage as 0.75 x average hourly wage in 2013 plus 0.25 x average hourly wage in 2014.

Primary care clinics were then mapped to BLS areas using the Federal Information Processing Standard (FIPS) codes and assigned the two IV measures for that area. For the 1% of FIPS that mapped to multiple areas, we constructed a weighted average of mean hourly wages based on the number of jobs in each area within the FIPS before constructing the IVs.

<u>Covariates.</u> We constructed several measures to control for patient and local area characteristics that could affect service utilization as posited by Anderson's model of health service use.[113] We measured each patient's age, gender, race (white, Black, all other races), marital status

(married, never married or single, divorced or separated, widowed, and missing), and whether they were eligible for copayment-exempt VHA care for the given quarter using VHA administrative data. Copay-exemption is a measure of patients' income and/or disability status. Veterans may qualify for copay-exempt VHA care if they have income below a means-tested threshold or are sufficiently disabled due to their military service. We calculated the distance from the patients' residence ZIP code to the ZIP code of the nearest VHA clinic using the Haversine-based geodesic distance.[67] Patient covariates also included two binary indicators for whether the patient had any ED visits and any hospitalizations in the 4 quarters before the given quarter.

Using VHA inpatient and outpatient claims data, for each patient in each quarter, we measured patient comorbidity burden using the Gagne comorbidity score—a weighted composite of 20 conditions from the Charlson and Elixhauser comorbidity measures.[60] The Gagne score has been validated in the population of adults age 65+. We first identified patients' conditions from hospital discharges and outpatient physician services using the ICD-9 and ICD-10 diagnosis codes on the medical claims following Quan et al. 2005.[114] We flagged a patient as having a condition if they had any claims with the associated ICD-9 or ICD-10 codes in a given quarter (based on the data of the outpatient visit or the discharge date for inpatient claims). Condition indicators were then weighted according to the Gagne measure specifications.[60] Condition weights were based on predicting 1-year mortality and ranged from -1 for Hypertension and HIV/AIDs to 5 for Metastatic cancer. Gagne scores could range from -2 to 24. Following the literature, we categorized patients with a Gagne score ≥ 2 as having high comorbidity burden and those < 2 as patients with low comorbidity.[28] Additionally, we denoted whether the patient had each of the 20 comorbidities in the Gagne measure.

Local area covariates included the unemployment rate in patients' residence county to account for changes in outcomes influenced by economic conditions, and the number of hospital beds to control for variations in the health care services environment.[30]

3.2.6 *Statistical analysis*

We estimated the effect of access to primary care on total and potentially preventable/avoidable measures of ED visits and hospitalizations using repeated cross-sectional data and the Person-centered Treatment Effects (PeT effects) IV estimator.[104] The person-centered treatment effect instrumental variables (PeT IV) estimator—a relatively new extension of local instrumental variable methods—constructs individual-specific treatment effects that can be averaged across the sample or subsets of the sample to produce average treatment effects for the entire sample or to explore treatment effect heterogeneity. Similar to other IV approaches, we used the following two-step process:

<u>Stage 1. Identify and evaluate the instrumental variables.</u>

During the first stage, we modeled the variation in access using logistic regressions as a function of the IVs, the patient and local area characteristics that were our control variables, and unobserved clinic and patient characteristics captured in the error term (*u* in equation 3.1).

$$Access_{ijt} = \beta_0 + \beta_1 RWG\_HP_{jt} + \beta_2 RWG\_MA_{jt} + \sum \beta_p X_{pit} + u_{it} \qquad (3.1)$$

where *Access* is the clinic's dichotomized access score for patient *i*, in clinic *j*, at time *t*. *RWG_HP* and RWG_MA are the instrumental variables measuring the relative wage growth among healthcare practitioners and medical assistants, respectively, for clinic *j*'s local area at time *t*. *X* is the vector of patient and local area characteristics. Following the PeT IV procedure[115] we used equation 1 to predict propensity scores that measured an individual's proclivity to be in a high-access clinic given the labor market conditions and other patient characteristics.

We tested the predictive power and validity of the IV using joint F-tests.[116] An F-statistic larger than 10 indicates that the IV has sufficient predictive power. We also compared the imbalance in the covariates across access categories with the imbalance in the covariates across the IVs.

Stage 2. Estimate individualized treatment effects and patient outcomes

In the second stage, we modeled the variation in each of the eight outcomes as a function of the propensity scores derived from equation 3.1, and the patient and local area characteristics. We calculated PeT effects for each individual in the sample using a local instrumental variables approach as described in Basu (2014) (these are referred to as individualized treatment effects) and specified in equation 3.2.[104] For the count outcomes, we used negative binomial regressions to account for right skewness in the distribution of the outcomes. For binary outcomes, we used logistic regressions.

$$Y_{it} = \alpha_0 + \alpha_1 X_{it} + \alpha_2 \hat{p}_{it} X_{it} + \alpha_3 T_{it} + K(\alpha; \hat{p}_{it}) \quad (3.2)$$

where Y is the outcome for individual i at time t, X is the vector of patient and local area characteristics, $\hat{p}$ is the person-time specific propensity score derived from equation 3.1, and *K()* is the polynomial of $\hat{p}$ that we determined to fit the model best through likelihood ratio tests.[115] We tested polynomials of degree 1, 2, and 3. For count outcomes, the appropriate degree of polynomials was 3 for ED visits, 2 for preventable ED visits, and 1 for total and ACSC hospitalizations. For binary outcomes, the appropriate degrees of polynomials were 1 for ED visits, 2 for preventable ED visits, and 1 for total and ACSC hospitalizations.

We operationalized this approach using the *petiv* package in Stata.[115] To calculate the individualized treatment effects, we first compute marginal treatment effects by calculating the partial derivative of equation 3.2 with respect to $\hat{p}$. This produces the change in outcome given a marginal change in an individual's propensity to be in a high-access clinic. Notably, at the margin of one's propensity score there is no unobserved confounding because at the margin individuals are identical except for a small change in the IVs. Second, we compute 1000 marginal treatment effects for each individual using multiple values of the propensity score drawn randomly from the support of the propensity scores for the sample.[115] Third, we arrive at the treatment effect for each individual by averaging the 1000 marginal treatment effects for them over the values of the propensity score for which they would be in the high-access clinic. By aggregating across marginal treatment effects, we obtain average treatment effects rather than local average treatment effects which would be vulnerable to the hypothesized presence of treatment effect heterogeneity.

Using the individualized treatment effects, we calculated (1) the average effect of greater access across the entire sample (i.e., the average treatment effect [ATE]), (2) the average effect of access among patients in high-access clinics (i.e., the average treatment effect on the treated [ATT]), and (3) the average effect of greater access among patients in low-access clinics (i.e., the average treatment effect on the untreated [ATU]).[117] These calculations represent conditional means of the individualized treatment effects. Lastly, using the same conditional means approach, we calculated the average treatment effects of subgroups of patients based on risk-status, gender, race, marital status, patients' residential distance to nearest VHA clinic, and eligibility for copayment exempt VHA care. When calculating treatment effects, we calculated 100 replicate bootstrap standard errors.

Secondary analysis

We conducted several exploratory analyses to better understand which individual components of access might be driving potential effects of the composite access measure. We estimated the relative contributions of each of the 11 access components on each of our outcomes using standard regression methods and controlling for the same patient and local-area characteristics. We modeled the access components jointly, in a single regression model, to account for correlation between access components. The 11 items which are described above and presented in Appendix Table 3.2 were measured as z-scores, and at the clinic level. We used negative binomial regressions for count outcomes and logistic regressions for binary outcomes. All models used heteroskedastic robust standard errors.

All statistical analyses were performed using Stata version 15.0 (Stata Corp., College Station, TX). We considered effects to be statistically significant at the 5% significance level. This study was granted exemption from review by the VA Puget Sound Healthcare System Institutional Review Board (IRB).

3.3 RESULTS

3.3.1 *Descriptive statistics*

At the beginning of the study, patients were on average 75 years old, and mostly male (98%), white (89%), married (64%), and exempt from VHA copayments (68%) (Table 3.1). Patients had on average a Gagne score of 0.4 (SD=1.5), indicating few comorbidities on average. Sixty-three percent of patients had hypertension in the prior year and 15% had COPD. Fewer patients had other chronic conditions. About one-third of patients had an ED visit in the prior year and 20% had a hospital stay. Most patient characteristics were similar at the end of the study period. The exceptions were that more patients were exempt from VHA copayments (75% at the end of the study period versus 68% at the start) and had diabetes (17% versus 7%).

Table 3.1. Characteristics of the VHA Patients aged 65+ at the beginning and end of the study period

	Q1-2012	Q4-2016
Number of patients	41,772	48,199
Male (%)	98.2	97.8
Age (mean/sd)	75.3 (8.3)	74.7 (8.1)
Race (%)		
White	88.8	88.3
Black	9.6	9.9
Other	1.5	1.7
Marital Status (%)		
Never married	4.5	5.8
Married	63.5	61.2
Separated or divorced	18.2	21.2
Widowed	10.1	8.6
Exempt from VHA copayments (%)		
Non-exempt	31.6	24.5
Exempt due to service	44.6	56.1
Exempt due to income	23.6	18.6
Miles to nearest VHA clinic (%)		
<5	34.7	32.7
5 to <10	21.2	23
10 to <20	21.7	21.7
30 to <40	17.9	16.2
40 or more	3.1	3
Gagne score (mean/sd)	0.4 (1.5)	0.7 (1.8)
Comorbidities in the prior year (%)[a]		
Congestive heart failure	5.9	6.4
Cardiac arrhythmias	12	12.8
Peripheral Vascular Disorder	6.5	7.4
Chronic Pulmonary Disease	14.8	14.8
Complicated Diabetes	6.7	16.5
Renal Failure	8.1	9.1
Weight Loss	1.9	2.2
Fluid/Electrolyte Disorder	3.8	4.4
Deficiency anemias	2.5	3.8
Alcohol abuse	3.7	4.1
Psychosis	1.9	1.2
Dementia	1.3	3.8

Any tumor	11.6	9.1
Hypertension	63	61.8
ED visit in prior year (%)	34.3	35.7
Hospital visit in prior year (%)	20.1	19.6
Hospital beds per 1,000 population (mean/sd)	3.2 (2.6)	3.0 (2.5)
Unemployment rate (mean/sd)	8.4 (2.3)	5.0 (1.5)

[a] These conditions represent a subset of the conditions included as covariates in the models. In the models, we included each of the 20 conditions included in the Gagne index.
VHA = Veterans Health Administration; sd = standard deviation; ED = emergency department

3.3.2 *Instrumental variables*

The IVs satisfied the necessary conditions for instrumenting access. The IVs had strong explanatory power of clinic-level access (F-statistic=1195, p<0.001; Appendix Table 3.3) and were not individually or jointly associated with the eight outcomes (F-statistics<4, p>0.150 for the modeled associations with each outcome; Appendix Table 3.4). Testing for over-identifying restrictions using Sargan's and Basmann's chi-squared tests confirmed that the two IVs were valid and not endogenous for each of the eight models (Chi-sq values between 0.04 and 0.92, p-values>0.400; Appendix Table 3.5).[118,119] Finally, Appendix Figure 3.3 shows that the IVs reduced the imbalance in the observed factors used as covariates in the models considerably. The support of the IV-based predicted propensity score ranged from 0.035 to 0.958 (Appendix Figure 3.4).

3.3.3 *Average treatment effects*

Overall, greater access was associated with increased likelihood of having ED visits (average treatment effect [ATE] of 4.7 percentage points [p.p.], p=0.015) and potentially preventable ED visits (3.1 p.p., p=0.009) but had no effect on the *number* of ED or preventable ED visits per 1000 patients per quarter, or on both measures of total and ACSC hospitalizations (Figures 3.1 and 3.2).

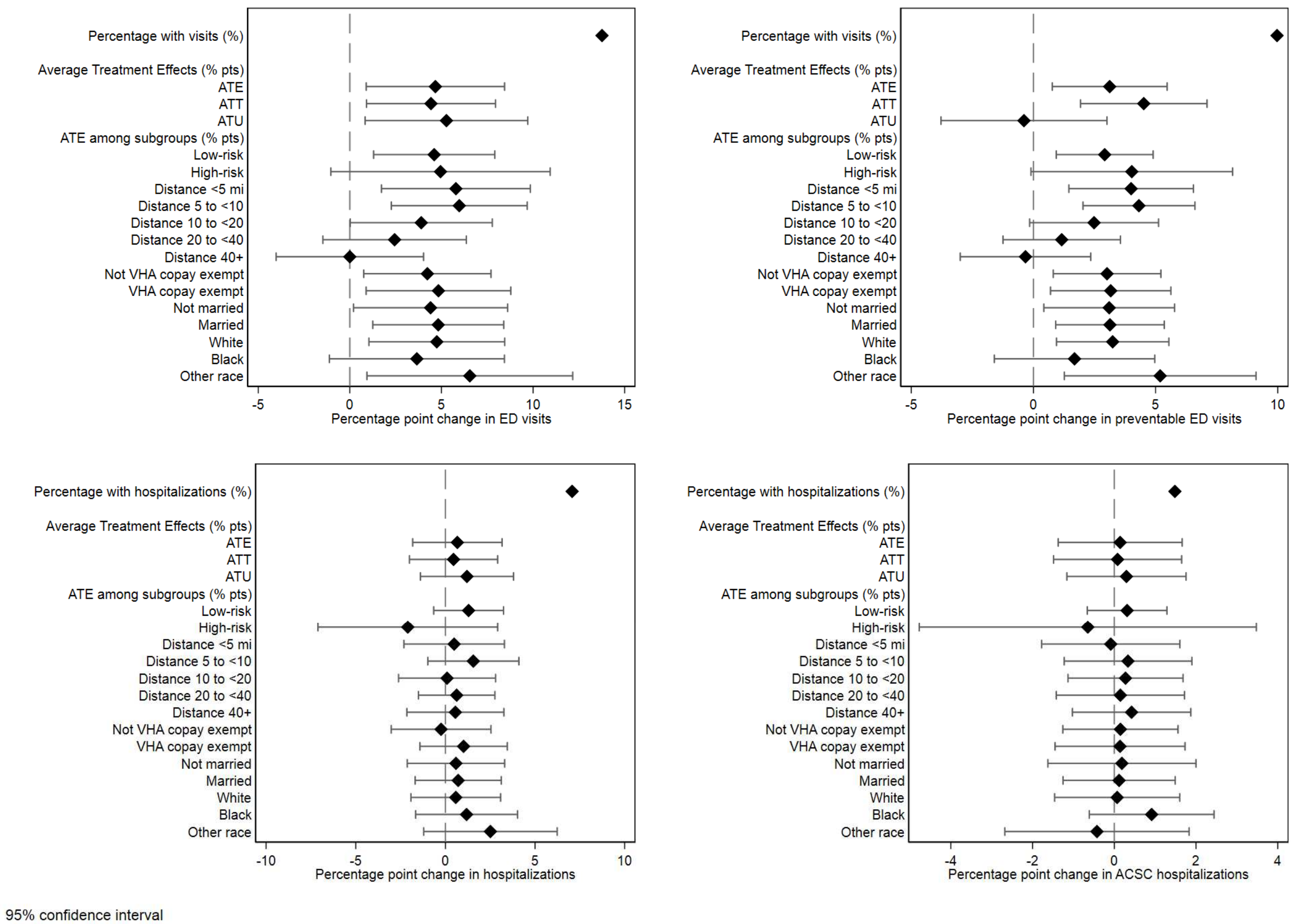

Figure 3.1. Probability utilizing health care services and the average treatment effect of improved PACT access overall and by patient characteristics, by each utilization outcome

Notes: High-risk is defined as patients with a Gagne comorbidity score ≥2, all other patients are considered low-risk. Distance measured the distance in miles from the patient's residence zip code to the nearest VHA clinic. VHA copayment exempt means the patient does not have to pay copayments for care covered by the VHA.

ED = emergency department; ACSC = ambulatory care-sensitive condition; PACT = Patient-Aligned Care Team initiative; ATE = average treatment effect; ATT = average treatment effect among the treated (patients in already high-access clinics); ATU = average treatment effect among the untreated (patients in low-access clinics); CI = confidence interval.

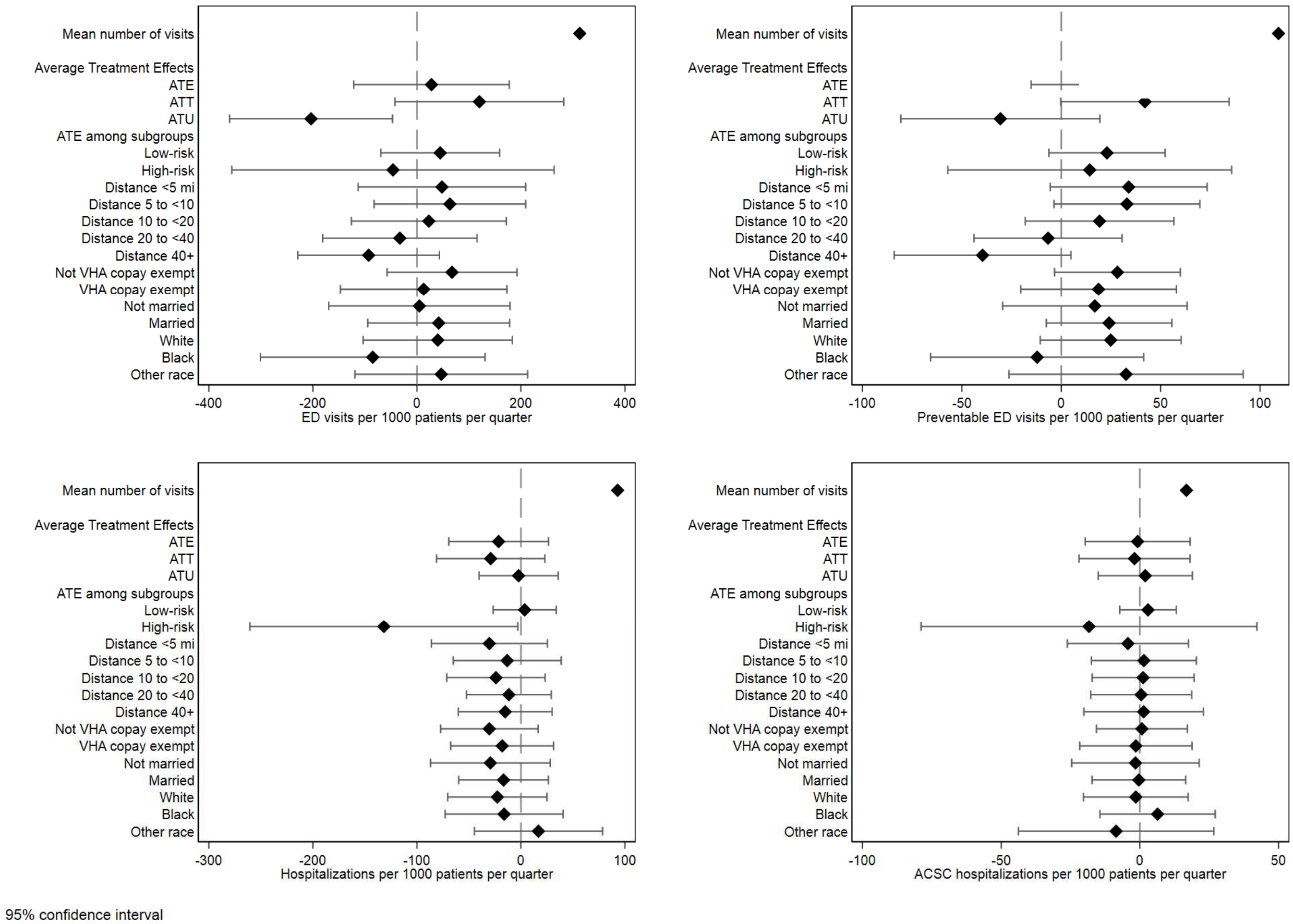

Figure 3.2. Mean number of health services utilized per 1000 patients per quarter and the average treatment effect of improved PACT access overall and by patient characteristics, by each utilization outcome

Notes: High-risk is defined as patients with a Gagne comorbidity score ≥2, all other patients are considered low-risk. Distance measured the distance in miles from the patient's residence zip code to the nearest VHA clinic. VHA copayment exempt means the patient does not have to pay copayments for care covered by the VHA.

ED = emergency department; ACSC = ambulatory care-sensitive condition; PACT = Patient-Aligned Care Team initiative; ATE = average treatment effect; ATT = average treatment effect among the treated (patients in already high-access clinics); ATU = average treatment effect among the untreated (patients in low-access clinics); CI = confidence interval.

The distributions of the individual treatment effects across the sample for each of the eight outcomes are in Appendix Figures 3.5-3.8. The distributions show that between 81% and 95% of patients are expected to experience an increase in their probability of having an ED visit (95%), potentially preventable ED visit (87%), ACSC hospitalization (81%), and hospitalization for any reason (81%) as a result of improved access to care. Between 70% and 82% of patients are expected to experience an increase in the number of total ED visits (70%), hospitalizations (74%), potentially preventable ED visits (78%), and ACSC hospitalizations (82%) as a result of greater access.

ATT estimates indicate that among patients in already-high-access clinics, greater access increased the probability of having an ED visit and potentially preventable ED visit in a quarter by 4.4 (p=0.014) and 4.5 (p=0.001) percentage points, respectively. Greater access had no effect on the number of ED or preventable ED visits or on both measures of total and ACSC hospitalizations (Figures 3.1 and 3.2).

ATU estimates indicate that among patients in low-access clinics, greater access increased the probability of having an ED visit by 5.3 pp (p=0.020) but resulted in a decrease of 204 ED visits per 1000 patients per quarter (p=0.011). There were no effects on the probability or total number of potentially preventable ED visits or on our measures of total and ACSC hospitalizations among patients in low-access clinics.

3.3.4 *Differential effects by patient characteristics*

The effect of greater access to primary care on ED and preventable ED visits was markedly larger for subgroups of patients that lived closer to VHA clinics and who were of non-white and non-Black race. For ED visits, average effects of greater access to care were 5.8 percentage points (p=0.005), 6.0 percentage points (p=0.002), and 3.9 percentage points (p=0.049) for patients living <5 miles, 5 to <10 miles, and 10 to <20 miles from a VHA clinic, respectively. In contrast, no effect was identified for patients living farther from VHA clinics. The ATT capturing the average effects of greater access to care was 4.7 percentage points for white patients that identified as white (p=0.012) compared to 6.6 percentage points for those that identified as non-white and non-Black (p=0.022). There was no statistically significant effect of access on Black patients.

For potentially preventable ED visits, greater access to care increased the likelihood of having a potentially preventable ED visits by 4.0 percentage points (p=0.002) for patients living <5 miles from a VHA facility and 4.3 percentage points (p<0.001) for patients living 5 to <10 miles from a VHA facilities. There were no effects on patients living farther away. Average effects of greater access to care were 3.2 percentage points for patients that identified as white (p=0.006) compared to 5.2 percentage points for those that identified as non-white and non-Black (p=0.010). There was no statistically significant effect of access on Black patients.

There were no differential effects based on other patient characteristics such as risk status, qualifying for copay exempt care, and marital status.

3.3.5 *Access component analysis*

Measures of longer wait times for appointments and care, availability of after-hours care, and use of secure messaging were consistently associated with increased ED and/or hospitalization use. The remaining seven components of access were not consistently associated with utilization (see Appendix Tables 3.6 and 3.7 for detailed results).

Waiting more days for an appointment for care needed right away was associated with increased log-odds of having an ED visit for any reason or a preventable ED visit in the quarter

(0.045 [p<0.001], 0.059 [p<0.001]), and with 34.3 more preventable ED visits per 1000 patients per quarter (p=0.007). Similarly, patients' reports of more often being seen by their provider within 15 minutes of appointment time was associated with a *decrease* in the log-odds of having an ED visit (0.034 decrease in the log-odds, p<0.001), preventable ED visit (-0.017, p=0.017), hospitalization for any reason (-0.051, p<0.001), or an ACSC hospitalization (-0.069, p<0.001). Shorter appointment wait times were also associated with between 13 and 67 fewer all-cause ED, all-cause hospitalizations, or ACSC hospitalization visits per 1000 patients per quarter (p<0.050).

Patients' ability to get care during evenings, weekends, and holidays was associated with increases in the log-odds of having an ED visit (0.092, p<0.001), preventable ED visit (0.080, p=0.007), and hospitalization (0.030, p<0.001), and with a decrease in the log-odds of having an ACSC hospitalization (-0.057, p=0.003) in a given quarter. Additionally, patients' ability to get this after-hours care was associated with more ED visits (13.3 per 1000 patients per quarter, p=0.050), more preventable ED visits (50.8, p<0.001) and more hospitalizations (40.2, p<0.001), but fewer ACSC hospitalizations (-69.7, p<0.001).

A clinic's use of secure messaging was associated with increased odds of having all-cause or preventable ED visits, and more of these visits. Greater use of secure messaging was associated with an increase of 0.022 and 0.021 in the log-odds of having any ED visit (p<0.001) and a preventable ED visit (p=0.003) in a given quarter, respectively. Greater use of secure messaging was associated with 13.6 (p<0.001) and 26.0 (p<0.001) more ED visits and preventable ED visits per 1000 patients per quarter, respectively.

3.4 DISCUSSION

In this study, we estimated the extent to which improved access through the VHA's PCMH initiative—PACT—affected total and potentially preventable/avoidable ED and hospital use using a new instrumental variables approach. This study is the first to estimate individual effects of improved access to primary care on the use of high-cost and potentially avoidable health care service use and improves substantially on previous studies that do not adequately address the endogeneity inherent in access measures. Additionally, this study is the first to examine the extent to which 11 individual components of access to care are associated with patients' utilization.

We hypothesized that PACT's key access components—enhanced use of non-face-to-face visits, increased availability and use of same-day visits, use of an internet-based secure messaging portal,[120] and proactive outreach to patients by their care team—would reduce use of EDs and hospitals. We hypothesized that improved access would reduce unnecessary use of EDs for non-emergent or potentially preventable reasons and that patients could more readily receive care at their primary care clinic. Similarly, we hypothesized that improved access and contact with primary care providers would foster better management of chronic conditions and reduce exacerbations that could result in urgent ED use and hospital stays.

However, we found that improved access through PACT increased the likelihood of having an ED or potentially preventable ED visit in a quarter but had no effects on the total number of these ED visits. Among patients in low-access clinics (ATU), greater access led to an increase in the probability of having an ED visit but resulted in a reduction in the number of ED visits. Additionally, greater access had larger effects on ED use for patients living closer to VHA facilities. There were no effects of greater access on the probability of having or number of total or ACSC hospitalizations.

These findings challenge the literature that has found that access to primary care reduces ED visits and hospitalizations. Chiefly, our study's unique use of a multidimensional measure of access and instrumental variables may better represent and measure the effect of access on utilization than previous studies. But, additionally, there are several reasons why improved access might not have the intended effects. Improving patients' ability to access providers and care could induce health care use by increasing patients' engagement. For example, first, care team members may refer patients to EDs following changes in patient conditions identified during more routine visits or contact. A few studies suggest that healthcare provider referral is a substantial driver of non-urgent ED use, with about one-half of patients who presented to the ED during business hours being advised to do so by their primary care provider.[5,121,122] We also found that some measures of patients' ability to receive timely care, such as their ability to receive care after hours was associated with more use of EDs and/or hospitals.

Second, to the extent that enhanced access improves health care engagement, patients may require more use of outpatient and acute care services to care for "new" or exacerbated conditions. This may include conditions that have long been present in the patient but not addressed by VHA providers due to no or low-use of health care services. Indeed, findings from the Oregon Experiment found that increased access to primary care via Medicaid coverage led to increased diagnosis of some chronic conditions and an increase in preventable hospitalizations.[47,86,100] Older military veterans might be particularly susceptible to this mechanism. Studies have found that traits associated with military culture such as stoicism, toughness, and perseverance are related to poor physical and mental health.[43,44] Older male veterans, in particular, have been shown to decline specialists referrals, underreport presence and intensity of pain, and have undiagnosed conditions. Thus, by engaging these patients in their health care and supporting them with a patient-centered care team, we might expect to see increased utilization of services to help manage otherwise ignored or downplayed patient conditions.

Third, providing patients with additional modes to communicate with their providers and care team like secure messaging, enhances patient-provider contact and leads to increased utilization, via the two examples above. Previous literature has found that use of patient portals improves patient-provider communication, and that increased use of telephone visits and secure messaging portals increases the number of primary care office visits. [39,87] In this study, we also found that PACT's use of secure messaging was correlated with more all-cause and preventable ED visits.

Finally, we would not expect to see reductions in high-cost utilization attributable to improved access if more fundamental barriers to accessing care persisted. For example, in a national study, patients were more likely to visit the ED if they reported barriers to getting an appointment when they had availability, waiting too long in the doctor's office, or that they did not have transportation—components of access not directly targeted by PACT.[85] In our study, we found no effects attributable to improved access among patients that lived further away from VHA clinics and no differential effects between patients of different risk levels or different socioeconomic status (proxied by whether the patient was exempt from VHA copayments). This suggests that the primary care needs of the most vulnerable populations might not have been fully met.

3.4.1 *Limitations*

This study has several limitations. First, access was not measured until 2012, nearly two years after PACT was first implemented. Notably, primary care transformation takes time and by 2012, clinics were still transitioning into PACT. However, the two-year lag misses variation in early PACT implementation.[123] Additionally, although our access composite has been validated in prior research, it should be noted that elements of this measure rely on patient and clinic self-report which are subject to response, recall, and social desirability biases. Second, one of our IVs captures wage growth among a broad occupational group—"healthcare practitioners and technical occupations"—that include non-primary care providers, limiting the IVs power to measure labor-market competitiveness specific to primary care and PACT. Third, the sensitivity of the NYU ED Algorithm to changes in utilization may be insufficient for assessing the effects of interventions like PACT.[91,92] Additionally, the algorithm's use of principal diagnosis codes ignores other diagnoses requiring emergency care or hospital admission.[91,93] Fourth, restricting our sample to older veterans allowed for more comprehensive measurement of service utilization, but limits generalizability to previous VHA studies, younger populations, and female patients.[35] Though, prior research has demonstrated substantial overlap in characteristics between VHA enrollees and Medicare FFS beneficiaries.[94] Fifth, patients may have non-VHA care providers that could affect utilization decisions and dilute PACT effects. However, more than 90% of VHA enrollees age 65+ are dually enrolled in Medicare,[124] and after the exclusion of patients enrolled in Medicare Advantage, we would anticipate this outside use to be minimal.

3.4.2 *Conclusions*

Our study examined the implementation of one of the nation's largest PCMH models to better quantify how improving access to primary care influences ED and hospital use among older U.S. adults. This study improves upon earlier studies by accounting for endogeneity in access studies by applying an IV approach to estimate the causal effect of improved primary care access on patient outcomes. In recognizing that timely access to primary care is critical to improving patients' health and quality of care, improving access to care has been a key institutional priority for the VHA, AHRQ, and the U.S. Department of Health and Human Services more broadly.[14–16] While our findings suggest that improved access through PACT mostly increased the likelihood of ED and hospital use, researchers should continue to advance our understanding of the benefits and potential consequences of improving access and to understand whether unintended increases in utilization, as seen in our study, in fact represent improvements in quality of care.

3.5 APPENDIX

3.5.1 *Appendix tables*

Table 3.2. Appendix Table: Composition of the PACT Implementation Progress Index

Access Domain

Short name	**CAHPS-PCMH questions** **In the last 12 months…**	**Values**
Care Received	Among patients who phoned their providers office, when patient phoned provider's office to get an appointment for care needed right away, how often patient got an appointment as soon as needed.	1 = Never 2 = Sometimes 3 = Usually 4 = Always
Care Wait	Among patients who phoned their providers office, number of days patient usually waited for an appointment for care needed right away.	1 = Same day 2 = 1 day 3 = 2 to 3 days 4 = 4 to 7 days 5 = More than 7 days
Care After Hours Received	How often patient was able to get care from the provider's office during evenings, weekends, of holidays, among patients needing this type of care.	1 = Never 2 = Sometimes 3 = Usually 4 = Always
Checkup Received	Among patients who made an appointment, when patient made an appointment for check-up or routine care, how often patient got an appointment as soon as needed.	1 = Never 2= Sometimes 3 = Usually 4 = Always
Question Office Hours Answer	Among patients who phoned their provider's office, when patient phoned provider's office during regular off hours, how often patient got an answer to a medical question that same day.	1 = Never 2= Sometimes 3 = Usually 4 = Always
Question After Hours Answer	Among patients who phoned their provider's office after regular office hours, how often patient got an answer to a medical question as soon as needed.	1 = Never 2= Sometimes 3 = Usually 4 = Always
Appointment Wait Time	How often patient saw the provider within 15 minutes of appointment time.	1 = Never 2= Sometimes 3 = Usually 4 = Always
	Administrative data	**Values**
Same-day Appointment	Clinic access - Same day access	Proportion of total primary care appointments, 0-1
Phone Visit	Use of non-face-to-face modalities – Telephone clinics	Proportion of total primary care encounters, 0-1

Group Visit	Use of non-face-to-face modalities – Group visits	Proportion of total primary care encounters, 0-1
Secure Messaging	Electronic access – Secure messaging, % use	Proportion of patients who either sent or received a message in the past year, 0-1

Notes: CAHPS-PCMH questions were administered to selected patients annually. Administrative data come from the Corporate Data Warehouse.

Table 3.3. Appendix Table: Relationship between the instrumental variables and clinic-level access

	Coef (SE)	p-value
IVs: Relative wage growth of		
Healthcare practitioners and technical occupations	-3.4	0.000
Medical assistants	-1.6	0.000
F-test statistic	1195	0.000

Notes: All models controlled for the same patient and local area characteristics included in the analytic models.
Coef = coefficient; SE = standard error

Table 3.4. Appendix Table: Relationship between the instrumental variables and outcomes

	Total ED visits				Preventable ED visits				Total hospitalizations				ACSC hospitalizations			
	Number (count outcome)		Probability (binary)		Number		Probability		Number		Probability		Number		Probability	
	Coef (SE)	p-value	Coef (SE)	p-value	Coef (SE)	p-value	Coef (SE)	p-value	Coef (SE)	p-value	Coef (SE)	p-value	Coef (SE)	p-value	Coef (SE)	p-value
IVs: Relative wage growth of																
Healthcare practitioners and technical occupations	0.005 (0.048)	0.913	-0.226 (0.149)	0.129	0.003 (0.020)	0.862	0.007 (0.170)	0.969	0.020 (0.017)	0.240	0.070 (0.200)	0.728	-0.001 (0.008)	0.865	0.021 (0.467)	0.963
Medical assistants	0.024 (0.042)	0.569	-0.144 (0.128)	0.262	0.011 (0.017)	0.534	-0.169 (0.146)	0.246	-0.004 (0.015)	0.773	-0.136 (0.171)	0.428	-0.003 (0.007)	0.694	-0.340 (0.383)	0.374
F-test statistic	0.17	0.843	3.66	0.160	0.21	0.809	1.34	0.511	0.73	0.483	0.73	0.694	0.09	0.910	0.79	0.674

Notes: All models controlled for the same patient and local area characteristics included in the analytic models.
Coef = coefficient; SE = standard error; ED = emergency department; ACSC = ambulatory care-sensitive condition

Table 3.5. Appendix Table: Test for overidentifying restrictions

Outcome	Chi-sq	P-value
Count outcomes (number of visits per quarter)		
ED visits	0.196	0.658
Preventable ED visits	0.211	0.646
Hospitalizations	0.636	0.425
ACSC hospitalizations	0.047	0.828
Binary indicator for any visit in the quarter		
ED visits	0.054	0.817
Preventable ED visits	0.921	0.337
Hospitalizations	0.580	0.446
ACSC hospitalizations	0.303	0.582

Notes: The null hypothesis is that the multiple instruments are valid and not endogenous. All models controlled for the same patient and local area characteristics included in the analytic models.
ED = emergency department; ACSC = ambulatory care-sensitive condition

Table 3.6. Appendix Table: Regression-adjusted effect of access components on outcomes (per 1000 patients per quarter)

	Total ED visits				Preventable ED visits				Total Hospitalizations				ACSC Hospitalizations			
Access component	**Coef.**	**Std. Err.**	**P**	**95% CI**	**Coef.**	**Std. Err.**	**P**	**95% CI**	**Coef.**	**Std. Err.**	**P**	**95% CI**	**Coef.**	**Std. Err.**	**P**	**95% CI**
Appointment Wait Time	-13.0	6.6	0.049	(-26.0, 0.0)	-2.1	7.8	0.789	(-17.4, 13.2)	-64.2	8.1	0.000	(-80.1, -48.2)	-67.4	18.8	0.000	(-104.2, -30.7)
Care After Hours Received	13.3	6.8	0.050	(0.0, 26.5)	50.8	7.9	0.000	(35.3, 66.3)	40.2	8.1	0.000	(24.4, 56.1)	-69.7	19.1	0.000	(-107.1, -32.2)
Care Received	-34.0	13.6	0.013	(-60.7, -7.2)	-6.6	15.9	0.678	(-37.8, 24.6)	-54.2	16.5	0.001	(-86.4, -21.9)	-21.8	37.7	0.563	(-95.7, 52.1)
Care Wait	0.0	10.7	0.998	(-21.0, 21.0)	34.3	12.7	0.007	(9.5, 59.2)	-10.8	12.9	0.405	(-36.1, 14.6)	-28.8	30.3	0.342	(-88.2, 30.6)
Checkup Received	3.8	11.4	0.736	(-18.5, 26.1)	-13.4	13.1	0.307	(-39.1, 12.3)	37.2	13.8	0.007	(10.2, 64.2)	42.7	31.9	0.180	(-19.8, 105.2)
Group Visit	11.5	2.0	0.000	(7.5, 15.5)	10.7	2.4	0.000	(5.9, 15.4)	4.1	2.6	0.113	(-1.0, 9.2)	-1.8	6.0	0.768	(-13.6, 10.0)
Question After Hours Answer	7.7	8.0	0.334	(-7.9, 23.4)	9.5	9.3	0.309	(-8.8, 27.8)	3.9	9.6	0.686	(-14.9, 22.6)	-15.3	22.1	0.488	(-58.6, 28.0)
Question Office Hours Answer	18.7	10.1	0.066	(-1.2, 38.5)	18.1	11.8	0.125	(-5.0, 41.2)	40.2	12.2	0.001	(16.2, 64.1)	6.8	27.9	0.808	(-47.9, 61.5)
Same-day Appointment	0.0	3.8	0.996	(-7.5, 7.5)	-4.9	4.5	0.281	(-13.7, 4.0)	4.1	4.6	0.378	(-5.0, 13.2)	-9.2	11.4	0.419	(-31.4, 13.1)
Secure Messaging	13.6	2.3	0.000	(9.0, 18.2)	26.0	2.7	0.000	(20.7, 31.4)	-3.7	3.0	0.212	(-9.6, 2.1)	3.5	7.7	0.653	(-11.6, 18.6)
Phone Visit	-14.6	4.8	0.002	(-24.0, -5.3)	-12.3	5.6	0.027	(-23.2, -1.4)	2.3	5.7	0.686	(-8.9, 13.6)	-1.6	14.0	0.910	(-29.0, 25.9)

Notes: The 11 access components were modeled jointly. See Appendix Table 3.2 for a description of each of the access components.
ED = emergency department; ACSC = ambulatory care-sensitive condition; Std.Err. = standard error; CI = confidence interval; P = p-value on a two-sided t-test

Table 3.7. Appendix Table: Regression-adjusted effect of access components on likelihood of having an ED or hospital visit in a given quarter

	Total ED visits				Preventable ED visits				Hospitalizations				ACSC Hospitalizations			
Access component	**Coef.**	**Std. Err.**	**P**	**95% CI**	**Coef.**	**Std. Err.**	**P**	**95% CI**	**Coef.**	**Std. Err.**	**P**	**95% CI**	**Coef.**	**Std. Err.**	**P**	**95% CI**
Appointment Wait Time	-0.034	0.006	0.000	(-0.046, -0.022)	-0.017	0.007	0.017	(-0.031, -0.003)	-0.051	0.008	0.000	(-0.067, -0.035)	-0.069	0.019	0.000	(-0.105, -0.032)
Care After Hours Received	0.092	0.006	0.000	(0.080, 0.104)	0.080	0.007	0.000	(0.066, 0.094)	0.030	0.008	0.000	(0.014, 0.046)	-0.057	0.019	0.003	(-0.094, -0.020)
Care Received	-0.015	0.013	0.228	(-0.040, 0.010)	-0.002	0.014	0.909	(-0.030, 0.026)	-0.062	0.017	0.000	(-0.094, -0.029)	-0.030	0.038	0.427	(-0.104, 0.044)
Care Wait	0.045	0.010	0.000	(0.026, 0.065)	0.059	0.011	0.000	(0.037, 0.081)	-0.016	0.013	0.229	(-0.041, 0.010)	-0.052	0.030	0.087	(-0.111, 0.008)
Checkup Received	0.001	0.010	0.930	(-0.020, 0.021)	-0.012	0.012	0.315	(-0.035, 0.011)	0.041	0.014	0.003	(0.014, 0.068)	0.031	0.031	0.322	(-0.031, 0.093)
Group Visit	0.014	0.002	0.000	(0.011, 0.018)	0.011	0.002	0.000	(0.007, 0.016)	0.003	0.003	0.224	(-0.002, 0.008)	-0.001	0.006	0.802	(-0.013, 0.010)
Question After Hours Answer	-0.001	0.007	0.945	(-0.015, 0.014)	0.004	0.008	0.633	(-0.012, 0.020)	0.000	0.010	0.959	(-0.019, 0.018)	-0.023	0.022	0.295	(-0.066, 0.020)
Question Office Hours Answer	0.017	0.009	0.070	(-0.001, 0.036)	0.020	0.011	0.061	(-0.001, 0.041)	0.039	0.012	0.002	(0.015, 0.064)	0.012	0.028	0.663	(-0.043, 0.067)
Same-day Appointment	0.000	0.004	0.966	(-0.007, 0.007)	-0.001	0.004	0.723	(-0.009, 0.006)	0.007	0.005	0.163	(-0.003, 0.016)	-0.012	0.011	0.268	(-0.034, 0.010)
Secure Messaging	0.022	0.002	0.000	(0.017, 0.026)	0.021	0.003	0.000	(0.016, 0.026)	-0.003	0.003	0.362	(-0.009, 0.003)	0.008	0.008	0.301	(-0.007, 0.023)
Phone Visit	0.008	0.004	0.081	(-0.001, 0.016)	0.006	0.005	0.237	(-0.004, 0.016)	-0.003	0.006	0.575	(-0.015, 0.008)	-0.013	0.014	0.361	(-0.040, 0.014)

Notes: The 11 access components were modeled jointly. The coefficient represents the change in the log-odds of having a visit in a given quarter. See Appendix Table 3.2 for a description of each of the access components.

ED = emergency department; ACSC = ambulatory care-sensitive condition; Std.Err. = standard error; CI = confidence interval; P = p-value on a two-sided t-test

3.5.2 *Appendix figures*

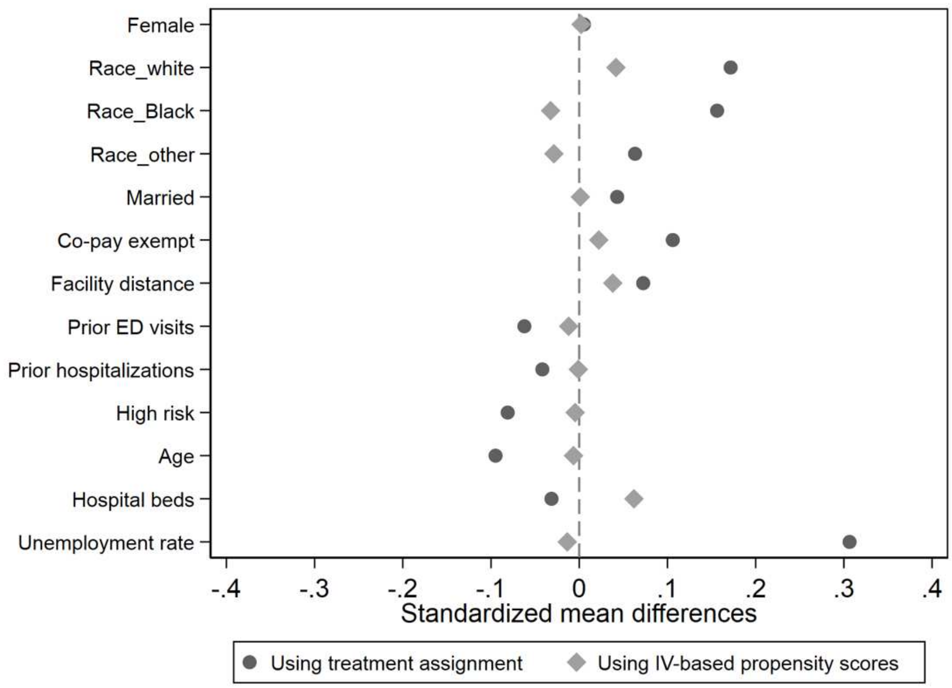

Figure 3.3. Appendix Figure: Covariate imbalance across treatment groups and the instrumental variable-based propensity score

Note: This figure plots the standardized mean differences between high-access and low-access groups based on (1) the treatment assignment (whether the clinic-level access score of the patient was considered to indicate high- or low-access) and (2) the patients' propensity scores for being in the high-access clinic based on the instrumental variables. The IVs provide better balance across the covariates.

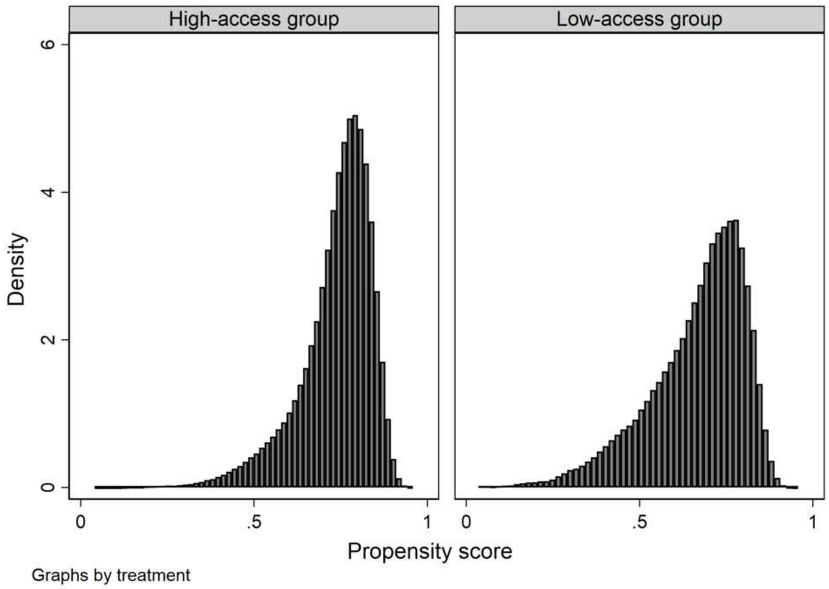

Figure 3.4. Appendix Figure: The support of the IV-based predicted propensity score by treatment group

Note: This figure plots the values of the IV-based propensity score where there is overlap among the two treatment groups, meaning that individuals in both treatment groups have propensity scores within the minimum and maximum values. This is referred to as the support, and the analysis is restricted to individuals within the support.

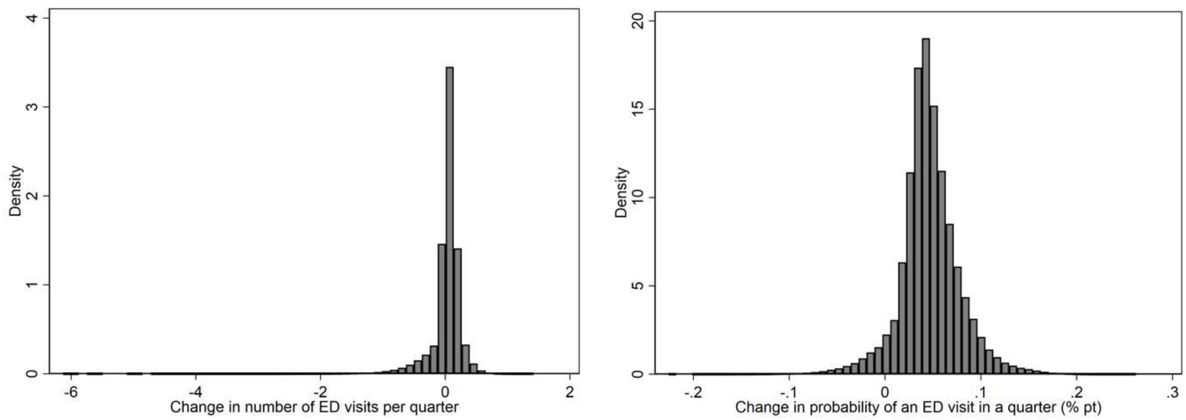

Figure 3.5. Appendix Figure: Distribution of individualized effect of improved clinic-level access on number of ED visits per quarter (left) and probability of having an ED visit in a quarter (right)

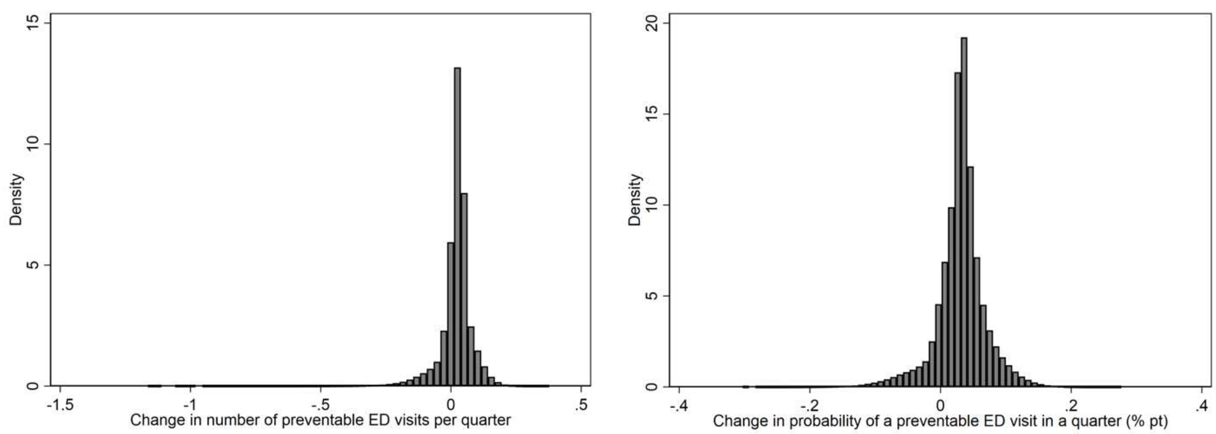

Figure 3.6. Appendix Figure: Distribution of individualized effect of improved clinic-level access on number of potentially preventable ED visits per quarter (left) and probability of having a preventable ED visit in a quarter (right)

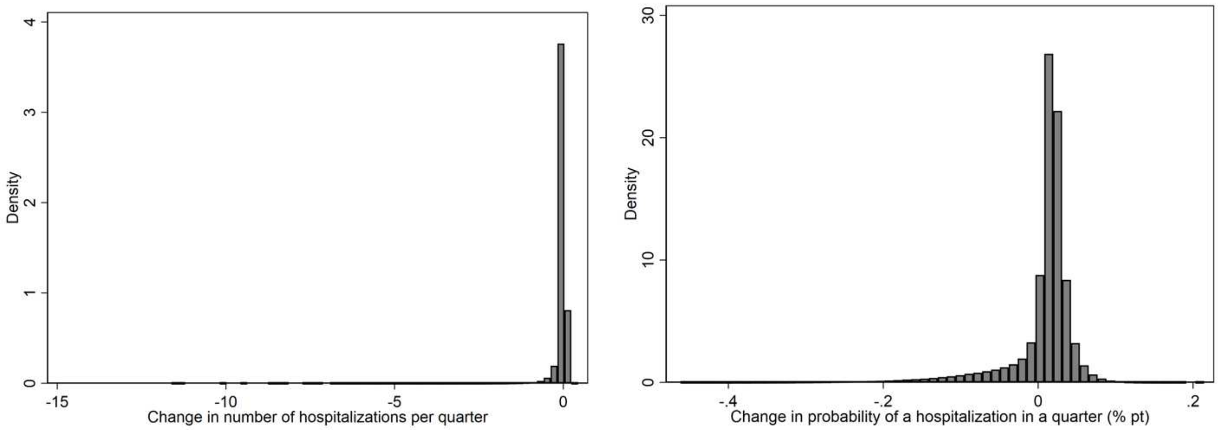

Figure 3.7. Appendix Figure: Distribution of individualized effect of improved clinic-level access on number of hospitalizations per quarter (left) and probability of having a hospitalization in a quarter (right)

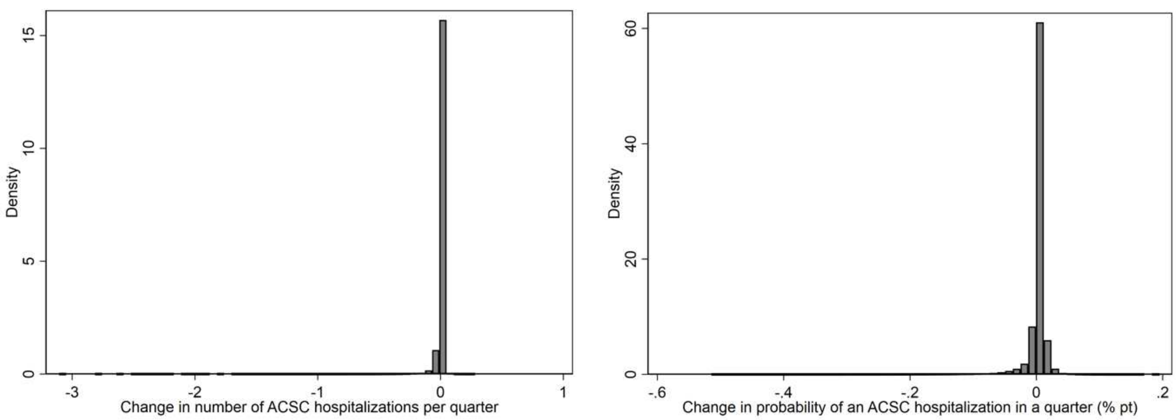

Figure 3.8. Appendix Figure: Distribution of individualized effect of improved clinic-level access on number of ACSC hospitalizations per quarter (left) and probability of having an ACSC hospitalization in a quarter (right)

Chapter 4. INTENSIVE CARE MANAGEMENT FOR HIGH-RISK VETERANS IN A PATIENT-CENTERED MEDICAL HOME—DO SOME VETERANS BENEFIT MORE THAN OTHERS?

4.1 INTRODUCTION

High-risk patients are older and have a high prevalence of chronic medical conditions and mental health disorders, and functional limitations.[125,126] To manage their multiple conditions, high-risk patients usually receive care from multiple providers, ranging from primary care providers and specialty physicians to social workers, pharmacists, and physical therapists.[126] Indeed, this small group of high-risk patients, representing as little as 5% of all patients, can account for over half of health care costs in the U.S.[127] Among these high-risk patients, more than 40% of their health care expenses are for hospitalizations.

To better meet the care needs and reduce utilization of patients at high risk for hospitalization, health care systems have been testing intensive management programs that provide a higher intensity of care and a broader range of services in the outpatient setting.[126,128] Intensive management programs utilize interdisciplinary care teams to coordinate patient care, and provide care management, mental health, and social services to reduce hospitalizations. However, the evidence that intensive management programs reduce acute care utilization is mixed.[126] A systematic review of 18 primary care intensive management interventions concluded that there was only "moderate- to low-strength" evidence that some programs were associated with fewer hospitalizations and found little impact on emergency department (ED) visits.[126]

One key limitation of previous work is that the average effects may mask the heterogenous effects that intensive management programs have on specific populations. Although the target populations for these programs are at high risk for hospitalization, these patients are heterogenous across a variety of characteristics that differentially affect their health care needs and service use, such as travel distances and disabilities,[39,40] age and gender,[43,44] race,[41,42] risk-status,[45] marital status,[46] and income.[47] Previous studies also fail to account for social factors that compound the complexity of patients' health conditions.[129] Markers of social instability, such as the number of times a patient changes their residence and history of hospital discharge against medical advice (AMA), have been strongly associated with 30-day hospital readmissions, and are predictive of patients' high-risk status.[48,49] Housing instability and homelessness have also been linked to greater hospitalizations and additional barriers to accessing care.[50,51] To better understand the effect of care improvement programs like intensive management, we must look beyond the average effects and understand how demographic and social characteristics may differentially affect patients' outcomes.

In this study, we examined whether the primary care intensive management program within the Veterans Health Administration (VHA) differentially affected ED visits and hospitalizations across patient subgroups. The intensive management program was launched as a randomized clinical quality improvement trial in five sites in 2014 and sought to improve outcomes for patients at high risk for hospitalization. Earlier evidence suggests that intensive management did not affect VHA hospitalizations and ED visits on average, across all participants.[53,130,131] We expand upon earlier evidence in three ways: (1) applied analytical methods designed to identify heterogenous effects across subgroups defined by combinations of characteristics and include measures of social instability, (2) measured utilization within and outside of the VHA via Medicare claims and estimate the probability of ED and hospital use in addition to count outcomes, and (3) used a larger study sample, about 60% more patients.

This study provides a unique opportunity to discern the characteristics of patients most likely to benefit from intensive primary care management. Findings from this study will help health care systems and other providers identify and target patients for future care augmenting interventions. Understanding the types of patients most likely to be responsive to these types of interventions has become more critical as we shift toward a more value-based payment environment that holds providers accountable for patients' costs and service use.

4.2 METHODS

4.2.1 *Setting*

The Veterans Health Administration (VHA) is one of the largest integrated health care systems in the U.S. with more than 8 million enrollees.[23] Veterans served by the VHA have more chronic physical and mental illness and are more socioeconomically vulnerable than the general population.[25,29,30] Notably, VHA enrollees are at higher risk for homelessness compared to the general population, and the VHA is the largest provider of health care services for homeless veterans.[31]

Primary care is the foundation of VHA health care and is generally the VHA-enrolled veterans' first point of contact with the health system. Primary care in the VHA is delivered via the Patient Aligned Care Team (PACT) model—a patient-centered medical home focused on delivering team-based, accessible, and comprehensive primary care to all patients.[24,25,33,105]

In 2014, the VHA launched a primary care intensive management program, the PACT Intensive Management (PIM) demonstration, as a randomized quality improvement trial (Clinical Trial NCT03100526). Through PIM, the VHA sought to test whether augmenting usual care provided via the VHA's PCMH model with intensive management would lower utilization and costs for patients at the highest risk for hospitalization.[53] Five sites in Georgia, Ohio, Wisconsin, North Carolina, and California were selected among 39 applicants to serve as the demonstration sites. Sites were selected based on 1) geographic diversity; 2) an interdisciplinary team that included a mental health provider or social worker; and 3) planned provision of services that would increase veteran access to healthcare, including home visits and telehealth. Each site developed their intensive management program specific to their patients' needs, local staffing, and local priorities and context. However, all programs provided comprehensive patient assessment, interdisciplinary team care, transitional care management, pharmaceutical care, care management, home visits and coaching.[53]

4.2.2 *Study design*

We conducted a post-hoc analysis of the PIM program using secondary data routinely collected by VHA. We applied an intent-to-treat analysis using difference-in-differences regression methods to estimate the heterogenous effect of PIM on patients' hospitalization and ED use. We compared one-year pre-post differences between patients randomized to PIM and usual care.

4.2.3 *Data*

Data for this study come from the VHA Corporate Data Warehouse (CDW), a national repository that contains administrative and clinical data for all inpatient and outpatient encounters within the VHA. CDW data were linked to Medicare fee-for-service (FFS) claims, to measure utilization outside of the VHA. We used data from the Veterans Administration Site Tracking System (VAST) to obtain information on the physical locations of VHA facilities. Finally, we used data from the Health Resources & Services Administration's Area Health Resources File to obtain characteristics of the patients' residential county.

4.2.4 *Study sample*

We identified 3,794 high-risk primary care patients who received care from one of the five facilities selected as a PIM demonstration site and participated in the trial: 1,904 patients who were randomized to receive PIM (i.e., treatment group) and 1,890 randomized to continue receiving usual care (i.e., control group). The patients were enrolled in the trial between August 2014 and March 2017.

Patient eligibility for the trial was determined using national administrative data. Eligible patients met the following criteria: had a risk score for 90-day hospitalization in the 90th percentile, had a recent hospitalization or ED visit, and were not in another intensive care management program or receiving hospice, palliative, or post-acute care.[53,130] The evaluation team randomly assigned eligible patients to intensive management or usual care in a 1:1 ratio by site and sex.[53] The duration of patients' enrollment in PIM varied, but most patients were enrolled for more than one year. The evaluation study was designed as an intent-to-treat analysis and examined all patients who met these overarching exclusion criteria. The full protocol is detailed in Chang et al. 2018.[130]

Among the 3,794 participants, we excluded 261 patients (127 patients that were randomized to PIM and 141 from the usual care group, standardized difference=0.07) from the primary analysis who died during the two-year study period and another 24 patients (11 from the PIM group and 13 from the usual care group) due to missing data. Finally, we excluded 17 patients because we could not uniquely identify them in the claims data. Our final sample included 3,492 patients: 1,761 patients randomized to the PIM intervention (inclusive of patients that were ultimately deemed inappropriate for intensive management services) and 1,731 randomized to usual care.

4.2.5 *Measures*

Outcome measures. We estimated the effect of PIM on all-cause ED visits and hospitalizations. Unlike previous PIM studies,[53,131] we included utilization within the VHA and outside of the VHA via Medicare claims for eligible patients.

- *ED visits* were identified in VHA administrative data and Medicare outpatient claims. Following Liu et al. 2018, we identified ED visits using the 15 Healthcare Common Procedure Coding System (HCPCS) codes associated with the Berenson-Eggers Type of Service (BETOS) code M3-emergency room visit, and VHA encounter stop codes (for ED visits in the VHA) and place of service codes (for ED visits outside of the VHA) that indicate the type of facility that provided the care.[61]
- *Hospitalizations* were identified in VHA administrative data and Medicare inpatient claims. Measures included *all* hospitalizations including but not limited to medical, surgical, psychiatric hospitalizations, but excludes transfers within a hospital or from another hospital.

For each of the two types of service use, we measured the outcomes in the respective 1-year periods pre-and post-randomization. Outcomes included: 1) a count measure denoting the number of visits in the four quarters before and after their randomization, and 2) a binary indicator for whether the patient had any visits during that time.

Covariates. We constructed several measures of patient and local area characteristics that could affect service utilization as posited by Anderson's model of health service use.[113] We measured each patient's age, gender, race (white, Black, all other races), whether the patient was married, and whether they were eligible for copayment-exempt VHA care using VHA administrative data. Copay-exemption is a measure of patients' income and/or disability status. Veterans may qualify for copay-exempt VHA care if they have income below a means-tested threshold or are sufficiently disabled due to their military service. Additionally, we included three measures of social instability as tracked in VHA administrative data: (1) whether the patient experienced homelessness, (2) whether the patient had multiple residence ZIP codes in the pre-period, and (3) whether the patient had any hospital discharges against medical advice (AMA).[132,133] Hospital discharges AMA were identified using discharge type codes in VHA inpatient records. Homelessness was identified using a previously validated algorithm that uses VHA clinic stop codes and ICD-9 and ICD-10 diagnosis codes (v60.0 and z59.0, respectively) from VHA outpatient claims.[31] We calculated the distance from the patients' residence ZIP code to the ZIP code of the nearest VHA clinic using the Haversine-based geodesic distance.[67]

Using VHA inpatient and outpatient administrative data, we measured patient comorbidity burden using the Gagne comorbidity score—a weighted composite of 20 conditions from the Charlson and Elixhauser comorbidity measures.[60] The Gagne measure has been validated within a Medicare population. We first identified patients' conditions from hospital discharges and outpatient services using the ICD-9 and ICD-10 diagnosis codes on the medical claims following Quan et al. 2005.[114] We flagged a patient as having a condition if they had any claims with the associated ICD-9 or ICD-10 codes in the four-quarter period (based on the data of the outpatient visit or the discharge date for inpatient claims). Condition indicators were then weighted according to the Gagne measure specifications.[60] Condition weights were based on predicting 1-year mortality and ranged from -1 for Hypertension and HIV/AIDs to 5 for Metastatic cancer. Gagne scores could range from -2 to 24 with higher scores indicating greater comorbidity burden.

Local area covariates included the unemployment rate in patients' residence county to account for changes in outcomes influenced by economic conditions, and the total number of hospital beds in the county to control for variations in the health care services environment.[30]

4.2.6 *Statistical analysis*

We first estimated the effect of PIM on each of the outcomes using standard regression methods and a differences-in-differences (DID) framework to understand the average effect of PIM and to help put the heterogenous effects in context with the average patient. We then estimated the heterogenous treatment effects of PIM using the machine learning method of model-based recursive partitioning.[134,135]

All models in this study compared pre-post differences in outcomes between PIM and usual care groups. The pre-period was measured using the four quarters immediately preceding the quarter in which the patient was randomized to PIM or usual care. The four-quarter post-period measured outcomes in the four quarters immediately following the randomization quarter. We did not include observations from the quarter of randomization to ensure we clearly delineated utilization that overlapped exposure to PIM.

To estimate the average effect of PIM, we modeled the number of ED visits and hospitalizations using negative binomial regressions. Correspondingly, we modeled two binary outcomes denoting any ED visits or any hospitalizations using logistic regressions. Each regression model included three components to estimate the effect of PIM: (1) a binary variable indicating whether the patient was randomized to PIM, (2) a binary indicator denoting the one-year follow-up (i.e., post) period, and (3) and interaction between post-period and PIM indicators. All models included variables adjusting for baseline patient and local area characteristics measured during the pre-period. The only time varying measures included were the four outcome measures.

To estimate changes in outcomes attributable to PIM, we calculated differences in the predicted visits or probabilities holding all covariates at their sample mean using the method of recycled predictions.[69] Predicted utilization was calculated for the pre- and post-period separately for the PIM and usual care groups. We then calculated the difference in the pre-post change in predicted utilization between the two groups. This difference-in-difference quantity is the estimated effect of PIM. All model parameter estimates used heteroskedastic robust standard errors, and the delta method to calculate standard errors for the predictions.[70]

Modeling the heterogenous effects of PIM. We estimated the heterogeneous treatment effects of PIM using model-based recursive partitioning.[134,135] This machine learning method employs a data-driven approach to test whether parameter estimates from a regression model meaningfully differ across levels of covariates. The recursive partitioning approach has the flexibility to test for differences across individual (e.g., Black race) or combinations of covariates (e.g., homeless + Black race + married).

The algorithm begins by estimating the DID model used for the regression analysis described previously across all observations and testing whether the DID parameters meaningfully differ across any of the pre-specified partitioning variables. If meaningful differences exist, the algorithm determines the partitioning variable where the most substantial variation exists and subsamples across levels of this variable. The regression model is then estimated across each subsample, and the assessment of DID parameter differences and further subsampling is repeated. The recursive partitioning process concludes when the DID parameter is sufficiently similar across all split subsamples.

Similar to the regression analysis used to estimate the main effects, we modeled the two binary outcomes using logistic regressions. We modeled the two count outcomes using a quasi-

Poisson specification to account for over dispersion in the two utilization measures. Negative binomial specification was not available in the statistical package.

We allowed the tree-based model to be split on all of our regression covariates: age, sex, race, marital status, distance to nearest VHA facility, VHA copay exemption, Gagne score, history of AMA discharge, homelessness, multiple residence ZIP codes, number of hospital beds in residence county, and unemployment rate. To assess the stability of tree splits within recursive partitioning models, we applied the "stablelearner" package in R, which generated 1000 sets of parameter estimates via bootstrap sampling to assess the degree of certainty in splitting variables and the cut points.[136] Within this process, we calculated the percentage of bootstrap samples that split on each variable considered. A higher percentage reflects greater certainty in heterogenous effects across different levels of a splitting variable.

4.2.7 *Sensitivity analysis*

We conducted two sensitivity analyses to test the robustness of our findings to two potential censoring biases. First, we repeated the analysis excluding patients that were enrolled in Medicare Advantage at any point during the study period. These patients accounted for 14% of the study sample. We excluded these individuals because we do not have Medicare Advantage claims and therefore cannot capture their utilization outside of the VHA. Second, we repeated the analysis including the 261 (6%) patients that died during the post period to capture full utilization of all study participants.

For all analyses, we considered effects to be statistically significant at the 5% significance level. Statistical analyses were performed using Stata version 15.0 (Stata Corp., College Station, TX) and R version 4.0.2.[137] This study was granted exemption from review by the VA Puget Sound Healthcare System Institutional Review Board (IRB).

4.3 Results

4.3.1 *Descriptive statistics*

Our study included 1,761 patients randomized to participate in PIM and 1,731 patients randomized to continue receiving usual care. Patients in each group had similar characteristics during the baseline period (the year before randomization) with standardized differences less than 0.1 (Table 4.1). Patients were mostly male (89% of patients in each group), mean age was 62 years old (SD=12.7 for both groups), and about half were white. One-third of patients were married and about three-quarters lived within 10 miles to a VHA facility. Most patients (92% of PIM and 94% of usual care) were eligible for copayment exempt VHA care. Patients had an average Gagne comorbidity score of 1.7 (SD=2.0) and 1.8 (SD=2.1) for the PIM and usual care groups, respectively. The literature considers Gagne scores of 2 or greater to denote high-comorbidity burden.[28]

Table 4.1.Baseline characteristics of the patients randomized to PACT intensive management and usual care groups

	PIM	Usual care	Standardized difference
N	1761	1731	
Demographics			
Male, %	89.2	89.0	0.004
Age at enrollment (mean, sd)	62.5 (12.7)	62.3 (12.7)	-0.020
Race, %			
White	51.2	50.2	0.042
Black	45.4	47.0	
Other	3.4	2.8	
Married in the pre-period, %	33.2	31.5	0.036
Distance to closest VHA facility in pre-period, %			
<5 miles	60.1	57.3	0.070
5 to <10 miles	18.2	19.2	
10 to <20 miles	14.8	16.9	
20 or more miles	6.8	6.6	
Copayment exempt at all during the pre-period, %	91.7	93.5	0.072

Gagne score in pre-period (mean, sd)	1.7 (2.0)	1.8 (2.1)	0.050
Medicare Advantage participant, %	12.0	13.2	0.038
Social instability			
AMA discharge in the pre-period, %	1.4	0.9	0.047
Homeless at any time in the pre-period, %	11.1	12.0	0.028
Multiple zip codes in the pre-period, %	15.7	15.7	0.002
Characteristics of patients' residence area			
Number of hospital beds in patients' residence county per 1000 population (mean, sd)	3.3 (1.6)	3.3 (1.6)	-0.007
Unemployment rate in patients' residence county (mean, sd)	5.7 (1.4)	5.7 (1.3)	-0.024
Utilization			
Had an ED visit during the period, % (outcome)	86.3	87.6	0.038
Had a hospital stay, % (outcome)	45.8	46.0	0.003
Number of ED visits (mean, sd)	3.0 (3.4)	3.1 (3.5)	0.030
Number of hospitalizations (mean, sd)	0.8 (1.2)	0.8 (1.3)	0.002

PACT = Patient-Aligned Care Team (the Veteran Health Administrations primary care model); SD = standard deviation; AMA = hospital discharge against medical advice, ED = emergency department

For measures of social instability, few patients (less than 1.5%) in either group were discharged from a hospital stay against medical advice. About 12% of patients in either group were homeless, and 16% of patients in either group had more than one residence ZIP code during the year before randomization.

4.3.2 *Overall effect of PIM*

On average, PIM was not associated with changes in patients' utilization of EDs or hospitals one-year after enrollment. Utilization rates decreased for patients in both groups, but at similar rates (Figure 4.1). The regression analysis indicates that the three measures of social instability: homelessness, history of AMA discharge, and multiple residence ZIP codes; and Gagne comorbidity score consistently predicted greater ED and hospital use, all else equal (Appendix Table 4.3).

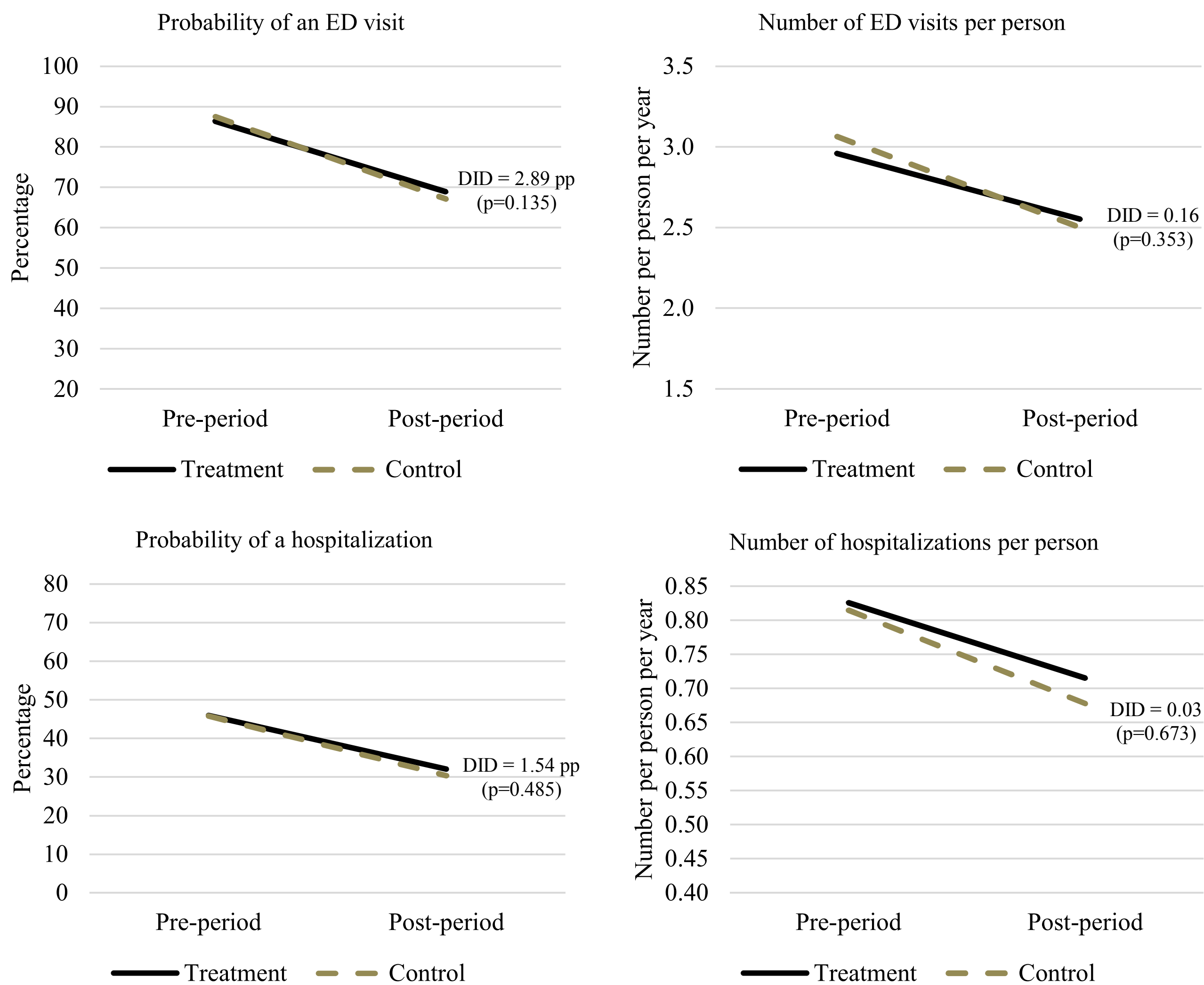

Figure 4.1. Estimated annualized probability and number of ED visits and hospitalizations in the pre- and post-period by group, and the difference-in-difference estimate

ED = emergency department; DID = difference-in-differences estimate; pp = percentage point

4.3.3 *Heterogeneous effects of PIM by patient characteristics*

In analyses of heterogeneous PIM effects, the tree-based recursive partitioning algorithm identified variation in parameter estimates by some demographic, socioeconomic, and social instability characteristics. However, within each distinct subgroup, the PIM effect was not statistically significant for any of the outcomes.

To illustrate the tree models, Figure 4.2 shows the regression tree modeling the effect of PIM on hospitalization count. Based on the branches, the algorithm determined that the best regression model estimating the effect of PIM on hospitalizations differs between individuals with a Gagne score > 2 (the right most branch) and those with a Gagne score ≤ 2. Likewise, proceeding down the tree to the left most branches, among individuals with a Gagne score ≤ 0 and no AMA discharges, PIM was associated with a 14% increase in the mean number of hospitalizations among individuals residing in a single ZIP code and a 30% decrease among individuals with multiple ZIP codes. However, the p-values for these estimates are large, p=0.545 and p=0.487 respectively, indicating that these effect sizes are not statistically significant. The trees for the remaining three outcomes are in Appendix Figures 4.3-4.5.

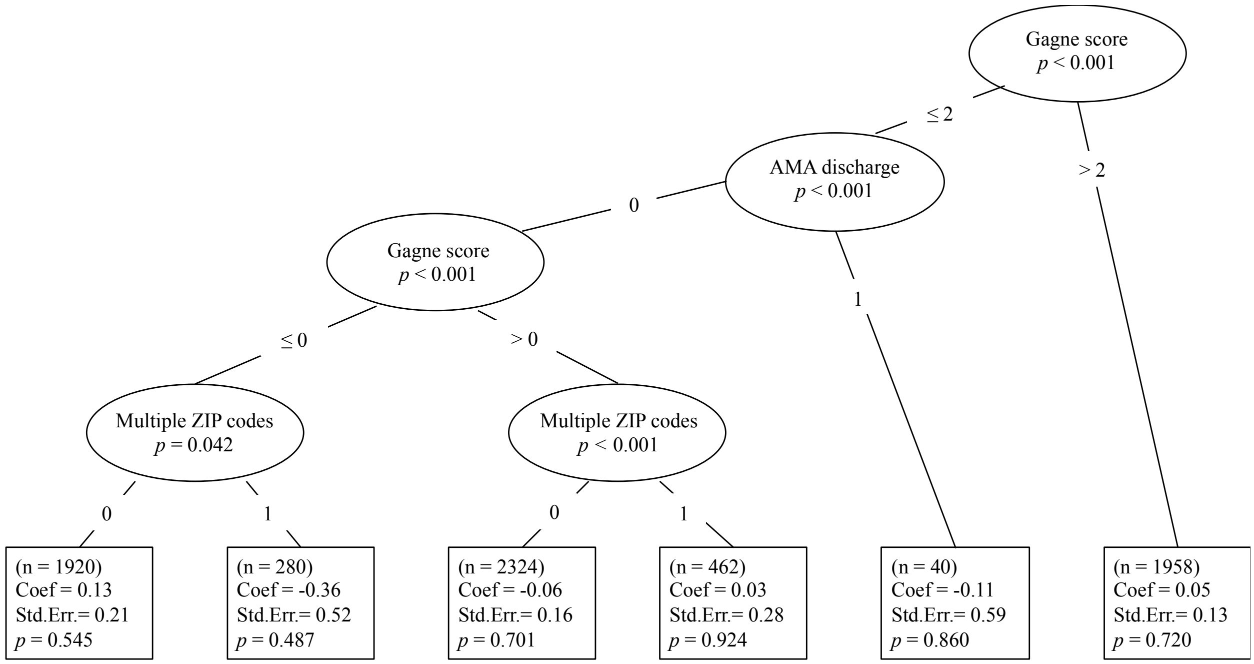

Figure 4.2. Regression tree modeling the heterogenous effect of PIM on the number of hospitalizations per patient in the year following randomization

Coef. = difference-in-difference estimate coefficient; Std. Err. = standard error; AMA = against medical advice

In tests of tree split stability, the recursive partitioning algorithm most frequently split on Gagne score, history of homelessness, and whether the patient had multiple residence ZIP codes during the year before enrollment. In 1,000 replicate bootstrap samples, the recursive partitioning algorithm split on Gagne score 100% of the time when modeling changes in the number of ED visits, number of hospitalizations and the probability of hospitalizations, and 78% of the time when modeling the probability of an ED visit (Table 4.2). History of homelessness was identified as a splitting variable 100% of the time when modeling number of ED visits, but less than 30% of replications for other outcomes. Multiple residence ZIP codes was a splitting variable 99% of the time when modeling number of ED visits, 87% of the time when modeling the probability of ED visit, but less than 30% of replications for hospitalization outcomes. The algorithm split less often on the other characteristics including gender, distance from nearest VHA facility, race, marital status, history of AMA discharge, exemption from copayments, age, and the two local area characteristics: number of hospital beds and unemployment rate.

Table 4.2. Tests of tree split stability: Percentage of 1000 replicate bootstrapped regression trees for which each characteristic is a splitting variable

	Models			
	Number of ED visits	Probability of ED visit	Number of hospitalizations	Probability of hospitalizations
Gagne score	100	78	100	100
History of homelessness	100	4	8	29
Multiple residence ZIP codes	99	87	9	25
Unemployment rate in patients' residence county	25	4	3	14
Female	21	1	0	0
Race	16	5	1	3
Age	13	6	1	4
Number of hospital beds in patients' residence county per 1000 population	1	7	0	3
Distance to closest VHA facility	1	2	0	1
Married	1	0	0	1
History of AMA discharge	0	0	1	0
Exempt for VHA copays	0	0	0	6

Notes: This table presents the percentage of times each characteristic was selected as a splitting variable among 1000 bootstrapped regression trees for each of the four outcomes. For example, Gagne score was selected in 1000 of 1000 (or 100% of) regression trees used to model the heterogenous effect of PIM on the number of ED visits and in 78% of the regression trees that modeled the heterogenous effect of PIM on the probability of an ED visit.

ED = emergency department; VHA = Veterans Health Administration; AMA = hospital discharge against medical advice; PIM = Patient-Aligned Care Team (PACT) intensive management.

4.3.4 *Sensitivity analyses*

Findings from the sensitivity analyses were comparable, suggesting no overall PIM effect and no effect of PIM within tree-based subgroups. Additionally, the tree algorithms continued to split on Gagne score, indicators of homelessness and whether the patient had multiple residence ZIP codes.

4.4 DISCUSSION

The literature on the effect of primary care intensive management programs has largely shown null effects.[126,129,130,138,139] We hypothesized that the average treatment effects estimated in previous studies were masking heterogeneous treatment effects among specific subpopulations. In this study, we estimated whether there were subgroups of high-risk patients that were more likely to benefit from VHA's primary care intensive management program. We used a data-driven approach rooted in machine learning to identify subgroups of high-risk patients that experienced heterogeneous treatment effects in ED and hospital use based on sociodemographic and social instability characteristics. This approach is more advantageous than conventional subgroup analyses (e.g., dividing patients serially by individual variables) that have lower statistical power.[140]

Earlier studies of utilization within the VHA found PIM was associated with reductions in nursing home days and increases in some outpatient care services including primary care visits and mental health services, but had no effect on ED use and hospitalizations one or two years after randomization.[53,131] Findings from this study, which expand the study sample and capture utilization outside of the VHA via Medicare claims, support these early findings. Like Yoon et al. 2018 and Chang et al. 2021, we found that reductions in ED use and hospitalizations over time were comparable between the two groups, indicating PIM had no net effect on patients' utilization one year after enrollment.[53,131] Additionally, in analyses of heterogeneous effects, the effect of PIM was not statistically significant across all distinct subgroups identified by the recursive partitioning algorithm. These subgroups included those characterized by medical complexity and housing instability: having multiple ZIP codes and homelessness.

There are several reasons that could explain why we did not observe effects attributable to PIM in any subgroup. First, only 44% of patients randomized to PIM received the full intervention (3 or more encounters with the intensive management team). More than one-third of treatment-group patients did not receive any aspects of the intervention because they were determined by the intensive management care team to be unlikely to benefit or could not be contacted. The remaining 18% were offered limited services or declined to participate after 1 or 2 encounters and resumed receiving usual care.[53] Patients that received the full intervention received an average of 14 intensive management encounters in the first 12 months compared to an average of 0.4 encounters for patients randomized to PIM that did not receive the full intervention. The large percentage of patients that were randomly assigned to receive PIM but did not participate indicates the complexity of systematically identifying the right patients for these types of programs. Future efforts are needed to better understand how to identify patients for these programs and to increase patients' engagement in intensive management.

Second, we must consider the context in which usual care was provided. Primary care in the VHA is provided through a PCMH that aims to provide patients with high-quality advanced primary care through enhanced access, care management, and coordination.[25] Through the PCMH, the VHA also sought to reduce hospitalizations and ED visits.[32] Therefore, it may be challenging to provide additional services beyond the PCMH and at a sufficient intensity to observe incremental changes in hospitalizations and ED use beyond usual-PCMH-based care. With patients randomized to the two study groups coming from the same five demonstration sites, we cannot discount the potential spillover effects from shared primary care sites. Additionally, intensive management programs like PIM focus on intensifying primary care services traditionally provided by PCMHs like care management and do not focus on addressing social determinants that affect utilization.[88]

The regression analysis and tree-based modeling indicated higher Gagne score (a measure of health risk status), homelessness, and having multiple residence ZIP codes in the year before enrollment were consistently associated with increased ED and hospital use. The relationship between these characteristics and health care utilization is well documented in the literature.[28,45,48–51] Our study's finding of no heterogenous PIM effects among patients described by these characteristics, however, suggests the limited ability of programs like these to influence the acute care use of vulnerable populations. The VHA has had some success in developing special-population primary care clinics that provided tailored, culturally competent access, care, and case management to high-risk and vulnerable populations including homeless veterans, women who were victims of military sexual trauma or PTSD, cognitively impaired older veterans, and veterans with severe mental illness.[89] These population-specific clinics were associated with improved disease management and increased use of primary care, but also with increased use of EDs and hospitalizations driven by a small number of patients in each group.

Finally, it may take more than one year for the effects of intensive management programs to manifest. Some literature suggests impacts develop two-years into intensive management. Although a two-year study of PIM continued to find no effects on acute care utilization.[126,131]

Although intensive management programs have been unable to reduce high cost utilization, patients' positive experiences with intensive management programs suggests the value in continuing to find ways to meet the health needs of high-risk patients.[129,141] In interviews with 51 patients participating in PIM, more than 70% reported extreme satisfaction with the program.[141] Patients emphasized improved relationships and communication with their providers as motivating positive changes to their health behaviors and perceived physical and mental health improvements. Patients experienced easier access to obtaining VA care and some felt more confident and empowered to manage their health because of their involvement in the program. In a separate study of the VHA's ImPACT program—an early, one-site, pilot intensive management program—96% of participating patients reported they would recommend the program to others.[129]

4.4.1 *Limitations*

This study has several limitations. First, the PIM demonstration was limited to 5 VHA primary care sites that were selected through a competitive process.[142] These sites were selected, in part, on the types of services they would provide participating patients and therefore might have more resources and experience providing advanced services than other primary care sites. Second, less than half of patients in the treatment group received the full intervention, restricting our ability to measure the effects of the intervention using the intent-to-treat design.[53] Third, we set out to identify subgroups of patients most likely to benefit from intensive management. However, several characteristics, including categories of social instability and race, described a small percentage of patients in some subgroups limiting our power to detect subgroup effects. Moreover, we are limited by the characteristics we can observe in administrative data. Although, we included measures of social instability absent from previous studies, we cannot overlook that heterogenous treatment effects might exist for characteristics not included in the study, like education.

4.4.2 *Conclusions*

Our study estimated the effect of augmenting PCMH primary care with an intensive management program for patients at high risk for hospitalization in the VHA. We sought to estimate the overall effect of the intensive management program and to identify subgroups of patients most likely to benefit from these programs using traditional demographic information and measures of social instability. We found that intensive management did not affect ED and hospital use on average or differentially for patients defined by demographic, economic, and social characteristics. More work is needed to discern the unique characteristics and needs of patients most likely to benefit from intensive management programs. This is particularly relevant as health care in the U.S. shifts toward a more value-based payment environment that holds providers accountable for patients' efficient use of services.

4.5 APPENDIX

4.5.1 *Appendix tables*

Table 4.3. Appendix Table: Regression output for the primary analysis

	Number of ED visits			Probability of ED visit			Number of hospitalizations			Probability of hospitalization		
	Coef.	**P-value**	**95% CI**	**Coef.**	**P-value**	**95% CI**	**Coef.**	**P-value**	**95% CI**	**Coef.**	**P-value**	**95% CI**
PIM enrollee (treatment)	-0.035	0.339	(-0.107, 0.037)	-0.102	0.313	(-0.299, 0.096)	0.013	0.782	(-0.079, 0.106)	0.005	0.941	(-0.131, 0.141)
One-year follow-up period (post period)	-0.203	0.000	(-0.292, -0.115)	-1.250	0.000	(-1.425, -1.075)	-0.184	0.003	(-0.304, -0.064)	-0.719	0.000	(-0.865, -0.574)
Treatment*Post	0.055	0.376	(-0.067, 0.177)	0.184	0.141	(-0.061, 0.428)	0.040	0.636	(-0.126, 0.206)	0.079	0.449	(-0.125, 0.283)
Female	0.059	0.260	(-0.044, 0.161)	0.157	0.127	(-0.045, 0.358)	-0.072	0.356	(-0.224, 0.080)	-0.053	0.552	(-0.228, 0.122)
Distance to nearest VHA facility (%)												
<5 miles												
5 to <10 miles	-0.086	0.039	(-0.168, -0.004)	-0.115	0.151	(-0.272, 0.042)	-0.073	0.206	(-0.186, 0.040)	-0.054	0.454	(-0.194, 0.087)
10 to <20 miles	-0.041	0.378	(-0.133, 0.051)	0.024	0.794	(-0.159, 0.208)	-0.073	0.267	(-0.202, 0.056)	-0.048	0.573	(-0.214, 0.118)
20 or more miles	-0.087	0.174	(-0.211, 0.038)	0.001	0.993	(-0.248, 0.250)	-0.190	0.047	(-0.377, -0.002)	-0.251	0.031	(-0.479, -0.023)
Race												
White												
Black	0.007	0.835	(-0.062, 0.077)	0.174	0.009	(0.044, 0.304)	-0.058	0.221	(-0.150, 0.035)	-0.060	0.305	(-0.174, 0.054)
Other	0.134	0.110	(-0.031, 0.300)	0.269	0.152	(-0.099, 0.636)	0.159	0.125	(-0.044, 0.362)	0.344	0.019	(0.056, 0.633)
Married	-0.025	0.446	(-0.090, 0.040)	0.046	0.484	(-0.083, 0.175)	-0.047	0.300	(-0.136, 0.042)	-0.042	0.470	(-0.156, 0.072)
History of AMA discharge at baseline	0.368	0.002	(0.139, 0.597)	0.765	0.037	(0.047, 1.482)	0.959	0.000	(0.748, 1.170)	1.699	0.000	(1.114, 2.285)
History of homelessness at baseline	0.402	0.000	(0.292, 0.511)	0.181	0.099	(-0.034, 0.397)	0.236	0.001	(0.093, 0.379)	0.212	0.017	(0.038, 0.386)
Exempt for VHA copays	0.177	0.001	(0.072, 0.282)	0.149	0.174	(-0.066, 0.364)	-0.048	0.550	(-0.206, 0.109)	-0.116	0.238	(-0.308, 0.076)
Multiple residence zip codes at baseline	0.365	0.000	(0.270, 0.459)	0.391	0.000	(0.203, 0.579)	0.296	0.000	(0.181, 0.411)	0.346	0.000	(0.197, 0.495)
Age	0.001	0.478	(-0.002, 0.003)	0.000	0.991	(-0.005, 0.005)	0.001	0.651	(-0.003, 0.004)	0.003	0.258	(-0.002, 0.007)
Gagne score	0.061	0.000	(0.046, 0.076)	0.075	0.000	(0.044, 0.107)	0.198	0.000	(0.179, 0.217)	0.246	0.000	(0.218, 0.273)
Number of hospital beds in patients' residence county per 1000 population	-0.003	0.796	(-0.023, 0.018)	0.023	0.297	(-0.020, 0.066)	0.026	0.072	(-0.002, 0.055)	0.019	0.339	(-0.020, 0.058)
Unemployment rate in patients' residence county	-0.049	0.000	(-0.073, -0.025)	-0.075	0.001	(-0.120, -0.030)	-0.005	0.764	(-0.038, 0.028)	-0.031	0.143	(-0.072, 0.010)
_Constant	0.955	0.000	(0.712, 1.199)	1.874	0.000	(1.361, 2.387)	-0.754	0.000	(-1.123, -0.386)	-0.548	0.019	(-1.006, -0.091)

ED = emergency department; Coef = Coefficient, parameter estimate; CI = Confidence interval; PIM = Patient-Aligned Care Team (PACT) Intensive Management ; VHA = Veterans Health Administration; AMA = Against medical advice.

4.5.2 *Appendix figures*

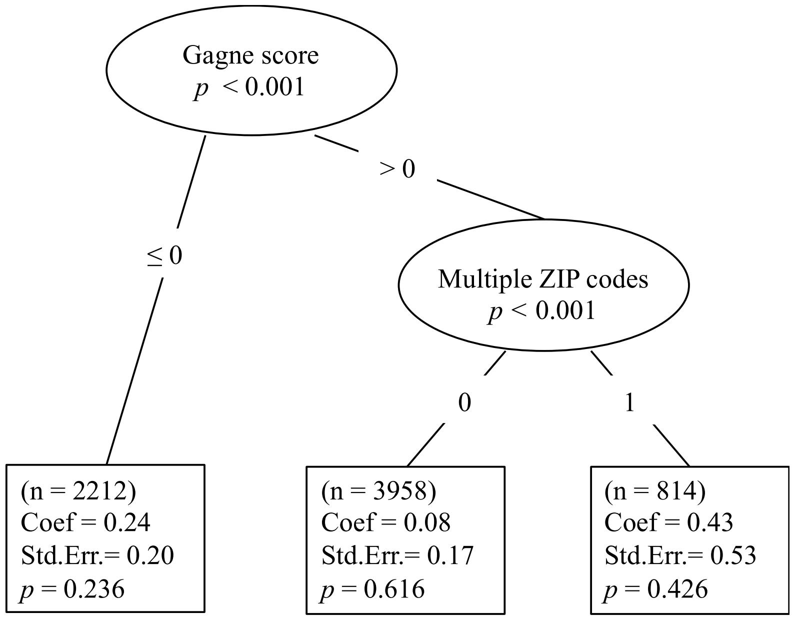

Figure 4.3. Appendix Figure: Regression tree modeling the heterogeneous effect of PIM on the probability of an ED visit in the year following randomization

ED = emergency department; Coef. = difference-in-difference estimate coefficient; Std. Err. = standard error

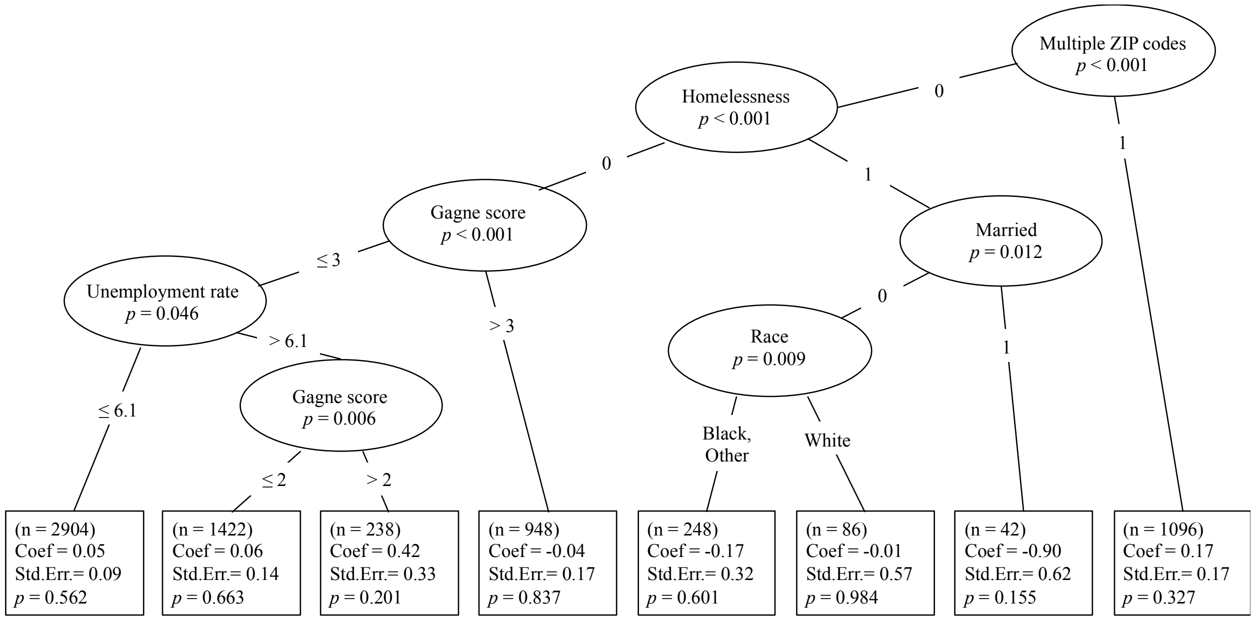

Figure 4.4. Appendix Figure: Regression tree modeling the heterogenous effect of PIM on the number of ED visits per patient in the year following randomization

ED = emergency department; Coef. = difference-in-difference estimate coefficient; Std. Err. = standard error

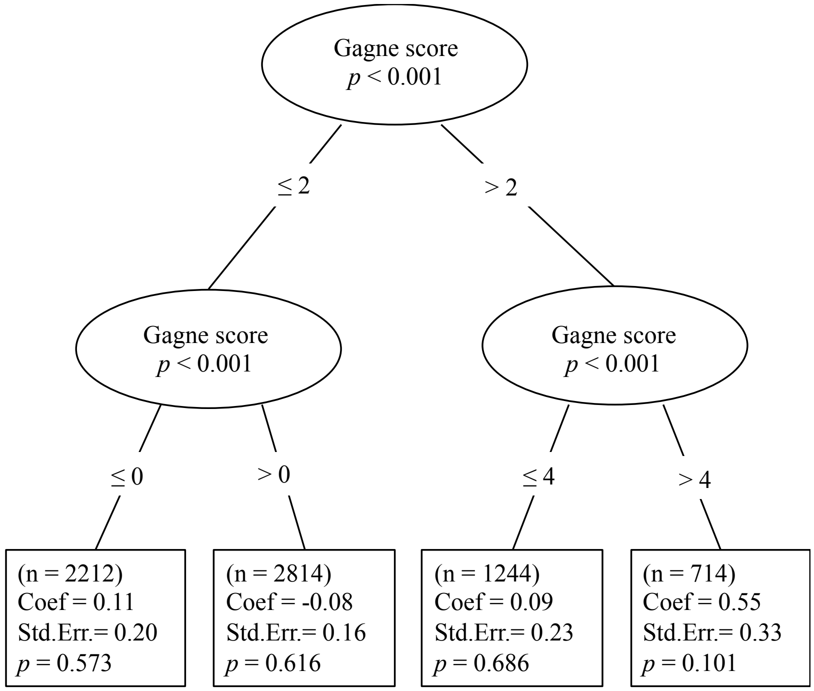

Figure 4.5. Appendix Figure: Regression tree modeling the heterogenous effect of PIM on the probability of a hospitalization in the year following randomization

Coef. = difference-in-difference estimate coefficient; Std. Err. = standard error

Chapter 5. POLICY IMPLICATIONS

5.1 SUMMARY OF FINDINGS

Using advanced analytic methods, this dissertation examined the extent to which two primary care initiatives in the Veterans Health Administration (VHA) differentially affected patients based on their demographic, health, social, and economic characteristics. Being one of the largest integrated health care systems in the U.S., the VHA provided a unique opportunity to rigorously estimate the extent to which improving primary care alters patients' use of high-cost services across a large population of diverse patients nationwide.

The current literature on the effect of patient-centered medical homes (PCMHs) and primary care intensive management programs—the focus of this dissertation—to shift utilization from high-cost settings like emergency departments (EDs) and hospitals toward primary care settings is mixed. We hypothesized, however, that previous studies estimating the average effects of these programs across all patients, may be obscuring differential effects in specific subpopulations. For example, we know that patient characteristics including chronic illness,[28,52] race,[41,42] age and gender,[43,44] marital status,[46] income,[47] and various measures of social stability[48–51] are associated with patients' utilization of health care services, and therefore differentially affect how patients interact with and benefit from primary care interventions.

Overall, we found little evidence of heterogeneous treatment effects of primary care transformation among VHA-enrolled veterans. In Chapter 2, we studied the extent to which the VHA's PCMH initiative—the Patient-Aligned Care Team (PACT) initiative—affected older veterans' use of total and potentially avoidable ED and hospital visits, and whether the associated PACT effect differed by patient comorbidity burden. We found that PACT was associated with comparable increases in total and preventable ED visits for patients with and without high-comorbidity burden, and that there were no effects on total or potentially avoidable hospitalizations.

In Chapter 3, we took a closer look at the effect of greater access to providers and care via PACT on patients' utilization of EDs and hospitals. Similarly, we found that improved access was associated with increased likelihood of having ED visits and potentially preventable ED visits, but did not affect patients' use of hospitals for any cause. We found few heterogenous treatment effects of improved PACT access. Notably, improved access had larger effects on patients in previously low-access clinics and on patients that lived closer to VHA facilities, but there were no heterogenous treatment effects based on other patient characteristics such as comorbidity burden, qualifying for copayment exempt care (a measure of income and disability status), and marital status. Our analysis of 11 individual components of PACT access found that longer wait times, availability of after-hours care, and use of secure messaging are driving factors of the effect of access on utilization of EDs and hospitals.

Finally, in Chapter 4, we found that augmenting PACT with intensive management for patients at high risk for hospitalization did not result in meaningful reductions in ED and hospital use overall or for distinct subgroups of patients identified by the recursive partitioning algorithm.

5.2 Policy implications

Our findings which generally align with the literature, have implications for the VHA and the broader health care environment as it continues to find ways to improve quality and reduce costs. While the VHA is a unique system, unlike any other in the U.S., the lessons we learn from studying programs and policy changes in the VHA can be broadly applicable.

First, introducing new models of care delivery may have unintended consequences, at least in the short run. PACT was expected to result in economic benefits through improved health outcomes, fewer preventable hospital admissions, reduced ED visits, improved patient engagement and lower per-patient costs.[32] However, nearly six years into implementation, PACT was still associated with increased ED and hospital use among the older veteran population, regardless of comorbidity burden or clinic's performance on measures of access. Unintended consequences are pervasive in health care initiatives. For example, a target to reduce emergency room wait times in the United Kingdom had the unintended effect of increasing hospital admissions and separately, efforts to improve access were associated with worsening continuity of care.[143,144]

However, unintended consequences might not always represent worse care. In our study, the unintended consequences of increased ED and hospital use may actually represent better care. PACT focused on improving patients' access to providers and care and engaging patients in managing their health conditions. Through these mechanisms, PACT may be newly engaging patients who have historically not sought care. The increased use of outpatient and acute care services to care for these patients' "new" or exacerbated conditions is a beneficial outcome of PACT. Indeed, findings from the Oregon Experiment found that increased access to primary care via Medicaid coverage led to increased diagnosis of some chronic conditions and an increase in preventable hospitalizations.[47,86,100] The intention of PCMH models is that through consistent engagement and longitudinal care management, patients will be able to manage conditions and reduce the likelihood of exacerbations that result in ED and hospital use in the long run. The VHA should evaluate the effectiveness of programs on their ability to deliver high-quality primary care and not necessarily on short-run cost savings. There are other ways in which the VHA can achieve shorter-run cost savings such as de-implementation of low-value services.

Second, health care delivery systems should ensure that high-quality primary care is implemented across practices serving their patients. This is particularly relevant as the VHA expands its community care program and high-quality care coordination across clinics will be crucial. In an early study of PACT, Nelson et al. 2014 found that primary care clinics with higher PACT implementation scores (i.e., higher functioning clinics) were associated with higher patient satisfaction and clinical quality scores and lower burnout, ED use, and potentially avoidable hospitalizations.[35] Additionally, in Chapter 3, we showed that improving access to primary care was associated with larger effects on ED use among patients in low-access clinics compared to high-access clinics. Thus, the VHA may have greater success in improving population-level health of enrolled veterans by focusing resources to improve care in low-functioning clinics.

Third, PCMHs might not meet the underlying needs of the population most at risk for acute care use; more tailored care might be needed to augment utilization among vulnerable populations. PACT, like many PCMHs focus on altering care for the broad primary care population, and not specifically on high-risk patients' preventive care needs.[88] Findings from our study as well as those from previous studies suggest that PCMHs are unable to adequately address the needs of high-risk patients while also caring for the broader patient population.[142] Our work to better understand heterogeneous treatment effects of PCMH and intensive management programs suggests more work is needed to target patients most likely to benefit from these programs.

Altering acute care use will require health care systems or payers to use non-routinely collected data to identify populations with modifiable risks. Studies of the VHA PCMH intensive management program (PIM) found that PIM was not associated with reductions in ED and hospital use compared to patients receiving usual care.[53,131] Notably, our analysis which included measures of social instability found that characteristics such as homelessness and having multiple residences in a year were consistently associated with increased ED and hospital use where other characteristics like routinely collected demographic information were not. Although the relationship between social instability and utilization is well documented in the literature, characteristics like these that are not routinely collected in administrative data are rarely used to identify populations for targeted intervention.[28,45,48–51] Health systems should invest in the systematic collection of social stability and other social determinants of health data to better target patients for intervention.

Similarly, to reduce the acute care use of higher-risk patients, the VHA may want to continue its efforts providing special-population primary care clinics. Combining our findings with those from previous studies suggests that the VHA's PCMH (which was designed to improve care for all patients) did not reduce acute care use or costs as intended, across all patients or among the older or high-risk subpopulations.[32] However, the VHA has had some success in developing special-population primary care clinics that provide tailored, culturally competent access, care, and case management to high-risk and vulnerable populations.[89,145] VHA has specialty PCMHs for several subpopulation including homeless veterans, women who were victims of military sexual trauma or PTSD, cognitively impaired older veterans, and veterans with severe mental illness.[89] These population-specific clinics have been associated with improved disease management, increased use of primary care, and better patient experiences, suggesting that tailoring the medical home model to the specific needs of high-risk populations could improve outcomes.[89,146]

5.3 FUTURE DIRECTIONS

As the VHA, other health systems, providers, and payers continue to find ways to improve health outcomes, quality, and experiences while reducing costs, research must continue to understand what works and for whom. By identifying for whom care delivery initiatives like PCMH and PIM benefit, delivery systems and payers can more efficiently allocate resources to maximize health benefits for those most likely to benefit without mitigating care for those least likely to benefit from practice transformation. Understanding the types of patients most likely to be responsive to these interventions has become more critical across the U.S. health care system as we shift toward a more value-based payment environment that holds providers accountable for patients' costs and use of services.

With this in mind, future work should continue to advance our understanding of heterogenous treatment effects. To do so, we need to develop a stronger understanding of social determinants of health, including advancing our ability to systematically collect data on patients' social context and environment.

Future research should also aim to expand the currently quantitatively-based literature to include qualitative studies. Qualitative studies such as those that utilize patient and provider perspectives (via interviews) will provide invaluable insights into why programs may and may not be working beyond what we can capture in administrative and claims data. At this point in the PCMH literature, our ability to shape future directions will depend on our ability to triangulate quantitative findings with patient and provider perspectives.

5.4 CONCLUSIONS

The collection of studies in this dissertation use rigorous analytic methods to estimate the presence of heterogenous treatment effects in one of the nation's largest PCMH initiatives. While our findings suggest that neither PACT nor PIM reduced acute care service use overall or for distinct subgroups of patients, our investigation of heterogeneity was limited by the demographic, social, and economic characteristics in administrative data. Future research should continue to expand our understanding of treatment effect heterogeneity in PCMH by developing, systematically collecting, and including additional measures of social context and other social determinants of health that we know affect patients' utilization of health care services. By expanding our knowledge of for whom primary care programs like PCMHs are most likely to benefit, we can better target intervention and patient outreach, particularly in resource-constrained environments.

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