Three Studies of Variation in Medical Decision-Making and Care Delivery by Physicians

by

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For my beloved wife Kelly

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Introduction

Decision-making by physicians, including both clinical and non-clinical (e.g., organizational) decisions, is the subject of much research by health economists and other health services researchers. In the U.S., because of the country's relatively high expenditures on health care services, its high health care expenditures growth rate, and its mixed record of quality, this work has focused substantially on the fee-for-service payment system and other financial incentives contributing to these outcomes. There are also many smaller literatures about the influence non-financial factors have on physician decision-making and, thereby, downstream outcomes of interest.

Among these are the literatures concerned with access to health care services and the role of public policy in encouraging physicians and physician practices to care for indigent populations. As in general, much of the work in this area concerns the effects of financial factors—in this case, the relatively low fees paid to most physicians who treat Medicaid beneficiaries. By contrast, it is surprisingly uncommon for researchers to examine how non-financial public policies also affect outcomes of access. In my first chapter, I consider the effects of one such overlooked set of policies: regulations of licensure, scope of practice, prescription authority, and other dimensions of practice for non-physician clinicians, particularly nurse practitioners and physician assistants. Specifically, I consider the effects of these laws and regulations on physician practices' participation in Medicaid, relying on both cross-sectional differences and within-state changes over time in the regulations to identify my estimates. My findings are informative for state policymakers evaluating the potential different policies may have for increasing Medicaid beneficiaries' access to primary care, including alternatives to raising Medicaid fees.

Another literature concerns the coordination of health care services among physicians. Principally, the focuses of this literature have been in the outpatient setting (e.g., between primary care physicians and specialists) and in transitions from inpatient to outpatient care. The importance of coordination among physicians may be greater still for vulnerable patients while they remain hospitalized. Interest in the coordination of inpatient physician services has grown in recent years with demonstrations of variation in the provision of consults for surgical inpatients (Wijeysundera et al., 2012; Stevens et al., 2013; Chen et al., 2014). Moreover, the decisions physicians make regarding when and how often to order and provide consults can quickly precipitate the use of significant healthcare resources. In my second dissertation chapter, I develop two theoretical frameworks to help explain observed patterns of consult provision and to consider the implications of suboptimal consult provision patterns for vulnerable patients' care management. The first is an application and extension of a well-known game theoretical model—the Bystander Effect—and the second is derived from the law of diminishing marginal product. I test these frameworks using a Medicare administrative claims dataset consisting of consults provided to Medicare beneficiaries undergoing coronary artery bypass graft or colectomy procedures in light of these patients' numerous comorbid conditions and complexity.

Finally, there are literatures concerned with observed geographic variation in physician decision-making and with the organizational features that may influence these decisions. The Veterans Health Administration (VA), because of its relative homogeneity in clinician reimbursement structures and patient mix, is an attractive setting in which to assess the importance of certain organizational factors and how they may affect geographic variation in physician decisions. In my third dissertation chapter I leverage this opportunity and the richness of the VA's Clinical Data Warehouse and other survey data sources to analyze key determinants of variation in VA quality of care. In particular, I explore the relevance of two geographic variation-based frameworks. First, I consider how different VA facilities' care resources (e.g., staff, space, IT) may enable physicians and other clinicians to render high-quality care and may also complicate their delivery efforts except, potentially, when effectively coordinated. And second, I explore the extent to which physicians who render care in two different VA organizations (e.g., because they moved) render care differently in accordance with local care patterns and in response to local organizational structures and resource constraints.

Each of these studies is intended to shed light on the relative importance of non-financial factors in driving variation in physician decisions and, thereby, health care use and quality outcomes. I seek through these chapters to inform both the academic literature on physician decision-making in these areas and also policy and administrative decisions that can shape the environments in which physicians practice.

Chapter One

Who Will See You Now? How Non-physician Clinician Regulations Influence Medicaid Participation in Primary Care Physician Practices

Abstract

Because of provisions of the Affordable Care Act (e.g., state health insurance exchanges) and state Medicaid expansions, there may be as many as 21 million new Medicaid and CHIP enrollees by 2022 (Holahan et al. 2012). Yet concerns are growing that primary care physicians (PCPs) and other providers increasingly indicate they will not accept new Medicaid patients (Decker, 2012; Decker, 2013). In recent decades many states have sought to increase access in primary care by reforming regulations for nurse practitioners (NPs) and physician assistants (PAs), who may also provide primary care services. The effects of these regulations are complicated, however, by the complex relationships NPs and PAs have with PCPs: PCPs often employ NPs and PAs in their practices, and they may also compete directly with NPs where NPs are permitted full practice autonomy.

This paper explores the effects of NP and PA regulation reforms on Medicaid participation in PCP practices, where most primary care is provided. I analyze these effects using a differences-in-differences framework and a robust, linked longitudinal data set that incorporates new data summarizing NP and PA regulations. My main findings indicate that states relaxing these regulations, independent of other policy measures, have realized mixed effects on access to PCP practices in Medicaid, including significant reductions in smaller PCP practices' participation in Medicaid. If policymakers implement such regulatory changes not independently but rather as parts of broader, more cohesive policy packages that recognize and

balance their complex effects, states may experience more significant and consistent improvements in primary care access.

Introduction

By 2022 there may be as many as 21 million new Medicaid and CHIP enrollees (Holahan et al. 2012). Much of this new enrollment will be concentrated in states taking advantage of the Affordable Care Act's (ACA) enhanced federal financing arrangements and expanding their Medicaid populations to include nearly all individuals with incomes below 133 percent of the Federal Poverty Level. As of August 2014, 27 states and the District of Columbia were expanding their Medicaid eligibility criteria, and three more were considering doing the same (Advisory Board, 2014). A stated goal of these expansions is to improve access to primary care and other health care services for many individuals and families; such improvements in access may lead to reductions in emergency room visits, inpatient hospitalizations, and mortality (Falik et al., 2001; Bindman et al., 2005; Laditka, Laditka, & Probst, 2005; Ansari, Laditka, & Laditka, 2006).

Yet concerns are growing that primary care physicians (PCPs) and other providers increasingly indicate they will not accept new Medicaid patients (Decker, 2012; Decker, 2013). Many factors have been proposed to explain this trend, including low physician fees relative to those paid by private insurers and Medicare, greater administrative (e.g., delayed reimbursement) and patient burdens, and difficulties securing specialist visits for referrals (Sloan, Mitchell, & Cromwell, 1978; Hadley, 1979; Davidson, 1982; Cunningham & Nichols, 2005; Decker, 2007; Cunningham & O'Malley, 2009; Sommers, Paradise, & Miller, 2011; Casalino, 2013; Long, 2013; Wilk, 2013).

The principal action Congress took to address these concerns in the ACA was to raise Medicaid fees for primary care services up to 100% of Medicare fee levels during 2013 and 2014 (Sommers, Swartz, & Epstein, 2011); this measure was included despite the provision's estimated $11.9 billion cost to the federal government (Kaiser Family Foundation, 2012) and evidence that the impact of higher fee levels on PCPs' Medicaid participation may be relatively small (Fanning & de Alteriis, 1993; Coburn, Long, & Marquis, 1999; Zuckerman et al., 2004;

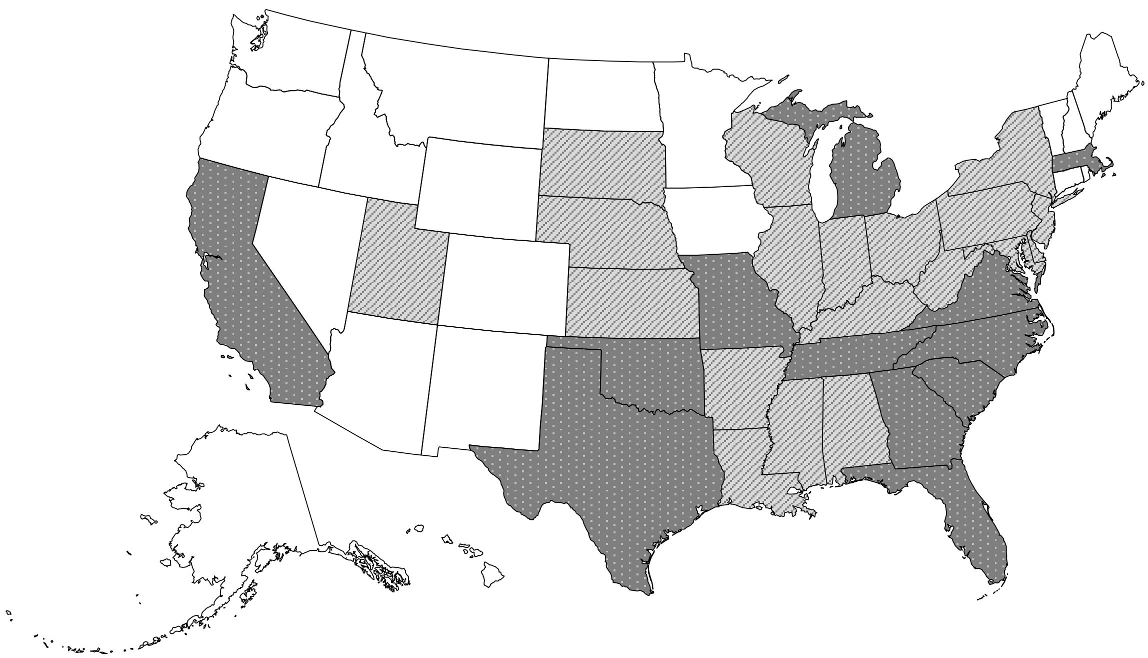
Wilk, 2013). States too have focused on fees as the principal mechanism for promoting Medicaid participation among their physicians. For example, seven states have elected to extend the ACA's primary care fee bump into 2015 (Galewitz, 2014; Robeznieks, 2015). Because the federal government will no longer fund these fee increases beginning in 2015, these state-funded fee increases may be cost-prohibitive in some states, especially where fee levels were particularly low before the ACA's fee increase went into effect. As examples, the estimated costs of such fee bump extensions were $32 million in Alabama and $451 million in Florida (Galewitz, 2014).

Because of the expense of these policies and similar fee-based measures proposed prior to the ACA, state policymakers have explored alternative measures to improve primary care access. Among these are reforms to licensure, practice autonomy, scope of practice, and prescription authority laws and regulations for nurse practitioners (NPs), physician assistants (PAs), and other non-physician clinicians (hereafter "NPC regulations"). NPC regulations vary considerably across states; NP regulations concerning independent practice authority exemplify this variation in Figure 1. Many states continue to debate actively whether to relax these regulations, weighing their capacity to improve access without sacrificing quality. The National Conference of State Legislatures reports that during 2011-2012, a total of 1,795 bills related to scope of practice were proposed and 349 were adopted or enacted across 54 states, territories, and the District of Columbia, and another 178 were proposed during the first quarter of 2013 (NCSL, 2013).

Naturally, the arguments about NPC regulations have focused on how these regulations will affect Medicaid beneficiaries' access to primary care delivered by NPCs. This is reinforced by physician organizations' warnings that care provided by independent NPCs poses a threat to patient health. However, most NPCs—and all PAs—are employed in physician-operated practices and deliver care under physician supervision. Moreover, with the rise of team-based care processes and increased training of NPs and PAs, it is expected physicians and NPCs will work together with increasing regularity in the coming years (Pohl, Barksdale, & Werner, 2014; Iglehart, 2014). It is important to account for the complexity of the interactions between PCPs and NPCs, who practice both as employees of PCP practices and as independent practitioners, when anticipating how relaxed NPC regulations will affect Medicaid beneficiaries' access to primary care.

This paper explores the effects of NPC regulations on Medicaid participation in PCP practices, where most primary care is provided. In particular, I assess how PCP practices' decisions to participate in Medicaid change following NPC regulation reforms, and I explore three hypothesized mechanisms that could explain these relationships. I test these hypotheses using a differences-in-differences framework and a robust, linked longitudinal data set that incorporates new data summarizing NPC regulations. My main findings indicate that states relaxing NPC regulations, independent of other policy measures, have realized mixed effects on access to PCP practices in Medicaid, including significant reductions in PCP practices' participation in Medicaid in some cases. By exploiting institutional differences in the practices of NPs and PAs (PCP practices may employ both NPs and PAs, but in states with relaxed practice regulations only NPs may practice independently), I am able to disentangle the conflicting mechanisms underlying relaxed NPC regulations that drive these mixed effects: reductions in PCP practices' marginal costs of care, competition between PCPs and NPs for privately insured and Medicare patients, and the willingness of PCPs to care for Medicaid beneficiaries as a public service. If policymakers implement NPC regulatory changes as parts of broader, more cohesive policy packages that recognize and effectively balance these complex effects of relaxed NPC regulations, they may achieve more significant and consistent improvements in primary care access.

Figure 1: Variation across States in Nurse Practitioners' Regulatory Authority to Practice Independently, 2014



Full Practice Authority (including prescribing)

Reduced Practice Authority (collaborative agreement required for medical practice or prescribing)

Restricted Practice Authority (supervision, delegation, or team management required for medical practice or prescribing)

Source: American Association of Nurse Practitioners. http://www.aanp.org/images/documents/state-leg-reg/stateregulatorymap.pdf.

Background

In 2010, the 56,000 NPs and 30,000 PAs in primary care represented 30% of the primary care workforce (AHRQ, 2012; Coplan, Cawley, & Stoehr, 2013; HRSA, 2013). In most states, NPs and physicians can provide similar sets of services in primary care; typically PAs provide a narrower, but still substantial range of services (Kaiser Family Foundation, 2011). NPCs' scope of practice regulations have converged over time (Towers, 2003; Towers, 2005), and NPs and PAs tend to practice similarly even where differences in these regulations persist (Mills & McSweeney, 2002; Henry, Hooker, & Yates, 2011). Combined, NPs and PAs provide at least 11% of outpatient medical services, the majority of which is primary care (Hooker & Everett, 2012).

Today, PCPs commonly work with NPCs (Sekscenski et al., 1994; Donelan et al., 2013; Kuo et al., 2013). In 2009, 55.4% of PCPs' primary sites of care employed non-physician clinicians, principally NPs or PAs. This arrangement is more common in larger and multi-specialty group practices (Park, Cherry, & Decker, 2011), Federally Qualified Health Centers (FQHCs) (Hing, Hooker, & Ashman, 2011; NACHC, 2013), public sector health care providers such as the Veterans Health Administration and Department of Defense (Hooker & Everett, 2012), and medical school-affiliated practices (Moote et al. 2011).[1] NPCs also may be more likely to take on expanded roles in newer, team-based models of care such as patient-centered medical homes and accountable care organizations (Cassidy, 2013).

Furthermore, it has been shown that the numbers of NPCs and the frequency of NPC employment in PCP practices are higher where NPC regulations are less restrictive (Sekscenski et al., 1994; Kuo et al., 2013). States vary in a range of NPC regulations pertaining to terms of licensing, scope of practice, requirements for physician supervision, prescription authority, and reimbursement relative to what physicians are paid for the same services; in many states these regulations have changed materially over the past two decades, generally becoming more relaxed.

Historically, NPCs in primary care have been more likely to care for substantial numbers of Medicaid beneficiaries than PCPs (Grumbach et al., 2003; Hansen-Turton et al., 2004). This is largely because NPCs—NPs in particular—have been more likely to locate in health professional shortage areas where Medicaid patients comprise a larger percentage of patients (Moody, Smith, & Glenn, 1999; Grumbach et al., 2003). If NPCs are more likely to treat Medicaid patients than PCPs, it follows that PCP practices that employ or are considering employing NPCs may look more to NPCs to help serve their Medicaid patients (McCormack, 2014) and possibly to increase the practice's participation in Medicaid overall when NPC regulations are relaxed. This is consistent with qualitative evidence from a recent study of physician groups participating

[1] These types of practices are also among those more likely than average to participate in Medicaid (Wilk, 2013).

in Medicaid, some of whom "would consider hiring a physician assistant or nurse practitioner to accommodate more demand from Medicaid" (Sommers, Paradise, and Miller, 2011). Other studies have provided evidence that physician practices are more likely to accept and treat Medicaid patients when they employ NPCs, but these studies have been descriptive (Park, Cherry, & Decker, 2011) or narrowly focused (Everett et al., 2013). By contrast, Hing, Hooker, and Ashman (2011) found no statistically significant difference in the probability that patients seen by NPs, PAs, or PCPs in community health centers were insured through Medicaid.

Research exploring the link between NPC regulations and Medicaid participation in physician practices has been limited. The most germane evidence to date was presented in a working paper by Richards and Polsky (2014), who conducted a simulated patient study of appointment availability for patients varying in insurance status and the urgency of the identified medical issue. They compared their findings in practices that had employed NPCs versus in those that had not and in states with "liberal" scope of practice laws versus in states with "moderate" or "restrictive" scope of practice laws. They found, unsurprisingly, that Medicaid patients were less likely to be offered an appointment than privately insured patients overall. However, practices with NPCs were relatively more likely to offer appointments to Medicaid patients. Furthermore, they found that the appointment rate gap was reduced most significantly in states with liberal scope of practice laws—that is, where physician practices could most effectively leverage their NPCs to increase access for Medicaid patients.

The work of Richards and Polsky has significant strengths, including its contemporary context and its use of an important measure of access—appointment availability. However, the study's cross-sectional design limits causal inference, and its assessments of appointment availability are not directly comparable to the effects on physician practices' participation in Medicaid estimated for other policy interventions in previous studies. By contrast, my study employs a longitudinal design and assesses effects on physician practices' Medicaid participation directly. It also examines the independent effects—as well as the aggregate effects—of multiple NPC practice regulations, rather than scope of practice regulations alone, giving policymakers a more complete picture of which regulations in particular can have important ramifications for access in Medicaid.

Theoretical Framework

To develop baseline predictions and illustrate how relaxing non-physician clinicians' NPC regulations affects physician practices' participation in Medicaid, I follow the approaches of Garthwaite (2012) and Wilk (2013) and apply the simple two-market model described by Sloan, Mitchell, and Cromwell (1978). In this model, physician practices maximize profits—patient care revenues minus the costs of care delivery—when producing medical care, measured in hours per week, to non-Medicaid patients (privately insured, insured through Medicare, or uninsured) and Medicaid patients. As shown in Figure 2, fees per hour of care, P_m, are fixed in the Medicaid market, while in the non-Medicaid market the physician practice faces a downward sloping demand curve, MR_p, the result of negotiations with heterogeneous private insurers and some limited price discrimination with privately insured patients and uninsured patients.[2] The practice's marginal costs of care increase in hours of care due to staff costs (hiring additional staff or paying overtime) as well as fatigue and opportunity costs; marginal costs may also increase if physicians selectively accept and treat patients on the basis of expected clinician time and effort per visit (Rowland & Salganicoff, 1994; Long, 2013).

As in classical profit maximization, the physician practice provides additional care until marginal revenues equal marginal costs. If marginal costs were small, the physician practice would first treat non-Medicaid patients until $MR_p = P_m$, when the practice would begin treating Medicaid patients until Medicaid demand were exhausted; at this point the practice would resume treating non-Medicaid patients for fees below P_m. Because in most practices marginal

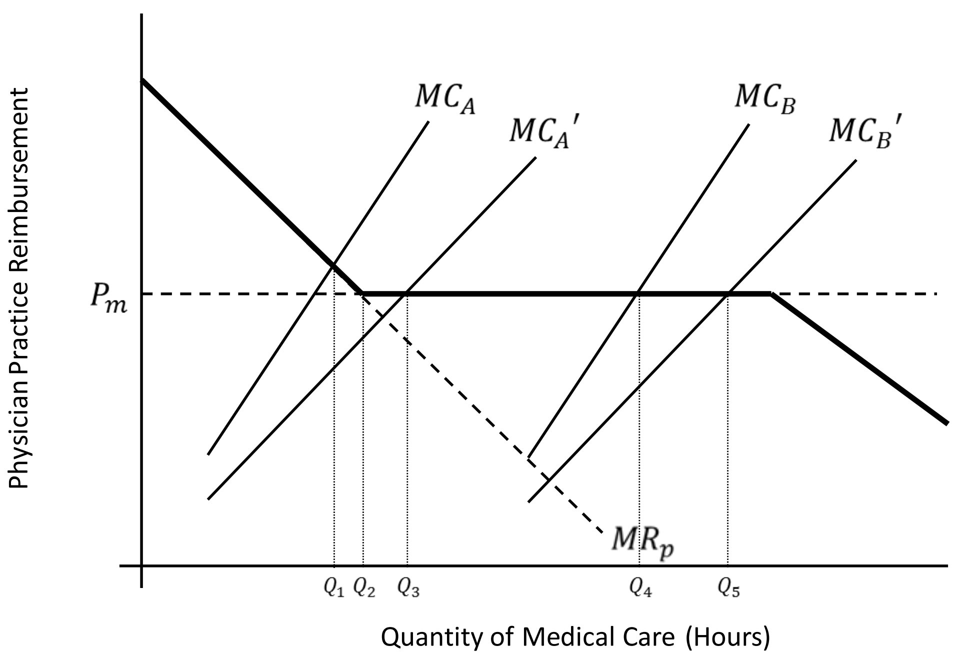
[2] In this model, Medicare patients are included among those I classify as non-Medicaid. Physician practices have no capacity to price-discriminate in the market for Medicare beneficiaries' primary care visits, as Medicare is a national insurance program with a fixed fee schedule. This could be represented in Figure 2 as a second flat curve segment above and to the left of P_m. Similarly, the negatively sloped curve segments representing the non-Medicaid market could be depicted as a series of flat curve segments, each representing an insurer with which the physician practice has entered into a network agreement. Figure 2 abstracts away from this model presentation by assuming the physician practice faces a continuous, downward-sloping demand curve for the sake of parsimony and because of this paper's focus on access to care for Medicaid beneficiaries.

costs are non-trivial and increasing, it is more common for practices to treat only non-Medicaid patients or to treat non-Medicaid patients and some Medicaid patients.

Marginal Cost Reduction

There are two principal mechanisms through which relaxing NPC regulations may affect the physician practice's equilibrium production of medical care and its patient mix (Medicaid versus non-Medicaid). The first of these is by reducing the marginal costs of care delivery. As NPC regulations are relaxed, physician practices may reduce their marginal costs either by substituting NP or PA labor for physician labor in the delivery of services for which such substitution was not permitted previously, or by lessening physicians' supervision duties when NPs or PAs provide care. The marginal cost reductions associated with such practice decisions may be substantial. Estimates of cost reductions are between 20% and 35% for NPs relative to PCPs (Naylor & Kurtzman, 2010) and 54% or more for PAs relative to PCPs (Grzybicki et al., 2002; Dueker et al., 2005).

Figure 2: Relaxing NPC Regulations Leads to Increased Participation in Medicaid among Physician Practices, Reduced Marginal Costs of Care Mechanism



Notes: Figure draws on the model of Sloan, Mitchell, and Cromwell (1978) and the applications of Garthwaite (2012) and Wilk (2013).

Such a shift in marginal cost curves is presented in Figure 2 for Practices *A* and *B* with pre-reform marginal cost curves MC_A and MC_B, respectively, and post-reform marginal cost curves MC_A' and MC_B', respectively. Before NPC regulation reform, Practice *A* produced Q_1 hours of medical care for non-Medicaid patients and zero hours for Medicaid patients. After NPC regulation reform, Practice *A* produces Q_3 total medical care hours, more than Q_1 before, and those hours are split between non-Medicaid patients (Q_2 hours) and a small number of Medicaid patients ($Q_3 – Q_2$ hours). Correspondingly, before NPC regulation reform, Practice *B* produced Q_2 hours of medical care for non-Medicaid patients and $Q_4 – Q_2$ hours for Medicaid patients. And after NPC regulation reform, Practice *B* produces Q_5 total medical care hours, more than Q_4 before, adding only additional Medicaid patients ($Q_5 – Q_4$ hours) to its already split panel. For both practices, the reduction of marginal costs of care leads to an increase in the number of hours allocated to Medicaid patients and either no change or an increase in total patient care hours—though total hours dedicated to patient care by physicians at the practice may decrease due to the substitution of NPC care—and hours allocated to non-Medicaid patients. Notably, while the reform has led Practice *A* to begin accepting Medicaid patients when it did not before and Practice *B* only to accept additional Medicaid patients, it is likely both practices would indicate that they were "accepting new Medicaid patients" in surveys such as the Community Tracking Study Physician Survey.

In states where NP practice regulations permit NPs to provide care unsupervised by physicians, the PCP practices that employ them still must choose the extent of physician supervision under which their NPs practice. This choice often has implications for the practices' marginal revenues as well as their marginal costs of care. This is because supervised NPs bill Medicaid or another insurer "incident to" their physician supervisors, whereas unsupervised NPs bill for their own care directly, often for less than what a PCP would bill for the same service. By law, Medicare pays for NP care billed directly 85% of what it pays for care billed incident to physicians, for example. Such reimbursement ratios vary widely across private insurers (Hansen-Turton et al., 2013; Yee et al., 2013),[3] though many follow Medicare's billing rules closely (Cassidy, 2013; Hansen-Turton et al., 2013), and fall between 75% and 100% across Medicaid programs (Naylor & Kurtzman, 2010; Kaiser Family Foundation, 2014). Because of these reimbursement deficits, PCP practices may discourage their NP employees from billing directly (Iglehart, 2014).

Moreover, private insurers may negotiate lower fees with PCP practices delivering a larger fraction of their care using NPCs if patients have a greater willingness to pay for physician care than they have for NPC care. To the extent such negotiations are driven by the care preferences of privately insured patients, however, evidence suggests that the expressed preferences of patients between PCPs and NPCs tend to be flexible and context-dependent (Laurant et al., 2008; Dill et al., 2013).

If profit-maximizing PCP practices face either of these two types of marginal revenue cuts when hiring new NPC staff or making more extensive use of existing NPC staff, which would shift the marginal revenue curve in Figure 2 inward, they will make NPC staffing decisions based on the net effects of decreased marginal revenues and decreased marginal costs. Whether these net effects are positive or negative can be expected to vary across practices. As such, the marginal revenue reduction implications of PCP practices' increased use of NPCs may moderate the effects of relaxed NPC regulations on practices' Medicaid participation as a result of reductions in marginal costs of care. Because most practices retain the authority to determine how much they supervise their NPs when the NPs deliver care and, thereby, how much revenue they receive for their NPs' services—at least when they treat Medicaid and Medicare patients—I expect most PCP practices will not be deterred from making increased use of NPCs by any anticipated decreases in revenue.

[3] Hansen-Turton and colleagues (2013) reported that in 2012 primary care fees were routinely lower for NPs than for PCPs in 27 percent of managed care organizations (in which 74 percent of Medicaid beneficiaries were enrolled in 2011 [CMS, 2012]) and "sometimes lower" in another 46 percent.

Competition

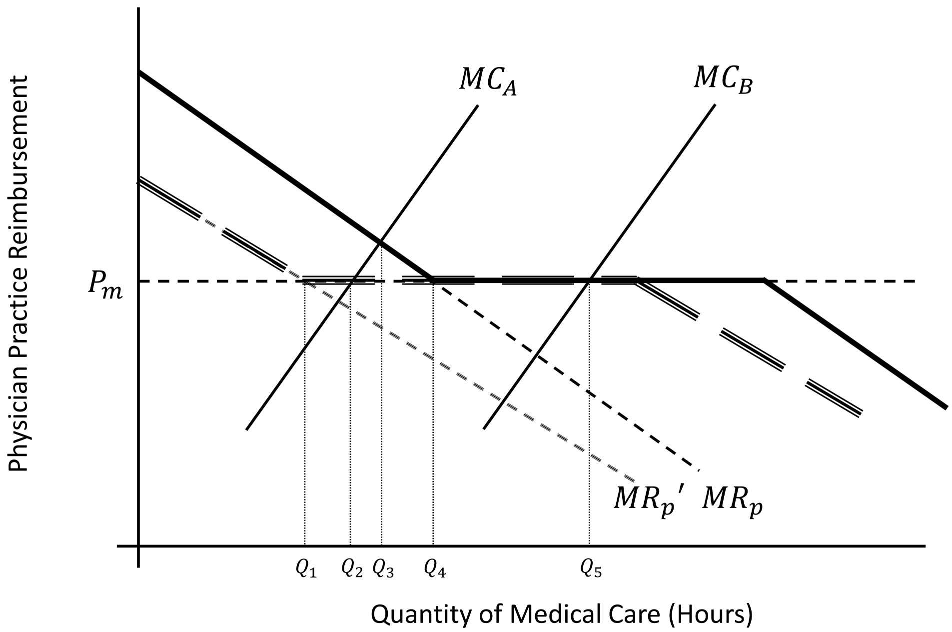
The second mechanism through which relaxed NPC regulations affect a PCP practice's marginal revenue-marginal cost balance is by increasing competition with PCP practices. The quality of NPC care is often cited by physician advocates as a reason for caution in NPC regulation debates. However, the absence of evidence distinguishing physicians' care quality from NPCs' (Naylor & Kurtzman, 2010; Newhouse et al., 2012) has led others to assert that these advocates have been motivated rather by a desire to defend "turf" (i.e., patients) and "thwart competition" from NP-operated practices or PCP practices employing NPCs disproportionately (LeBuhn & Swankin, 2010; Donelan et al., 2013; Vestal, 2013). In addition, retail clinics, where NPs are the main providers of care (Spetz et al., 2013), have expanded in states where regulations permit NPs full practice autonomy and permit direct reimbursement to retail clinics (Takach and Witgert, 2009). That these retail clinics typically treated only privately insured and self-pay patients—those who could pay up front—throughout the late 1990s and early 2000s (Pollack & Armstrong, 2009) further suggests PCP practices competed with NP-led practices for privately insured patients. Thus, there is some evidence that such competition could be meaningful, though empirical evidence of it is mixed (Dueker et al., 2005; Pittman and Williams, 2012).

In standard economic models of market competition, NPs would compete with PCPs to provide primary care services in states with relaxed NP practice regulations because of their similar service offerings. (Since PAs do not practice independently, they may not compete with PCPs directly.) Assuming the insurers cover NP services and that a substantial fraction of patients perceive PCPs and NPs to be substitutable under many circumstances (Laurant et al., 2008; Dill et al., 2013), PCPs and NPs would compete first for privately insured patients, second for Medicare beneficiaries, and third for Medicaid patients because of the differences in average fee levels across payers.

In most markets, this introduction of competition as a result of relaxed NPC regulation would induce the practice's non-Medicaid marginal revenue curve to shift to the left and to become more elastic. In Figure 3 this is represented by the shift from MR_p to MR_p'.[4] Before NPC regulation reform, Practice *A* produced Q_3 hours of medical care for non-Medicaid patients and zero hours for Medicaid patients. After NPC regulation reform, Practice *A* produces Q_2 total medical care hours, fewer than Q_3 before, and those hours are split between non-Medicaid patients (Q_1 hours) and a small number of Medicaid patients ($Q_2 – Q_1$ hours). By contrast, both before and after NPC regulation reform, Practice *B* produced Q_5 total hours of medical care. Before NPC regulation reform, Practice *B* produced Q_4 hours for non-Medicaid patients and $Q_5 – Q_4$ hours for Medicaid patients; after NPC regulation reform, Practice *B* produced Q_1 hours for non-Medicaid patients and $Q_5 – Q_1$ hours for Medicaid patients, significantly increasing the Medicaid fraction of its panel. For both practices, the introduction of competition leads to an increase in the number of hours allocated to Medicaid patients—and the probability of indicating they were accepting new Medicaid patients in order to maintain larger Medicaid patient panels—a reduction in hours allocated to non-Medicaid patients, and either no change or a decrease in total patient care hours.

[4] In Figure 3 I have depicted a shift in the non-Medicaid marginal revenue curve without any commensurate changes to the Medicaid marginal revenue curve. It could be argued that the Medicaid market available to a given physician practice would shrink after the introduction of competition because some Medicaid patients would always seek care with the new entrant. However, the Medicaid market may grow after the introduction of competition if previously uninsured individuals are more likely to take up Medicaid coverage in the presence of greater options for care. While the direction of the net effect is unclear, neither meaningfully affects my predictions given the small numbers of physicians for whom the Medicaid market's total patient capacity is a binding constraint. In addition, as in Figure 2, Figure 3 assumes Practices *A* and *B* face the same marginal revenue curve MR_p, though this need not be the case, for simplicity.

Figure 3: Relaxing NPC Regulations Leads to Increased Participation in Medicaid among Physician Practices, Competition Mechanism



Notes: Figure draws on the model of Sloan, Mitchell, and Cromwell (1978) and the applications of Garthwaite (2012) and Wilk (2013).

Medicaid Participation as Public Good Production

An additional framework concerning the disposition of PCPs toward their role as safety net providers bears discussion in this context. A strong health care safety net is generally considered to be a valuable public good. However, physician practices providing safety net care face greater administrative and patient care burdens in Medicaid but do not internalize the full benefits of this service due to low reimbursement. Thus, as in the classic economic model of public good provision (Olson, 1968; Marwell & Ames, 1981), the individual PCP practice's incentive is to "free-ride" if it can be reasonably assured that the safety net will be adequately supported in its absence.[5] Notably, experimental evidence from investigations of free-riding

[5] Persistent declines in Medicaid participation among physicians over the last few decades led Casalino (2013) to discuss the ethical and professional implications of such free-riding behavior among physicians in this context.

behavior routinely find that agents contribute more to public goods than is predicted by economic models strictly focusing on individual financial incentives (McGinty and Milam, 2013). This may explain in part why many physician practices participate in Medicaid despite low reimbursement levels.

In the context of this study, the relaxation of NPC regulations may signify to PCP practices increases in the number of NPCs at hand with the opportunity to care for the Medicaid population. Thus, the PCP practices may be assured that Medicaid beneficiaries' access to care will not be significantly harmed by their decision to no longer accept Medicaid patients. Furthermore, NPCs themselves may be less likely to free-ride than PCPs if patients sort to PCPs or NPCs by their willingness to pay or if PCPs enjoy other competitive advantages (e.g., patients prefer continuity of care with their PCPs to seeking care with new NPCs). This intuition is consistent with recent evidence that retail clinics, which seldom participated in Medicaid during the late 1990s and early 2000s (Pollack & Armstrong, 2009), came to accept Medicaid patients as often as most PCP practices by 2008 (Rudavsky, Pollack, & Mehrotra, 2009). Thus relaxed NPC regulations and the presence of newly empowered NP-operated practices and retail clinics may cause PCP practices to withdraw from the Medicaid market; some practices may reallocate these patient care hours to non-Medicaid patients and also (because of non-Medicaid patients' greater reimbursement) increase total patient care hours. These predictions contradict those of the standard competition mechanism described above. It may be that PCP practices' free-riding behavior negates any increase in Medicaid participation due to increased competition.

Similarly, if physicians find caring for Medicaid beneficiaries distasteful or if they regard NPC care as sufficient to meet most Medicaid beneficiaries' needs—particularly when NPC regulations are relaxed—they may rely on NPCs in their practices to treat these patients in their stead. Specifically, they may hire additional NPCs, and they may transfer responsibility for Medicaid patients' care to their NPC staff. In this way, the predictions of the public good framework are consistent with those of the mechanism of reduced marginal costs.

Other Mechanisms

The mechanisms described above represent short-run responses in partial equilibrium. There are other mechanisms consistent with general equilibrium or long-run responses to NPC regulation reforms that merit consideration. Evaluating these mechanisms is beyond the scope of this study, though most can be investigated using available data.

In general equilibrium, the decline in marginal costs associated with substituting NPCs for physicians may be partially offset if relaxed NPC regulations lead to increased NPC productivity and, thereby, commensurately increased NPC wages (Dueker et al., 2005; Kleiner & Park, 2010; Kleiner et al., 2014). However, there are other general equilibrium effects at work that may dampen this offset. Among these are NPC labor market frictions (e.g., opposing views of physicians and NPs regarding optimal NP utilization in primary care [Naylor & Kurtzman, 2010; Donelan et al., 2013], leading to inertia in practices' distribution of labor across NPCs and physicians), inelasticity in derived demand for NPC labor inputs, and increasing local supply of NPCs in response to relaxed NPC regulations (Sekscenski et al., 1994; Kuo et al., 2013). The increasing local supply of NPCs may, in fact, lead to an increase in competitive effects if the associated perceived improvements in the probability of gaining access to primary care services in Medicaid persuade local Medicaid beneficiaries to increase their demand for visits or, perhaps, encourage a greater fraction of the local population to take up Medicaid insurance.

There are other reasons to anticipate offsets to the predicted effects of reduced marginal costs. These reductions may not be sufficient to entice PCPs to partner with NPs and increase their participation in Medicaid if the effects of competition include sizeable increases in the marginal costs of recruiting and treating patients. Competition may also affect the mix of patients physician practices accept within the non-Medicaid or Medicaid markets. If this mix becomes less favorable, PCPs may need to spend more time per patient or invest more in support staff (e.g., bilingual nurses), increasing their marginal costs of care without corresponding increases in revenue. Such increases in costs may be observable through increases in relative value units of care expended per patient, minutes per visit, or referral rates to social workers or medical specialists. In 2013 and 2014, when the ACA's increase in fees for primary care services for Medicaid beneficiaries is in effect—notably, this fee increase is not extended to NPCs (Cassidy, 2013)—the benefits of increasing participation in Medicaid through partnering with NPs are even less attractive. Even if we assume these competitive effects are not as significant as the potential benefits in reduced marginal costs, however, relaxed NP practice regulations should still increase participation in Medicaid among those PCPs with the financial capacity to collaborate with NPs; these should include the larger, hospital-based, or medical school-affiliated practices, which Wilk (2013) identified as more likely to participate in Medicaid than their peers.

Hypotheses

When either PA or NP practice regulations are relaxed, PCP practices' reduced marginal costs should lead to increased participation in Medicaid. In addition, for NPs only, relaxed practice regulations may also induce increases in competition and further increase Medicaid participation relative to the effects of reduced marginal costs alone. Alternately, relaxed NP practice regulations may enable free-riding behavior by PCP practices, reducing Medicaid participation relative to the effects of reduced marginal costs alone.

It is not possible to separately estimate the effects of relaxed NP practice regulations attributable to reduced marginal costs of care because of the co-incidence of multiple resulting mechanisms and the limitations of available data. However, if we assume the reduced marginal cost effects of relaxed NP and PA practice regulations are similar, the difference between observed effects of NP practice regulations and the observed effects of PA practice regulations may serve as an estimate of the net effects of competition and free-riding. Therefore my principal hypotheses concerning the marginal effects of relaxing NPC regulations on Medicaid participation (*M*) for NPs $\left(\frac{dM}{dNP}\right)$ and PAs $\left(\frac{dM}{dPA}\right)$—defined both in terms of the extensive margin (any versus none) and the intensive margin (fraction of all patient care)—are as stated below (*H1-H2*).

H1. $\frac{dM}{dPA} > 0$ (marginal cost reduction mechanism)

H2. $\frac{dM}{dNP} > (<) \frac{dM}{dPA}$ [competition dominates (is dominated by) free-riding]

I conduct three additional tests of the competition and free-riding mechanisms. First, I examine effects of relaxing NP regulations on PCP practices' non-Medicaid (*nonM*) and total (*Tot*) patient care. As described above, reduced marginal costs may lead to increases in care for non-Medicaid patients and total patient care in PCP practices, though total patient care may also decline. In addition, my framework suggests that increased competition may cause PCP practices to dedicate fewer hours to care for non-Medicaid patients and possibly fewer total hours of care, while free-riding behavior could bring about the opposite effects. The testable hypotheses corresponding to these predictions parallel hypotheses *H1-H2*, as summarized below (*H3-H6*).

H3.	$\frac{dnonM}{dPA} > 0$	(marginal cost reduction mechanism)
H4.	$\frac{dnonM}{dNP} < (>) \frac{dnonM}{dPA}$	[competition dominates (is dominated by) free-riding]
H5.	$\frac{dTot}{dPA} > 0$	(marginal cost reduction mechanism)
H6.	$\frac{dTot}{dNP} < (>) \frac{dTot}{dPA}$	[competition dominates (is dominated by) free-riding]

Second, I explore whether the net effects of competition and free-riding may be stronger in states with lower fractions of Medicaid beneficiaries' benefits administered through managed care organizations (*lowMC*) versus in states with greater fractions of Medicaid beneficiaries in managed care (*hiMC*). This hypothesis is stated below (*H7*). Managed care penetration may attenuate competition and free-riding effect estimates where managed care organizations do not credential NPs as primary care providers (Schiff, 2012); Hansen-Turton, Ritter, and Torgan (2008) found that only half of surveyed managed care organizations credentialed NPs as primary care providers in 2007. Such policies effectively inhibit NPs from practicing independently and competing (or supporting the safety net in the place of PCPs), though PCP practices may still hire NPs and thereby reduce their average marginal costs of care in response to relaxed regulations.

H7. $\left|\frac{d(M|lowMC)}{dNP} - \frac{d(M|lowMC)}{dPA}\right| > \left|\frac{d(M|hiMC)}{dNP} - \frac{d(M|hiMC)}{dPA}\right|$

Third, additional evidence of the competition and free-riding effects may be obtained comparing the effects of relaxing NP practice regulations on PCP practices' Medicaid participation in markets with a higher density of NP-operated care facilities (*hiNP*), such as retail clinics, versus in markets with a lower density (*lowNP*). I test this hypothesis as stated below (*H8*).

H8. $$\left|\frac{d(M|hiNP)}{dNP} - \frac{d(M|hiNP)}{dPA}\right| > \left|\frac{d(M|lowNP)}{dNP} - \frac{d(M|lowNP)}{dPA}\right|$$

Finally, I conduct an additional test of the reduced marginal cost hypothesis. In the previous section, I asserted that the effects of relaxing NPC regulations may be different for different PCP practice types because their pre-reform marginal costs of care may have been sufficiently high or low that the reduction in marginal costs associated with relaxed NPC regulations would not affect the practice's participation in Medicaid. More specifically, the marginal costs of care for small one- and two-physician practices (*Sm*) may have been high enough that the potential reduction in marginal costs associated with greater use of NPCs post-reform would be too small to effect change in their Medicaid participation (they may also have insufficient capital to hire additional NP or PA staff in response to changing NPC regulations). Similarly, the marginal costs of large, hospital-based and medical school-affiliated practices (*Lg*) may have been low enough that any potential reduction in marginal costs associated with greater use of NPCs post-reform would be immaterial. Physician group practices with three or more physicians (*Med*), however, may be more responsive to changes in NPC regulations in terms of their use of PAs and NPs along both the intensive margin (greater use of employed NP and PA staff) and the extensive margin (hiring additional NPs or PAs).

H9. $\frac{d(M|Med)}{dNP} > \frac{d(M|Lg)}{dNP}, \frac{d(M|Med)}{dNP} > \frac{d(M|Sm)}{dNP}$ and $\frac{d(M|Med)}{dPA} > \frac{d(M|Lg)}{dPA}, \frac{d(M|Med)}{dPA} > \frac{d(M|Sm)}{dPA}$

Data and Empirical Framework

To test these hypotheses, I employ empirical models that leverage the heterogeneity and variation within state regulatory environments over time as well as repeated surveys of physician practices to track how these environments affect PCP practices' participation in

Medicaid. My physician practice data are drawn from the Community Tracking Study Physician Surveys (CTSPS) from 1996-1997, 1998-1999, 2000-2001, and 2004-2005. The CTSPS are nationally representative surveys of non-federal physicians' practices directed by the Center for Studying Health System Change. They contain information about the extent of physicians' participation in Medicaid and a variety of other physician and practice characteristics. Most of the survey items relevant to this study were retained in nearly identical formats across surveys; only minor recoding was needed to ensure regression variables were populated for all study observations. The question "Is your practice accepting all, most, some, or no new patients who are insured through MEDICAID, including Medicaid managed care patients?," is among the questions posed consistently across surveys. To simplify my analyses and to mirror methods used in other studies of physician participation in Medicaid (Cunningham & O'Malley, 2009; Sommers, Paradise, & Miller, 2011; Wilk, 2013), I code this question by identifying physicians accepting some, most, or all new Medicaid patients as accepting new Medicaid patients and ignore the residual heterogeneity.

For this study I also constructed a new data set of NPC regulation information gathered from a large collection of scholarly and proprietary resources. For NP practice regulations, I capture information on the extent to which NPs may practice independently (set to 1 if only the state board of nursing has authority over any scope of practice restrictions and if there are "no statutory or regulatory requirements for physician collaboration, direction, or supervision" in NP practices, 0 otherwise) and the extent of their prescribing authority (set to 1 if NPs may prescribe "independent of any physician involvement," 0 otherwise). I record this information—derived from annual updates on legal and regulatory changes for NPs, state by state, by Pearson (1994-2004) and Phillips (2005-2008)—in separate variables but otherwise use the same approach as Kuo and colleagues (2013) to code NP practice regulations. For PAs I capture information on scope of practice regulations, licensure requirements, physician supervision and proximity requirements, limitations of prescription authority, and maximum PA-to-physician ratios. I identify these PA practice regulations using a collection of proprietary and publicly available reports produced by the American Academy of Physician Assistants (AAPA, 1994-2008). Most of the PA regulation variables I include in my analyses have values set to 1 for a given state-year if that state's regulation was very unrestrictive and 0 otherwise. While this coding scheme fails to distinguish between states with moderately restrictive regulations and those with highly restrictive regulations, it simplifies my analysis and leverages findings that fully relaxed NPC regulations have the most significant effects on provider market outcomes (Kalist & Spurr, 2004; Kuo et al., 2013).

I obtained average Medicaid-Medicare fee ratios for primary care services in 1993, 1998, 2003, and 2008 from published estimates based on the Urban Institute Physician Survey (Norton 1995; Norton 1999; Zuckerman et al. 2004; Zuckerman, Williams, and Stockley 2009).[6] For years in which these fee data do not coincide with the physician surveys, I interpolated fee ratio values using exponential trending. Use of alternative interpolation methods (e.g., linear trending, selection of the nearest available value) did not meaningfully affect my findings. In addition, I drew several state- and county-level independent variables for each study year from the 2009-2010 update of the Area Health Resource File and Medicaid managed care enrollment fractions from Medicaid Analytic eXtract Chartbooks produced by the Centers for Medicare and Medicaid Services. As with the Medicaid fee ratio data, these Medicaid managed care enrollment fractions data were interpolated for select years.

My empirical framework employs difference-in-differences (DD) designs in regression models of Medicaid participation in PCP practices—defining PCPs to be physicians in family practice, general practice, internal medicine, or pediatrics. For each PCP practice i in state s in the year t, I estimate logit models of two different measures of Medicaid participation M_{ist}. These are an indicator of whether the PCP practice is currently accepting any new Medicaid patients (specified as described above) and a set of indicators of whether at least X percent of the practice's revenue came from Medicaid, where X represents each integer value between 1 and 100. I present full model results for 2 percent, 5 percent, or 10 percent, as these correspond to the 10th, 25th, and 50th percentiles, respectively, among responses from PCP

[6] This study's sample is limited to the 42 states (including the District of Columbia) for which average Medicaid-Medicare fee ratios were available.

practices indicating they received non-zero revenues from Medicaid (Wilk, 2013). The results of my models of accepting any new Medicaid patients are of interest because they can be compared to the findings of previous studies and because of policy interest in access to care for new Medicaid beneficiaries. I include the revenue-based measures of Medicaid participation among my dependent variables so as to capture effects on the intensive margin of Medicaid participation (i.e., how significantly practices participate, conditional on treating at least some Medicaid patients) as well as the extensive margin (i.e., treating any new Medicaid patients, yes or no). Conducting this analysis for the full range of percentages between 1 and 100 also supports the identification of any heterogeneous effects across the spectrum of Medicaid participation.

In my tests of hypotheses *H1* and *H2*, constructed using equation (1) below, my key independent variables are the vectors of NP and PA regulation variables NP_{st} and PA_{st}, respectively, which reflect the "POST × TREATMENT" term of interest in the classic DD design. Both NP and PA regulations are included in my main regressions; in supplemental analyses I include the NP and PA regulations in separate regressions, and I find that within-state changes in NP and PA regulations are not well correlated statistically. To satisfy the remaining requirements of the DD design, these models also include sets of year fixed effects Y_t for the "POST" term and state fixed effects S_s for the "TREATMENT" term. The year fixed effects control for changes over time in national economic conditions and national health care market conditions (e.g., Medicare program characteristics, medical technology). The state fixed effects, on the other hand, control for time-invariant differences across states in Medicaid eligibility criteria and benefit structures, provider integration, other laws and regulations (e.g., statutory limits on the ratio of fees paid to NPCs versus to physicians for the same services; Yee et al., 2013), and unmeasured socioeconomic factors.

$$M_{ist} = \Lambda(\beta_0 + \beta_{NP}NP_{st} + \beta_{PA}PA_{st} + \beta_C C_{it} + Y_t + S_s) + \varepsilon_{ist} \tag{1}$$

In these equations, Λ represents the logistic function, the β_{NP} and β_{PA} terms represent my parameters of interest, and ε_{ist} represents the error term. My control variables C_{it} are intended to include physician and practice characteristics that may change over time as well as the most significant time-variant characteristics of state markets that may be coincident with changes in NPC practice regulations and affect Medicaid participation by PCP practices. They account for differences across physicians in experience (year began practice), salary and practice ownership status, international medical graduate status, board certification status, and recent history of free care provision, differences across practices in practice type (solo or two-physician practice, groups of three or more physicians [ref.], HMO, medical school-affiliated practice, hospital-based practice, or other) and capacity constraints (accepting most or all new Medicare and privately insured patients), and differences across counties in the densities of all physicians and general practice physicians, the demand for Medicaid primary care services (total county population, number of Medicaid-eligible individuals per 1,000 population in the county, metro versus non-metro area, and county unemployment rate), the fraction of Medicaid beneficiaries enrolled in managed care in the state, and relative Medicaid reimbursement levels (average Medicaid-Medicare fee ratios for primary care services). This full set of control variables is included in all principal and supplemental analyses except where specified or where select variables are dropped due to data limitations or multicollinearity.

To test hypothesis *H1*, I review all individual PA practice regulation variables' marginal effect estimates, and I also construct a χ^2 test of the collective significance of these estimates. Likewise, for hypothesis *H2*, I construct a χ^2 test of the difference between the marginal effects of NP practice regulations and PA practice regulations. To further illustrate this difference, I predict for all PCP practices in my sample the effect of changing NPC regulations from those in a state with more restrictive NPC regulations to those in a state with less restrictive NPC regulations. I identify these states by constructing an index of NPC regulation restrictiveness using all NP and PA regulations included in my regressions and the status of these regulations in each state as of 2008; I then selected randomly a state from among the ten least restrictive and a state from among the ten most restrictive for comparison.

For my test of hypotheses *H3* through *H6*, I introduce two new dependent variables. For *H3* and *H4*, my dependent variable is an indicator that the practice is accepting most or all new Medicare and privately insured patients $nonM_{ist}$ (this variable is not included in the vector of controls C'_{it} in these regressions), and for *H5* and *H6*, my dependent variable is a measure of total hours the surveyed PCP spent in patient care during the previous week Tot_{ist}. Information about the total number of hours the practice dedicates to patient care overall is not collected in the CTSPS. These new regression equations (2) and (3), which parallel equation (1) in most respects, are presented below. In addition, for hypotheses *H4* and *H6*—as with hypothesis *H2*—I compare the magnitude of relaxed NP and PA regulations' effects for states with regulations akin to those in a typical restrictive state and a typical unrestrictive state in 2008, as identified using the methodology described above.

$$nonM_{ist} = \Lambda(\beta_0 + \beta(nonM)_{NP}NP_{st} + \beta(nonM)_{PA}PA_{st} + \beta_{C'}C'_{it} + Y_t + S_s) + \sigma_{ist} \quad (2)$$

$$Tot_{ist} = \Lambda(\beta_0 + \beta(Tot)_{NP}NP_{st} + \beta(Tot)_{PA}PA_{st} + \beta_C C_{it} + Y_t + S_s) + \omega_{ist} \quad (3)$$

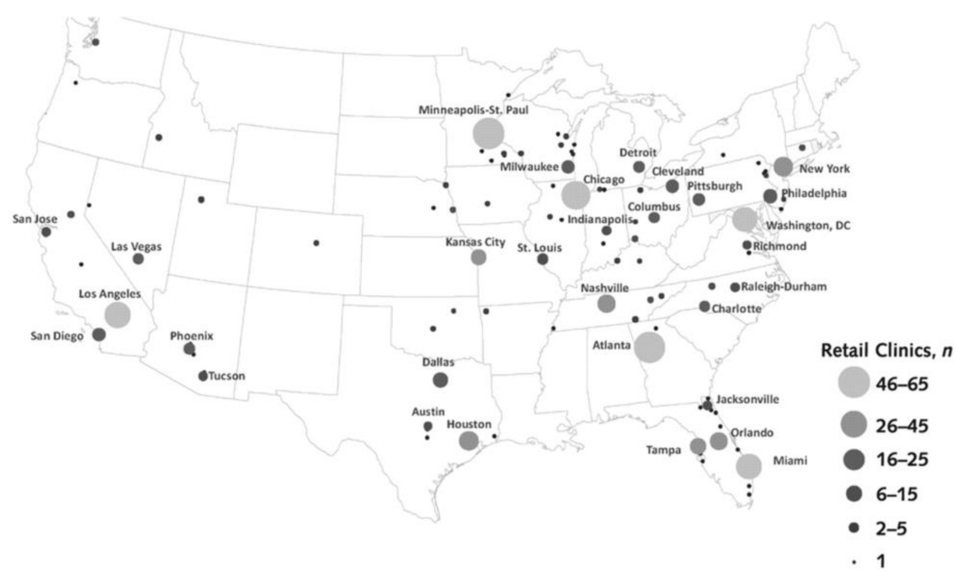
In my regressions for testing hypotheses *H7*, *H8*, and *H9*, I include terms interacting NPC regulations with other practice- or market-level variables of interest. For my test of hypothesis *H7*, this variable of interest is the fraction of the state's Medicaid beneficiaries enrolled in managed care. This variable is not included among the model's controls C''_{it}—see equation (4) below. Specifically, for this hypothesis test I compare the marginal effect estimates of relaxing NPC regulations in states above and below the median of managed care penetration (34.5%), denoted $hiMC_{st} = 1$.

$$M_{ist} = \Lambda(\beta_0 + \beta_{NP}NP_{st} + \beta_{PA}PA_{st} + \beta_{hiMC}hiMC_{st} + \beta_{X\times NP}X_{it} \times NP_{st} + \beta_{hiMC\times PA}hiMC_{st} \times PA_{st} + \beta_{C''}C''_{it} + Y_t + S_s) + \varepsilon_{ist} \quad (4)$$

For my test of hypothesis *H8*, my variable of interest is a measure of the local density of NP-operated care facilities relative to the population. This measure is derived from a 2008 survey of the distribution of retail clinics, a commonly NP-led primary care practice structure, conducted by Rudavsky, Pollack, and Mehrotra (2009) and 2008 population estimates from the U.S. Census. Using their data, I identify select Combined Statistical Areas and Metropolitan Statistical Areas in Minnesota (Minneapolis-St. Paul), Missouri (Kansas City), Illinois (Chicago), Texas (Houston), Florida (Miami, Orlando, Tampa), Georgia (Atlanta), North Carolina (Charlotte), Ohio (Columbus, Cleveland), Pennsylvania (Pittsburgh), Tennessee (Nashville), Wisconsin (Milwaukee), and the District of Columbia to be "high-NP" markets. These are markets where competition or free-riding effects of relaxed NP regulations are most likely to be observed. Figure 4, reprinted from the work of Rudavsky, Pollack, and Mehrotra (2009), gives some sense as to where NP retail clinics had their largest market footprints in 2008. In particular, I compare estimated marginal effects in markets with high retail clinic density—higher retail clinic count per resident than the national average among markets with at least one retail clinic, denoted $hiNP_{it}$ = 1—with reference estimates. Because my identifying variation is strictly cross-sectional in this case, I do not include year fixed effects in this model – see equation (5) below.

$$M_{ist} = \Lambda(\beta_0 + \beta_{NP}NP_{st} + \beta_{PA}PA_{st} + \beta_{hiNP}hiNP_{it} + \beta_{hiNP\times NP}hiNP_{it} \times NP_{st} + \beta_{hiNP\times PA}hiNP_{it} \times PA_{st} + \beta_C C_{it} + S_s) + \varepsilon_{ist} \quad (5)$$

Figure 4: Distribution of Retail Clinics in the Continental United States, 2008



Source: Rudavksy, Pollack, and Mehrotra, 2009.

Finally, to test hypothesis *H9*, my variables of interest are indicators of small practice size (solo or two-physician practice) and large practice size (medical school-affiliated or hospital-based practice), Sm_{it} and Lg_{it}, respectively. In this model (equation [6] below, in which NPC_{st} replaces $NP_{st} + PA_{st}$ to simplify notation), my set of controls C'''_{it} excludes corresponding indicators of practice type. Using this model's results, I compare marginal effect estimates for relaxed NPC regulations in small, medium-sized (reference group), and large practices.

$$M_{ist} = \Lambda\big(\beta_0 + \beta_{NPC}NPC_{st} + \beta_{Sm}Sm_{it} + \beta_{Lg}Lg_{it} + \beta_{Sm\times NPC}Sm_{it} \times NPC_{st} + \beta_{Lg\times NPC}Lg_{it} \times NPC_{st} + \beta_{C'''}C'''_{it} + Y_t + S_s\big) + \varepsilon_{ist} \quad (6)$$

I cluster standard errors at the state level in all analyses and employ the Stata command *margins* for estimating marginal effects, following the approach described by Karaca-Mandic, Norton, and Dowd (2012) where my specification includes interaction effects. I conduct my analyses using Stata/IC 13.1 (StataCorp, 2013). This study was deemed IRB-exempt by the University of Michigan Health Sciences and Behavioral Sciences Institutional Review Board.

Results

I identify 24,299 PCP practice-year records in the CTSPS data in the 42 states for which primary care fee data are available. Of these, 16,528 pertain to 6,222 unique practices (40 states) for which more than one complete survey was collected across CTSPS survey waves and complete county- and state-level data are available. Descriptive statistics from the 1996-1997 surveys and 2004-2005 surveys for these practices and the respondent physicians are presented in Table 1 and Table 2. Overall, 77.1% of my sample's physician practices accepted at least some new Medicaid patients in the 1996-1997 survey versus 70.6% of physician practices in the 2004-2005 survey. In 1996, 81.4% derived at least 2% of practice revenues from Medicaid, 74.0% derived at least 5% of practice revenues from Medicaid, and 54.6% derived at least 10% of practice revenues from Medicaid, versus 79.0%, 72.2%, and 56.6%, respectively, in 2004. In both surveys, the majority of physician respondents were non-salaried, full or part owners of their practices, board certified, and practicing in small or moderate-sized physician group practices. Market-level characteristics of these physicians and their practices do not appear to change considerably between the 1996 and 2004 survey waves.

Across the states where these samples of physicians practice, there is considerable heterogeneity in NP and, in particular, PA practice regulations over time. The differences between the regulation statistics for the 1996 and 2004 surveys reflects further heterogeneity in NPC regulations over time within states as well as, to a lesser degree, in the mix of physicians surveyed. As examples, state board licensure was required for PAs to practice in the states where 47.8% of sample PCPs practiced in 1996 versus 72.9% in 2004, and the state allowed practice sites to determine PAs' scope of practice limitations (rather than they themselves establishing such constraints) where 40.8% of sample PCPs practiced in 1996 versus 51.7% in 2004.

Information about the complete practice sample's Medicaid revenue fractions is presented in Figure 5. The data are presented as a reverse cumulative distribution plot so as to indicate clearly, for each threshold percent value, the fraction of sample practices receiving at least as much of their revenue from Medicaid; in this way the figure reflects my models' dependent variables. The stair-step structure of this figure, especially rigid above 9 percent of revenue from Medicaid, reflects rounding by respondents. Because the distribution is highly skewed—less than 20 percent of practices report receiving more than 25 percent of their revenues from Medicaid—few of my models of practices receiving large fractions of their revenues from Medicaid yield precise estimates. Indeed, models cannot be estimated for practices receiving more than 90 percent of their revenue from Medicaid, because such practices are too few in my sample. This portion of the distribution is excluded from the figure.

Table 1: Final Sample Physician and Practice Descriptive Statistics, 1996 and 2004 CTSPS Survey Waves – Select Dependent and Independent Variables

	Unique Physicians - 1996-1997 Survey		Unique Physicians - 2004-2005 Survey	
Variable	Mean/%	(SD)	Mean/%	(SD)
Dependent Variables				
Accepting new Medicaid patients	77.1%	(42.1%)	70.6%	(45.6%)
≥ 2% Medicaid revenues	81.4%	(38.9%)	79.0%	(40.7%)
≥ 5% Medicaid revenues	74.0%	(43.8%)	72.2%	(44.8%)
≥ 10% Medicaid revenues	54.6%	(49.8%)	56.6%	(49.6%)
Physician Assistant Practice Regulations				
Practice requires license	47.8%	(50.0%)	72.9%	(44.4%)
Site determines scope of practice	40.8%	(49.2%)	51.7%	(50.0%)
No restrictions on prescribing	15.4%	(36.1%)	19.9%	(39.9%)
MD co-signature not required	7.6%	(26.6%)	13.7%	(34.4%)
MD proximity req. not specified	27.1%	(44.4%)	20.6%	(40.4%)
No restrictions on PA/MD ratios	1.4%	(11.9%)	6.9%	(25.4%)
Nurse Practitioner Practice Regulations				
MD supervision not required	35.5%	(47.8%)	27.9%	(44.8%)
Full prescription authority	11.7%	(32.1%)	8.1%	(27.2%)
N	3,609		2,147	

Table 2: Final Sample Physician and Practice Descriptive Statistics, 1996 and 2004 CTSPS Survey Waves – Control Variables

	Unique Physicians - 1996-1997 Survey		**Unique Physicians - 2004-2005 Survey**	
Variable	Mean/%	(SD)	Mean/%	(SD)
Physician-level controls				
Year began practice	1,961.2	(10.5)	1,965.8	(9.9)
Salaried	35.4%	(47.8%)	29.6%	(45.7%)
Full or part owner of practice	51.6%	(50.0%)	55.3%	(49.7%)
International medical graduate	21.0%	(40.8%)	22.2%	(41.5%)
Not board certified	19.3%	(39.5%)	12.8%	(33.4%)
Hours free care previous month (/10)	0.6	(1.3)	0.6	(1.3)
Practice-level controls				
1-2 MD practice	35.6%	(47.9%)	38.0%	(48.6%)
3+ MD group practice (ref.)	25.4%	(43.5%)	26.4%	(44.1%)
HMO	9.5%	(29.3%)	4.9%	(21.6%)
Medical school-affiliated	5.0%	(21.7%)	6.1%	(23.9%)
Hospital based	14.0%	(34.8%)	12.1%	(32.6%)
Other practice type	10.5%	(30.7%)	12.6%	(33.2%)
Accepting most or all Medicare and privately insured patients	64.2%	(48.0%)	63.9%	(48.1%)
Market-level controls				
General practitioner density‡	0.2	(0.1)	0.3	(0.1)
Physician density‡	3.1	(1.9)	3.2	(2.0)
Population‡	988.0	(1328.6)	1,088.9	(1765.1)
Medicaid eligibles density‡	20.6	(7.9)	19.0	(8.3)
Non-metropolitan area	8.6%	(28.1%)	13.1%	(33.8%)
Unemployment rate	5.0%	(1.9%)	5.5%	(1.6%)
Fraction of Medicaid beneficiaries enrolled in managed care	36.7%	(21.5%)	39.8%	(24.7%)
Medicaid/Medicare primary care fee ratio	64.0%	(21.4%)	63.4%	(15.0%)
In market with high NP-led practice density in 2008	21.1%	(40.8%)	21.2%	(40.9%)
N	3,609		2,147	

‡ Per 1,000 population

Figure 5: Revenue from Medicaid Among Sample PCP Practices, 1996-2004, Reverse Cumulative Distribution Plot

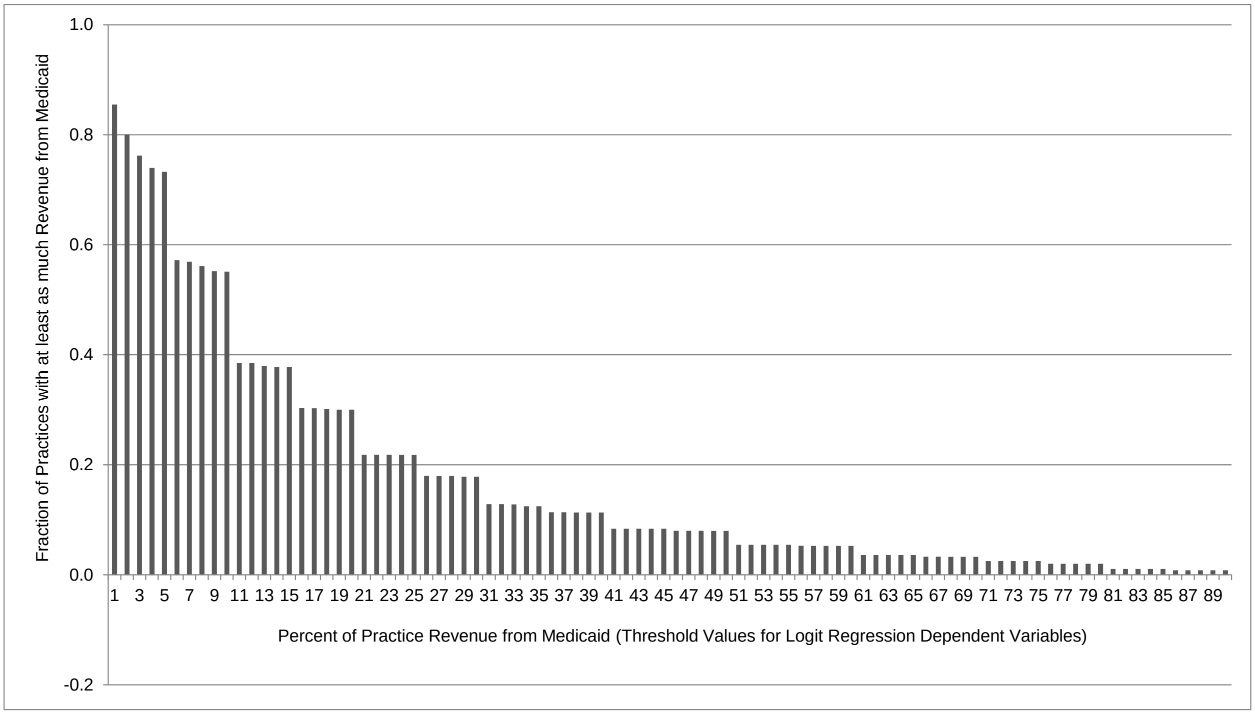


Table 3 provides additional summary information regarding the changes between CTSPS data years in the select NPC regulation variables included in my regression models. Notably, there are substantial numbers of state-years in which most NP and PA practice regulation variables change versus previous years, changes from which I derive my identifying variation. Only the variable for NP full prescription authority switches between years for fewer than seven states (two states: Wisconsin and Wyoming). The results for full prescription authority for NPs, therefore, may be less generalizable than those I generate for other NPC regulations.

This table also highlights that the NPC regulatory changes providing my study's identifying variation include both changes to lessen the restrictiveness of regulations and changes to tighten regulations. These changes to tighten regulations comprise a distinct minority (26% overall, 37% excluding state licensure requirements for PAs) of the regulatory changes I observe during the study period. Still, that my identifying variation comes from both forms of regulatory changes alleviates some concerns of endogeneity in my analyses due to the fact that efforts to relax regulations may be stronger in states where access to care has worsened. This concern is also partly addressed through the inclusion of physician and

Medicaid-eligible population density measures and an indicator of non-metropolitan areas among my models' control variables.

Table 3: State-level Summary of Changes in NPC Regulations, 1996-2004

Law or Regulation	# States, 1996	# States, 1998	# States, 2000	# States, 2004	Switch to Less Rest.	Switch to More Rest.
Physician Assistants						
Practice requires license	22	29	40	44	22	0
Site determines scope of practice	25	26	27	29	7	3
No restrictions on prescribing	8	9	14	17	10	1
MD co-signature not required	9	8	9	11	5	3
MD proximity req. not specified	6	6	6	6	3	3
No restrictions on PA/MD ratio	8	6	5	6	3	5
Nurse Practitioners						
MD supervision not required	23	23	23	24	4	3
Full prescription authority	12	12	13	12	1	1

Note: Table reflects policies in all fifty states and the District of Columbia, more states than are reflected in my analytic sample. "Practice requires license" is included as a fully unrestrictive regulatory requirement, relative to reference categories "practice requires certification" and "practice requires registration," because of the increased regulatory and subjective (for patients) legitimacy of the authority of licensed health care professionals as compared to unlicensed health care professionals. The AAPA observes that in most states the requirements imposed on PAs to obtain licensure, relative to the requirements imposed for obtaining certification or registration, are only nominally different.

Select analytic results for hypotheses *H1* and *H2* are presented in Table 4.[7] In this table I include, for each dependent variable, marginal effect estimates for NPC regulations as well as predicted probabilities generated from these marginal effect estimates. These predicted probability estimates reflect Medicaid participation levels if the state regulations for all physician practices were exchanged for those in a typical more restrictive state and those in a typical less restrictive state. I then estimate the difference between these predicted probabilities and calculate a Wald statistic to determine the difference's statistical significance.

[7] In Table 4 and subsequent figures, results are reported for NPC regulation changes only. Results for these models' full sets of covariates are available upon request.

Table 4: Medicaid Participation and the Marginal Effects of Changes in Non-Physician Clinician Regulations

Dependent Variable	**Accepting new Medicaid patients**		**≥ 2% Medicaid revenues**		**≥ 5% Medicaid revenues**		**≥ 10% Medicaid revenues**	
Marginal Effect / Pred. Prob.	Est.	SE	Est.	SE	Est.	SE	Est.	SE
Physician Assistant Practice Regulations								
Practice requires license	0.001	0.020	0.015	0.016	0.016	0.023	0.019	0.025
Site determines scope of practice	-0.026	0.025	-0.026	0.021	-0.029	0.046	-0.024	0.031
No restrictions on prescribing	0.035	0.021*	0.001	0.022	-0.005	0.031	-0.007	0.034
MD co-signature not required	-0.019	0.024	-0.033	0.019*	-0.013	0.027	-0.020	0.026
MD proximity req. not specified	0.020	0.016	0.004	0.019	0.029	0.043	-0.036	0.041
No restrictions on PA/MD ratios	0.026	0.018	-0.004	0.013	0.000	0.023	0.004	0.035
Nurse Practitioner Practice Regulations								
MD supervision not required	-0.029	0.026	-0.065	0.024***	-0.051	0.034	0.011	0.062
Full prescription authority	0.013	0.011	-0.114	0.016***	-0.038	0.014***	0.086	0.013***
Predicted Probabilities - PA Regulations								
Typical, more restrictive state	0.766	0.018	0.835	0.015	0.755	0.034	0.571	0.022
Typical, less restrictive state	0.810	0.023	0.830	0.023	0.766	0.041	0.568	0.033
Difference (less - more)	0.044 *		-0.005		0.012		-0.003	
Predicted Probabilities - NP Regulations								
Typical, more restrictive state	0.802	0.009	0.872	0.007	0.792	0.011	0.552	0.022
Typical, less restrictive state	0.786	0.023	0.675	0.034	0.700	0.030	0.649	0.041
Difference (less - more)	-0.016		-0.197 ***		-0.092 ***		0.096 **	
Predicted Probabilities - All NPC Regulations								
Typical, more restrictive state	0.775	0.023	0.865	0.016	0.776	0.038	0.558	0.033
Typical, less restrictive state	0.803	0.034	0.654	0.046	0.694	0.056	0.650	0.053
Difference (less - more)	0.028		-0.211 ***		-0.082		0.093 *	
N observations †	16,495		16,445		16,466		16,514	
Model pseudo-r^2	0.146		0.128		0.122		0.119	

*** $p < 0.01$. ** $p < 0.05$. * $p < 0.10$. † Select states' observations dropped due to collinearity in fixed effects.
Note: In addition to NPC regulations, model covariates include physician-level (e.g., year began practice), practice-level (e.g., practice type), and market-level (e.g., Medicaid relative reimbursement) controls, state fixed effects, and year fixed effects.

Across all individual PA practice regulations and all models, marginal effect estimates are typically small, and only a few are statistically significant. One of these suggests that relaxing restrictions on PAs' prescribing authority leads to a 3.5 percentage point increase in the probability a PCP practice accepts new Medicaid patients, and another suggests that relaxing co-signature requirements for PAs' physician supervisors reduces the probability a PCP practice receives at least 2% of its revenues from Medicaid by 3.3 percentage points. Overall, relaxing PA regulations from those in a typical more restrictive state to those in a typical less restrictive state increases the probability of accepting new Medicaid patients by 4.4 percentage points;

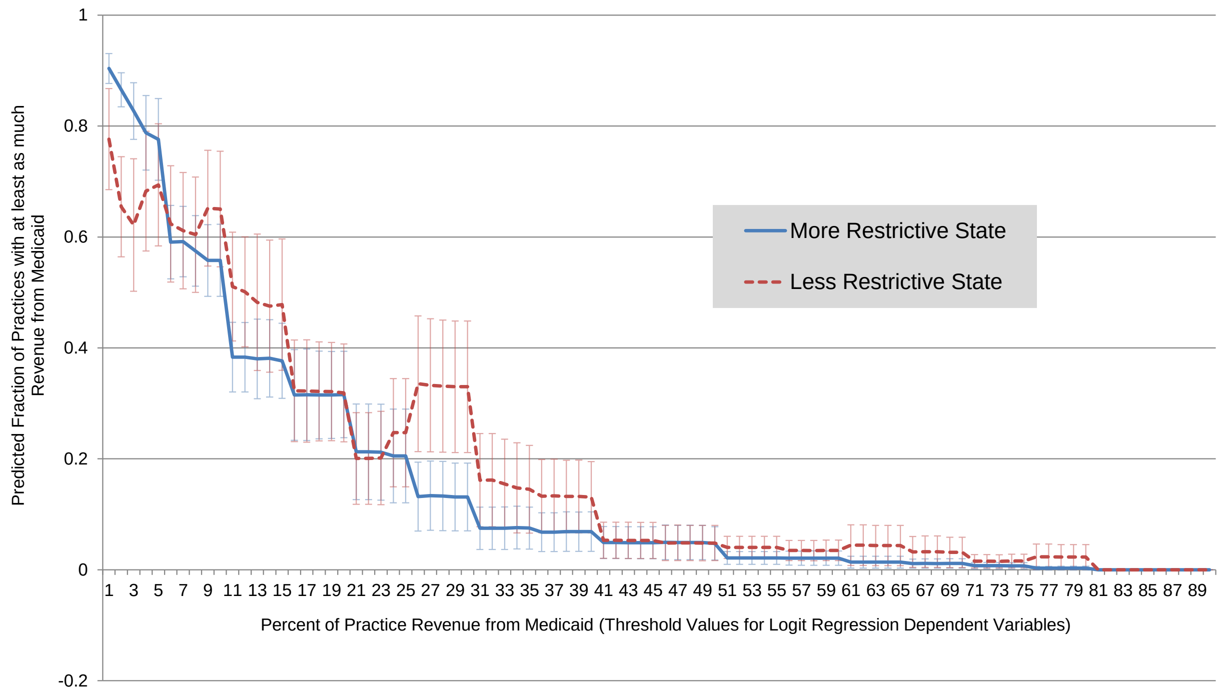
this modest, positive effect is driven principally by the positive effect I estimate for relaxing restrictions on PA prescribing authority. Overall effects on other measures of Medicaid participation are not statistically significant. These results suggest that relaxing PA regulations may have a small, positive effect on PCP practices' willingness to accept new Medicaid patients (consistent with hypothesis *H1*) but little effect on the composition of PCP practices' patient panels overall.

Marginal effects for both individual NP practice regulations are not statistically significant for the outcome of accepting new Medicaid patients; this may reflect the offsetting small effects of reduced marginal costs and free-riding behavior (or heterogeneous responses across physician practices), though the difference between the estimated effects for relaxed NP regulations and relaxed PA regulations is not statistically significantly different from zero at conventional levels (p = 0.43). However these two regulations' marginal effect estimates are strongly statistically significant and negative for the outcome of receiving at least 2% of practice revenues from Medicaid. Switching from a state regulation requiring physician supervision for NPs to a regulation that does not require such supervision reduces the probability a PCP practice receives at least 2% of its practice revenues from Medicaid by 6.5 percentage points, for example. The combined effect of these estimates—a reduction of 19.7 percentage points (versus a sample mean of 79.0% in 2004-2005) in the probability a PCP practice receives at least 2% of its revenues from Medicaid—is also significantly lower than the net estimated effect of relaxed PA regulations (p = 0.01), strongly indicative of free-riding behavior among some PCP practices (i.e., contrary to the competition-driven hypothesis *H2* as stated).

For the outcomes of receiving at least 5% or 10% of practice revenues from Medicaid, marginal effect estimates are not statistically significant for physician supervision regulations but significant and negative and significant and positive, respectively, for full prescription authority regulations. I estimate a smaller negative combined effect (9.2 percentage points) on the probability a practice receives at least 5% of its revenue from Medicaid and a positive combined effect (9.6 percentage points) on the probability a practice receives at least 10% of its revenue from Medicaid. The differences in predicted probabilities between more restrictive regulatory environments and less restrictive regulatory environments for all NPC regulations follow the same pattern across dependent variables. Likewise, the differences between the effects of relaxing NP regulations and the effects of relaxing PA regulations change in sign and significance across dependent variables.

Complete results for the effects of different regulatory environments for NPCs on practice revenues from Medicaid are presented in Figure 6. Predicted fractions of practices exceeding each Medicaid revenue percentage threshold, generated using NPC regulations from a typical more restrictive state or from a typical less restrictive state, are presented separately with 95% confidence intervals. For thresholds between 1% and 5% of practice revenue from Medicaid, the predicted fraction of practices reporting at least as much Medicaid revenue is significantly greater when NPC regulations are more restrictive. At every threshold value above this range, the predicted fraction of practices reporting at least as much Medicaid revenue is significantly greater when NPC regulations are less restrictive, or there is no statistically significant difference. The largest negative effect of relaxing NPC regulations on practice revenues from Medicaid is observed at the 2% threshold (see Table 4), and the largest positive effects—approximately 20 percentage point increases in the predicted probability that a practice receives at least as much revenue from Medicaid—are observed for thresholds between 25% and 29% of practice revenue from Medicaid.

Figure 6: Predicted Fractions of Practices Reporting Receipt of Medicaid Revenue above Different Levels, More Restrictive State NPC Regulations versus Less Restrictive State NPC Regulations



The heterogeneity of these estimates across models may reflect heterogeneous effects across practice types. Practices participating more marginally in Medicaid (e.g., 1 to 5% of practice revenues from Medicaid) may be more likely to withdraw from Medicaid participation and exhibit free-riding behavior than practices more committed to serving the Medicaid population. By contrast, larger practices (e.g., FQHCs, medical school-affiliated practices, and HMOs) that serve the Medicaid population as part of their missions and that make more regular use of NPCs may experience greater reduced marginal cost effects and exhibit less free-riding behavior. I explore this heterogeneity further in my test of hypothesis *H9* below.

Overall, the magnitudes of my effect estimates for individual regulations range from zero to 11.4 percentage points, though most of these individual effect estimates have magnitudes below four percentage points. Should a state relax multiple, selectively-chosen NPC regulations jointly, it may realize a larger net increase in physician practices' participation in Medicaid, depending on the state's pre-reform regulatory environment. These effect estimates are comparable to the estimated effects of large increases in Medicaid fees, such as those provided for through the ACA's "fee bump": Wilk (2013) found that these increases in fees would be associated with an increase in the proportion of physician practices accepting new Medicaid patients of about 5.3 percentage points. However, while the costs to states of relaxing NPC regulations can be minimal, the costs of maintaining or re-instituting such large fee increases may be prohibitive. Thus my analyses suggest that many states' NPC regulations offer a cost-effective opportunity to increase access to primary care services for Medicaid beneficiaries.

In supplemental analyses in which I include only NP practice regulations or only PA practice regulations in my models, I obtain estimates of greater statistical significance and magnitude in both NP-focused and PA-focused regressions. This represents evidence that the effects of relaxed NP and PA regulations are not independent and are achieved through similar mechanisms (e.g., reduced marginal costs of care).

The results of my tests of hypotheses *H3* through *H6*—regarding the relationships between NPC regulations and practices' willingness to accept new non-Medicaid (Medicare or privately insured, principally) patients as well as total patient care—are summarized in Table 5. In the model of access for non-Medicaid patients, marginal effects for most PA regulations are estimated to be positive, and a χ^2-test rejects the joint hypothesis that all of these estimates equal zero ($p < 0.01$), consistent with hypothesis *H3* that reduced marginal costs of care may lead PCP practices to increase access for non-Medicaid patients. However, since none of these individual regulation estimates is statistically significant, relaxed PA regulations may not strongly affect most PCP practices' capacity to treat non-Medicaid patients. (This is also consistent with my theoretical framework, which suggests only some physician practices would increase their hours allocated to non-Medicaid patients when PA regulations are relaxed.) My estimates of relaxed PA regulations' effects on the physician respondent's total patient care hours are not statistically significant, both individually and in aggregate ($p = 0.51$), thus failing to support hypothesis *H5*. This suggests that any increases in the use of PA staff in response to relaxed PA regulations may serve more to increase the practice's overall capacity rather than to substitute for physician care.

My estimates of the marginal effects of relaxed physician supervision regulations for NPs are not statistically significant, but my estimates of the marginal effects of relaxed NP prescription authority regulations are well-aligned with the predictions of free-riding behavior by PCP practices. In particular, when these prescription authority regulations are relaxed, the practice's probability of accepting new non-Medicaid patients increases 15.6 percentage points, a large effect, while total patient care delivered falls approximately 1.1 hours. These results are consistent with the hypothesis of free-riding behavior and contradict the competition hypothesis. However, while the net effect of relaxing both regulations on non-Medicaid patient access is positive and statistically significant ($p < 0.01$), the net effect on total patient care hours is not statistically different from zero ($p = 0.77$) because of the large and positive (though imprecise) estimate of the effect of relaxed supervision regulations. Additionally, the differences between the NP regulations' effects and the PA regulations' effects on both non-Medicaid access and total patient care are not distinguishable from zero ($p = 0.55$ and $p = 0.71$, respectively). These results appear to be a consequence of imprecise estimates of the effects of relaxed PA regulations in these regressions. Because of these imprecise estimates, my tests of hypotheses *H4* and *H6* yield only suggestive evidence of free-riding behavior among PCP practices.

Table 5: Marginal Effects of Relaxed NPC Regulations on Care for Non-Medicaid Patients and Total Patient Care

Dependent Variable	**Accepting most new Medicare, privately insured patients**		**Total patient care hours during previous week**	
Marginal Effect / Pred. Prob.	Est.	SE	Est.	SE
Physician Assistant Practice Regulations				
Practice requires license	0.000	0.021	-0.520	0.392
Site determines scope of practice	0.021	0.039	1.038	0.703
No restrictions on prescribing	0.056	0.038	-0.072	0.631
MD co-signature not required	0.034	0.035	-0.255	0.868
MD proximity req. not specified	-0.032	0.045	1.327	0.913
No restrictions on PA/MD ratios	0.029	0.043	-0.146	0.459
Nurse Practitioner Practice Regulations				
MD supervision not required	0.021	0.050	1.497	1.094
Full prescription authority	0.156	0.013***	-1.072	0.402**
Predicted Probabilities - All NPC Regulations				
Typical, more restrictive state	0.613	0.038	43.182	0.655
Typical, less restrictive state	0.832	0.032	42.242	1.229
Difference (less - more)	0.218 ***		-0.940	
N observations†	16,513		16,528	
Model pseudo-r^2	0.037		0.101	

*** p < 0.01. ** p < 0.05. * p < 0.10. † Select states' observations dropped due to collinearity in fixed effects.
Note: In addition to NPC regulations, model covariates include physician-level (e.g., year began practice), practice-level (e.g., practice type), and market-level (e.g., Medicaid relative reimbursement) controls, state fixed effects, and year fixed effects.

The full results of my tests of hypothesis *H7* and *H9* are presented in the Chapter One Appendix. Through my test of *H7*, I find evidence consistent with my hypothesis that competition and free-riding effects may be stronger in states with lower fractions of Medicaid beneficiaries enrolled in managed care plans. Specifically, these results suggest that the effects of free-riding behavior outstrip competition effects and that this difference is particularly great in states with lower Medicaid managed care penetration. My analyses of *H9* offer evidence that the benefits of reduced marginal costs of care associated with relaxed PA practice regulations are greater in moderate-sized physician practices with three or more physicians than in larger hospital-based or medical school-affiliated practices (which may, themselves, already benefit from low marginal costs of care) or smaller practices (for whom the benefits may be too small to bring about meaningful changes in Medicaid participation).

Finally, additional evidence of the effects of free-riding behavior emerges in my analysis of hypothesis *H8*, in which I examine how the effects of relaxed NPC regulations differed in areas where retail clinics, which are often NP-led, would make significant inroads by 2008. As shown in Table 6, my effect estimates for relaxed NP practice regulations—particularly physician supervision regulations—are lower and statistically significant in these high-NP-led markets. This is consistent with predictions of free-riding behavior by PCP practices where NP-led practices become a particularly important fixture in the local primary care market.

Table 6: Accepting New Medicaid Patients, Marginal Effects of NPC Regulations in Markets with Significant Retail Clinic Penetration in 2008

	Reference markets		High NP-led practice density, 2008	
Marginal Effect	Est.	SE	Est.	SE
Nurse Practitioner Practice Regulations				
MD supervision not required	-0.014	0.024	-0.205	0.040***
Full prescription authority	-0.004	0.050	0.008	0.050

*** p < 0.01. ** p < 0.05. * p < 0.10. n = 16,495. Note: In addition to NP regulations, model covariates include physician-level (e.g., year began practice), practice-level (e.g., practice type), and market-level (e.g., Medicaid relative reimbursement) controls, state fixed effects, and year fixed effects.

Limitations

My study has several limitations of note. Two concern the structure of physicians' and physician practices' optimization functions. First, physician practices may maximize more than just profits—several economic models hold that physicians also maximize quality and the benefit they provide to their patients and the community. My data do not support a nuanced examination of continuity of care, any disparities in quality of care between PCPs and NPCs, or practices' effectiveness as managers of NPC staff. Should a practice incorporate these issues into their decision processes in ways that evolve over time, my estimates of reduced marginal cost effects may be attenuated.

Similarly, PCP practices may respond to changes in NPC regulations by altering their quality production (e.g., time spent with patients per visit) as well as their patient mix. PCP practice investments in non-reimbursed patient care (e.g., phone calls, patient education, care coordination), for example, may meaningfully affect patient outcomes, and they may change as the practice adjusts to new mixes of staff and staff responsibilities. However, they cannot be measured using CTSPS or other like survey data sets. Garthwaite (2012) sought to draw inferences about the quality of care delivered to patients based on aggregate measures of time spent delivering medical care. Thus, while I have not explicitly modeled this in the theoretical framework, one could interpret the results of my models of total patient care to indicate that relaxed NP regulations cause PCP practices to cut back on the amount of time they spend per patient rather than the number of patients they treat overall. While time per patient may be an important measure for capturing patients' care experiences and may be related to other measures of clinical quality, it would be more valuable to examine patient outcomes or the quality of care processes in this research context.

It is a common criticism of the literature on physician participation in Medicaid that researchers use simplistic dependent variables (e.g., accepting any new Medicaid patients: yes or no), such as I use in this paper. Among the limitations of these measures is that they do not reflect well the real policy concern of Medicaid beneficiaries' access to care or questions of Medicaid care utilization (Aliu et al., 2014). Importantly, my study does not capture whether, when PCP practices withdraw from the Medicaid market, Medicaid patients are able to access primary care in other ambulatory settings (e.g., NP-led practices). Richards and Polsky (2014) contribute in this area through their simulated patient studies, described above, though their study has other limitations. Nevertheless, the benefits of the dependent variables I use include comparability with previous estimates, consistency with my physician-oriented theoretical framework, and the capacity to examine both extensive and intensive margins of PCP practice responses to policy changes. Still, given that Richards and Polsky likewise examine the effects of NP and PA practice regulations on access in Medicaid using different dependent variables, it may be said this paper and theirs are complementary.

Because my results are derived from a difference-in-differences design at the state level, I am effectively controlling for fixed differences across states that would affect physician participation in Medicaid. This design does not, by its structure, control for heterogeneity in market trends or asynchronous policy changes (other than NPC regulations) across states, which could bias my results. However, it is unlikely that such biases are significant in my results because I include among my empirical models' controls measures of the most important factors that changed significantly, varied across states, and could have affected PCP practices' participation in Medicaid during the study period. Among these measures are the relative generosity of Medicaid fees for primary care services (Wilk, 2013), the fraction of Medicaid beneficiaries enrolled in managed care (Adams & Herring, 2008), the mix of settings in which primary care was delivered (Wilk, 2013), and key drivers of demand for primary care services in Medicaid such as the local density of Medicaid-eligible individuals and unemployment levels. Moreover, in a series of falsification tests, I find no statistically significant effects of changes in state NPC practice regulations two years after CTSPS data years on PCP practices' reported participation in Medicaid. This suggests that my principal findings are not spurious and that they are not a consequence of other secular, state-specific trends.

One potential data-related limitation of my study is that, due to incomplete source data, I am not able to capture state- or county-level variation in the number of PAs or NPs in the observed PCPs' markets and, in particular, the mix of these PAs or NPs' specialties over time. This may be of concern because, since the mid-1990s, shifting incentives have led NPs and PAs to practice in primary care at a declining rate (Hooker & Everett, 2012). It may be that in some markets, unmeasured factors (e.g., inhospitable physician attitudes toward NPs and PAs) drive NPCs into or out of primary care in ways that affect PCPs' decisions to participate in Medicaid. Since the general trends have been toward lessening restrictions in NPC regulations and fewer NPCs practicing in primary care, it is likely that any associated bias would attenuate my estimates.

Data limitations also deter me from testing the full set of predictions emerging from my theoretical models of reduced marginal costs and competition and thereby offering further evidence supporting or controverting them. In particular, these models predict that relaxed NPC regulations lead to reduced care prices for privately insured patients; prices are not available through the CTSPS. Likewise, I am unable to test the effects of relaxed NPC regulations on PCP practices' employment of NPCs, as the CTSPS discontinued collection of this information following the 1998 survey wave.

My empirical strategy for identifying the competition or free-riding behavioral effects of relaxed NPC regulations relies on the assumption that PAs and NPs offer PCP practices similar opportunities to reduce their marginal costs of care relative to PCP staff. While both may provide many of the services PCPs can provide, typically NPs' scope of practice exceeds PAs'—thus NPs may be able to stand in for PCPs more frequently than PAs, all else equal. However, this difference is at least partially offset by the fact that NPs cost PCP practices significantly more in salary and benefits than PAs. Whether NPs or PAs more effectively reduce a practice's marginal costs may depend on the practice's effective care models and management structures, which are typically unobservable. Thus one of two biases may be introduced. If NPs can be used more effectively to reduce PCP practices' costs of care than PAs, then I may overestimate the extent of any competition effects and underestimate free-riding effects as driven by relaxed NP practice regulations. Alternately, if PAs can be used more effectively than NPs to reduce PCP practices' costs of care, then I may underestimate the extent of any competition effects and overestimate free-riding effects as driven by relaxed NP practice regulations. As such, the magnitudes of these effect estimates should be assessed with caution.

Yee and colleagues (2013) effectively identified another limitation of this analysis when they found that there may be considerably less variation in NPC practices across states than would be suggested by the heterogeneity in those states' practice regulations. Physician interviewees indicated that they supervised more closely NPs with less experience and less closely NPs with more experience and that practice culture could be a stronger determinant of NPs' autonomy in practice than NPC regulations. Moreover, regulations may vary in their ultimate effects on practice (Atwater et al., 2008) by region or practice type. It is not feasible to capture the gaps between NPC regulatory constraints and within-practice functional constraints using available data sources. These gaps should make my estimates of NPC regulations' effects on PCP practices' participation in Medicaid more conservative but also more reflective of the actual effects a state might expect upon relaxing its own regulations.

Similarly, the effects of relaxed NPC regulations may be attenuated by Medicaid managed care organization policies where they do not credential NPs as primary care providers

(Schiff, 2012). Among my results, I presented some evidence consistent with the notion that such policies may meaningfully mediate the relationship between NPC regulations and PCP practices' participation in Medicaid. It is unlikely my single, un-interacted control variable capturing the fraction of Medicaid beneficiaries enrolled in managed care is sufficient to control fully for these unmeasured policies, as this information is incomplete; more complete information on these policies within states over time is not accessible using publicly available data sources. Importantly, such information is unavailable for private insurers and Medicare Advantage plans as well; moreover is it not known how consistent or inconsistent these policies were over time within states and markets during the study period. Thus it is not clear how this dynamic should bias my results. More recently, the fraction of surveyed managed care organizations that do credential NPs as primary care providers has increased to 74% as of 2012 (Hansen-Turton et al., 2013). This suggests that any effects of changes in NPC regulations are less likely to be impeded by managed care organization credentialing policies moving forward.

Conclusions and Future Directions

This study concerns the important policy dilemma of limited access to primary care in Medicaid and the strategies state policymakers are considering to improve access. In the short-term, states are considering whether to extend or re-institute the ACA's temporary fee increases for primary care services in Medicaid in place during 2013-2014. However, because of this policy's high cost in many states (particularly where historically Medicaid fees have been lower), other policy alternatives are also receiving attention. My findings illustrate that when policymakers implement one such alternative, relaxing NPC practice regulations, they may inadvertently cause significant decreases in Medicaid participation among some PCP practices, perhaps offsetting gains in participation resulting from increased fees and other measures. States relaxing practice regulations for PAs between 1996 and 2004 saw modest increases in Medicaid participation among PCP practices—up to 4.4 percentage points, with smaller increases in other measures of Medicaid participation. However, states relaxing practice regulations for NPs saw heterogeneous responses among PCP practices: the proportion of PCP practices receiving at least 2% of their revenues from Medicaid was reduced 19.7 percentage points, and the proportion of PCP practices receiving at least 10% of their revenues from Medicaid rose 9.6 percentage points.

This paper also yields insights regarding the different mechanisms through which NPC regulations can affect PCP practices' decisions regarding participation in Medicaid. My findings suggest that relaxing these regulations may lead to small reductions in PCP practices' marginal costs of care and thereby encourage Medicaid participation. However, relaxed NP practice regulations that enable NPs to operate their own practices independently may also lead many PCP practices to withdraw from Medicaid if they believe the new NP-led market entrants will care for the Medicaid population in their place. This "free-riding" behavior by PCP practices is consistent with the concept of Medicaid participation as akin to the provision of a public good. It also appears to be inconsistent with concerns often attributed to physician advocates that relaxed NPC regulations will mean greater competition for PCP practices, particularly for desirable privately insured and Medicare patients.

This paper's findings do not indicate that the choice to relax NPC regulations should be taken off the table by state policymakers seeking to increase access to care in Medicaid. Importantly, it does not indicate that Medicaid patients may be less likely to have primary care access in states with relaxed NPC regulations. This is because my significant, negative estimated effects on Medicaid participation among some PCP practices may be offset from the Medicaid beneficiary's perspective by increases in access to NP-led primary care practices or an increasing concentration of the Medicaid market in a smaller number of larger primary care practices more focused on serving the Medicaid population.

Rather, it suggests that policymakers should not take it for granted that relaxed NPC regulations will have little effect on current Medicaid participants' willingness to see Medicaid patients and lead to improvements in access overall. More nuanced, thoughtful policy packages, possibly including the relaxing of such regulations, may be more productive in improving access than packages relaxing these regulations only. For example, when a state considers relaxing NP practice regulations, it should also consider including additional measures to prevent or account for PCPs' free-riding behavior. To prevent this behavior, states may seek to increase competition between PCPs and NPs in markets for non-Medicaid patients. They may do this by increasing the apparent legitimacy of NPs as primary care providers in the eyes of patients and insurers, as by establishing in state boards of nursing authority comparable to that enjoyed by state medical boards and equalizing payment for services that may be provided equally well by PCPs or by NPs. It may also be important to support public education campaigns or other measures, perhaps spearheaded by private entities (e.g., nursing agencies, insurers), to increase the public's willingness to look upon NPs as substitutable for PCPs in many cases. Because some of these measures are longer-term solutions, it may also be appropriate to account for free-riding behavior in the shorter term by empowering NPs to better serve the needs of the growing Medicaid population. Among the policy measures to consider in this context are putting into place regulations that permit Medicaid to reimburse retail clinics directly for their services (Takach & Witgert, 2009) and mandating that NPs be included in Medicaid managed care organizations' primary care provider credentialing processes alongside physicians.

The complex provisions of the ACA will almost certainly affect PCP practice decisions about Medicaid participation as well as the importance of NPCs and NPC regulations to their calculus. The law's support for electronic health records, medical homes, accountable care organizations, FQHCs, and medical education may be particularly important. As such, a full, general-equilibrium analysis of these changes' effects on access to care in Medicaid is not feasible. Perhaps the most significant change expected is marked growth in the number of patients insured through Medicaid who were previously uninsured or covered through private insurers. This change—as well as expected changes in average Medicaid patient demographics and health status and any associated reductions in Medicaid "churn" due to less stringent Medicaid eligibility criteria—will increase demand for Medicaid primary care visits as well as their relative attractiveness as new patients to PCPs. Primary care providers may respond by seeking to reduce marginal costs of practice to a level where they can meet the greater demand. Should a state choose to relax its NPC regulations in the coming years, it will be difficult to disentangle the effects of the NPC regulations from these and other, far-reaching effects of the ACA (Aliu et al., 2014).

Researchers may extend this paper's framework and findings in several ways. This study is limited to primary care services because current policy developments have focused principally on access to primary care rather than specialty care (e.g., temporary increases in Medicaid fees for primary care services). Yet Decker (2012; 2013), among others, has observed that access to specialty care is also a significant concern or Medicaid beneficiaries. While relaxed NP practice regulations may have more significant, heterogeneous effects in primary care because NPs disproportionately match in primary care and may compete with primary care physicians but not with specialists, the effects of relaxing PA regulations on specialists' participation in Medicaid should be evaluated in future work. Likewise, access to care for Medicare patients and patients dually eligible for Medicare and Medicaid is also increasingly a policy concern. Brunt and Jensen (2014) speak to this issue and spillover effects between insurance markets in their recent paper. My model could be extended (e.g., using more complex non-linear marginal revenue curves to reflect heterogeneity in insurance benefits among non-Medicaid patients) and used to generate hypotheses in this area; such an analysis is beyond the scope of this paper.

As non-physician clinicians come to play larger roles in the primary care market, policymakers are likely to pay closer attention to the regulations that govern their practices and also affect the behaviors of other clinicians. My study offers evidence of significant effects of this kind, though more work must be done to fully understand how these regulations interact with one another. This is necessary so that policies and incentives can be better informed and more effectively aligned to produce the desired outcome of sufficient access to care for Medicaid beneficiaries.

Chapter One Appendix

In my test of hypothesis *H7*—that the effects of competition and free-riding may be stronger in states with lesser Medicaid managed care (MMC) penetration—I assessed the marginal effects of relaxing NPC regulations in environments where a low fraction of Medicaid beneficiaries were enrolled in managed care and where a high fraction of Medicaid beneficiaries were enrolled in managed care. Results for the dependent variable of accepting new Medicaid patients are presented in Table 7—findings for the other dependent variables are broadly similar. In states with low Medicaid managed care penetration, the effects of relaxing PA practice regulations are mixed across regulations, though nearly all are statistically significant. By comparison, in states with higher Medicaid managed care penetration rates, most effects are statistically significant, but their signs are almost always flipped. In addition, I find that the effect of relaxing physician supervision regulations for NPs is not statistically significant in states with a lower fraction of Medicaid beneficiaries enrolled in managed care, but the effect is a 9.2 percentage point increase in the probability of accepting new Medicaid patients in states with higher Medicaid managed care penetration. Most pertinently, I find using a Wald test that the overall difference in relaxed NP and PA regulations' effects is greater in states with lower Medicaid managed care penetration ($p < 0.01$). This is consistent with my hypothesis that the effects of competition and free-riding—particularly the negative effects on Medicaid participation of free-riding behavior—may be stronger in these states.

Table 7: Accepting New Medicaid Patients, Marginal Effects of NPC Regulations Interacted with Indicator of Medicaid Managed Care (MMC) Enrollment Fraction above Median

	Low MMC		High MMC	
Marginal Effect	Est.	SE	Est.	SE
Physician Assistant Practice Regulations				
Practice requires license	-0.035	0.014**	0.016	0.020
Site determines scope of practice	-0.035	0.022	0.086	0.036**
No restrictions on prescribing	0.062	0.015***	-0.059	0.023***
MD co-signature not required	-0.043	0.011***	0.211	0.026***
MD proximity req. not specified	0.024	0.014*	0.113	0.019***
No restrictions on PA/MD ratios	0.042	0.009***	-0.013	0.024
Nurse Practitioner Practice Regulations				
MD supervision not required	-0.026	0.021	0.092	0.026***
Full prescription authority		(not estimable)		

*** p < 0.01. ** p < 0.05. * p < 0.10. n = 16,495. Note: In addition to NPC regulations, model covariates include physician-level (e.g., year began practice), practice-level (e.g., practice type), and market-level (e.g., Medicaid relative reimbursement) controls, state fixed effects, and year fixed effects.

The results of my tests of hypothesis *H9*—that small one- and two-physician practices and very large practices may be least likely to experience meaningful reductions in the marginal costs of care when NPC practice regulations are relaxed—for the decision to accept new Medicaid patients are presented in Table 8. Effect estimates for relaxed PA regulations are mixed across individual regulations. Direct Wald tests of the differences between the aggregate effects of relaxed PA regulations in large practices versus in moderate-sized practices (p = 0.06) and in small practices versus in moderate-sized practices (p = 0.12) suggest that the reduced marginal costs from relaxed PA regulations may be most likely to increase Medicaid participation among the moderate-sized PCP practices. Marginal effect estimates for relaxed NP practice regulations are generally small and not statistically significant, and comparative Wald tests identify no statistically significant differences between effects for small, moderate-sized, or large practices. Only a positive estimated effect of relaxed NP prescription authority regulations for practices with three or more physicians was statistically significantly different from zero, and these effects may be significantly offset for such practices by the effects of relaxed physician supervision regulations, which are imprecisely estimated. Overall, these results offer some evidence consistent with my hypotheses; my test of differential marginal effects of relaxed NP practice regulations across practice types may be under-powered.

Table 8: Accepting New Medicaid Patients, Marginal Effects of Relaxed NPC Regulations Interacted with Practice Type Indicators

	1-2 MD practices		3+ MD practices		Medical school-aff. or hosp.-based practice	
Marginal Effect	Est.	SE	Est.	SE	Est.	SE
Physician Assistant Practice Regulations						
Practice requires license	-0.017	0.033	-0.002	0.028	0.028	0.015*
Site determines scope of practice	-0.063	0.035*	-0.008	0.027	-0.033	0.023
No restrictions on prescribing	0.043	0.024*	0.052	0.028*	-0.049	0.027*
MD co-signature not required	-0.046	0.029	-0.003	0.058	0.008	0.024
MD proximity req. not specified	-0.033	0.029	0.039	0.025	0.070	0.027***
No restrictions on PA/MD ratios	0.041	0.021*	0.003	0.034	0.006	0.031
Nurse Practitioner Practice Regulations						
MD supervision not required	-0.017	0.034	-0.045	0.029	0.004	0.025
Full prescription authority	-0.015	0.041	0.031	0.017*	-0.002	0.026

*** $p < 0.01$. ** $p < 0.05$. * $p < 0.10$. n = 16,495. Note: In addition to NPC regulations, model covariates include physician-level (e.g., year began practice), practice-level (e.g., practice type), and market-level (e.g., Medicaid relative reimbursement) controls, state fixed effects, and year fixed effects.

Chapter Two

The Role of Medical Consultants in the Active Management of Complex Surgical Inpatients' Care

The costs of medical consultations in the inpatient hospital setting are high, and they are rising rapidly. Within Medicare, MedPAC (2013) reports that 37.5 percent of allowed charges for physician evaluation and management services in 2011 were for visits in the inpatient setting, and the costs of critical care visits grew 7.5 percent annually between 2006 and 2010. Journalists have also observed high consultation service costs borne directly by patients, whom out-of-network consulting physicians may "balance bill" for what insurance does not cover (Rosenthal, 2014).

What makes these high and rising costs disconcerting is the decidedly mixed evidence about the effects and benefits of consults: it is not clear what specific services consultants provide most commonly, whether they affect planned courses of treatment in cases of diagnostic uncertainty is in doubt (Gluck, Muñoz, & Wise, 1988; Katz et al., 1998; Mollema, Berger, & Girbes, 2000; Katz, Cimino, & Vitkun, 2005; PausJenssen, Ward, & Card, 2008; Burden et al., 2013), and associations between consult use and important patient care outcomes such as mortality appear to be significant for certain patient and organization types but not others (Gluck, Muñoz, & Wise, 1988; Katz, Cimino, & Vitkun, 2005; Wijeysundera et al., 2010). The dearth of evidence about benefits may have contributed too to the substantial variation in consult use across hospitals that researchers have observed in recent years (Wijeysundera et al., 2012; Stevens et al., 2013; Thilen et al., 2013a; Thilen et al., 2013b; Chen et al., 2014).

The difficulty in identifying the value of consults may be attributable in part to an insufficient understanding of what consultants actually do. The most readily apparent purpose consultants serve is to provide specialty-specific input, answering the attending physician's specialty-specific questions or monitoring a specialty-specific concern the attending physician feels ill-equipped to manage. A less-apparent purpose is to provide "active management": non-specialty-specific work alongside the attending physician to manage a particularly complex patient's case overall. The duties of a consultant taking on an active management role include coordinating the care of other providers, identifying and mitigating conflicting care orders and prescriptions, and assisting the attending physician in determining and evaluating the patient's care pathway.

It has been noted that vulnerable, complex patients may benefit most from such active management support (EWA & N3C, 2013; McCullough, Parente, & Town, 2013). While typically it is understood that these duties are carried out exclusively by primary care physicians, internists, and hospitalists, specialists provide active management as well, more commonly for the complex patients attending physicians are less well-equipped to manage independently. Recognition of this second role of consultants will be especially important as health care systems seek to streamline and expand access to inpatient specialty care through the use of e-consults and telemedicine services (Bailes et al., 1997; Dick, Filler, & Pavan, 1999; Sable et al., 2002; Marcin et al., 2004; McAdams, Cannavo, & Orlander, 2014; Wasfy et al., 2014; Ellenby & Marcin, 2015). The active management role of consultants will be compromised when their specialty-specific input is gathered through these more distant, narrowly-focused interactions (Mehrotra & Hussey, 2015).

How consultants respond to other consultants' behavior—in particular, to what extent they have demonstrated a willingness to help manage the patient's case—reflects recognition about the needs the patient may have for additional active management support. An understanding of consultants' activities based solely on their role as providers of specialty-specific input would not account for a consultant's decisions about how many consults to render being affected by such evidence of active management by other consultants. From this perspective, this study provides evidence of the active management role of medical consultants through an analysis of consultant interactions. My analyses also elucidate consultants' decision-making processes by differentiating among three theoretical frameworks with distinct predictions for patterns of consult provision. In doing so, this study is the first to present empirical evidence on the interpersonal and organizational factors that affect consultants' care for elderly, highly vulnerable or complex patients.

I find that medical consultants' decisions about how many visits to pay a patient are significantly affected by decisions of this same kind by other consultants before them. When previous consultants have given evidence they are taking on an active management role with a patient, the next consultant is significantly more likely to "sign off" sooner and move onto other cases rather than to stay on the case, following an "all hands on deck" mentality. Moreover, when all of the consults previously rendered have been provided more often by only one or a few consultants, I find the next consultant is more likely to step in and provide additional consults, more consistent with a framework of Diminishing Marginal Productivity than a framework akin to the Bystander Effect, as described by Stavert and Lott (2013). Both sets of findings are consistent with an understanding of consultants' second role as active managers of inpatient care. These findings are informative for hospital administrators and medical staffs looking to design incentives and effectively motivate their specialist consultants to improve the efficiency of their care and their patients' outcomes.

Theoretical Frameworks

In this section I describe briefly three theoretical frameworks and their different predictions for the behavior and care patterns of consultants in response to the decisions of other consultants before them. I call these frameworks All Hands on Deck, Diminishing Marginal Productivity, and the Bystander Effect. I summarize the hypotheses emerging from these frameworks in the following section.

All Hands on Deck

More complex patients' needs for additional specialist input and additional active management tend to be greater than less complex patients' needs. If patients' levels of complexity were apparent at admission, all needed specialists could be readied to meet those needs as early as possible. More typically, the full complexity of a patient's case only becomes clear during the course of the hospital stay, and specialists may be able to infer the complexity of the case only using imprecise signals. One such signal is the number of different specialists who have consulted on the case previously; intuitively, this number is positively correlated with the patient's complexity.

After a specialist reviews the patient's medical chart and observes this signal during her initial consult, she may infer from the number of prior consultants the patient's complexity and determine whether to "sign off" or to provide additional consults. The All Hands on Deck theory suggests that she would choose to provide these additional consults if she infers greater patient complexity because the consults would serve as additional opportunities to monitor the case and provide active management support as soon as they are needed. Moreover, the specialist can ensure that any implications of the chosen care pathway for the patient anatomy about which she has expertise are fully considered. More cynically, a specialist observing this signal of complexity may also spot an opportunity to provide and bill for additional consulting visits, even if the patient's level of complexity does not merit them.

If the predictions of the All Hands on Deck framework are realized, then the care patterns of consultants reflect suboptimal information-sharing and inefficient overprovision of consults when they may not be needed. It would be appropriate in this case for hospitals and medical staffs to realign consultants' incentives in order to reduce this inefficiency.

Diminishing Marginal Productivity

In production theory, the Law of Diminishing Marginal Productivity holds that as the number of inputs of equal measure is increased, the product derived per unit of input will eventually decrease. In this study's context, the Law suggests that, for a given patient case, as the number of consults or consulting physicians increases, the marginal value to the patient of additional consults or consulting physicians should fall. If consultants recognize this diminishing value in their own consults, they may be more inclined to "sign off" and discontinue seeing the patient in favor of providing more valuable care to other patients as the number of consultants already involved in the case increases. For this study (in particular for distinguishing the predictions of the Diminishing Marginal Productivity and Bystander Effect frameworks, as I describe below), it is important to note the marginal value of additional consults should diminish more rapidly than the marginal value of additional consulting physicians. New consultants will have greater opportunities to present new insights or perspectives valuable to the patient, while the same consultants providing additional consults will be less likely to contribute such breakthrough ideas.

If the predictions of this Diminishing Marginal Productivity framework hold, there is no inherent failure of the consulting care model. Hospitals and medical staffs should seek to maximize the efficiency of consultants' sign-off decisions by ensuring their information is as complete as possible when they join the case.

The most germane evidence of the Law of Diminishing Marginal Productivity in the context of inpatient physician services to complex patients was provided by Jensen and Morrisey (1986). Jensen and Morrisey's focus was the number of attending physicians on a hospital's medical staff and their productivity as measured using hospital admissions. While the evidence of diminishing marginal productivity in this context is compelling, it is not clear that the authors' findings translate to the numbers of consultants engaged in individual patient cases. Their theory suggested that their finding of diminishing marginal productivity arose from teaching hospitals' high physician labor-to-capital ratios, and these hospital-level ratios may not be pertinent at the individual patient level.

A key assumption of the theory of Diminishing Marginal Productivity is that the input units added are all of equal measure. In the context of medical consultations, this assumption may hold for the active management role of consultants, but it may not hold for the role of providing specialty-specific input. Different specialties, it may be said, provide consults of unequal measure. As such, controlling for consultants' specialties may be very important in isolating the effects of Diminishing Marginal Productivity in this study.

The Bystander Effect

The theory of the Bystander Effect, first formally defined by Darley and Latané (1968) in the experimental psychology literature, is stated as follows: "the more bystanders to an emergency, the less likely, or the more slowly, any one bystander will intervene to provide aid."

In general terms, the Bystander Effect suggests that as the number of individuals with an opportunity to intervene on a threatened party's behalf increases, each individual feels less personally responsible for intervening, and so the probability that any individual intervenes actually falls. Stavert and Lott (2013) cited this theory and the associated "diffusion of responsibility"[8] as a possible reason for failures of active management among larger groups of consulting physicians involved in a complex surgical patient's case. They reasoned that if the number of consulting physicians involved in patient cases increased—perhaps because of medical subspecialization and the increasing complexity of patient data—the average probability that any consultant would take responsibility for actively managing the patient's case would fall correspondingly. Similarly, Srivastava (2013) explained that consultants' failures of active management in such cases may be a consequence of all involved physicians subconsciously deferring to the implicit, collective confidence of their peers in the patient's established care pathway despite any concerns they held personally. The consequences of the Bystander Effect, if its predictions hold in consultant care, include more frequent poor patient outcomes, such as those Stavert and Lott (2013) and Srivastava (2013) described. In this case it would be appropriate for hospitals and medical staffs to realign consultant incentives to encourage active management. It may also be necessary to assign individual consultants as designated active managers.

The literature on the Bystander Effect offers little explicit evidence regarding physician behavior specifically. Several of the defining characteristics of physicians and physician care (e.g., no real threat to the bystander herself, no pre-established relationship between the bystander and the threatened party [Fischer et al., 2011]) are associated with stronger Bystander Effects, but this evidence is only suggestive. The complex incentives physicians face when deciding how actively to be involved in a patient case (different fees for new and established patients, institutional expectations of productivity, professional and institutional

[8] A similar concept termed "passenger syndrome" is described elsewhere (AHRQ, 2008).

norms about “patient ownership” and accountability, etc.) and their opportunities to be more deliberate in this decision clearly distinguish physicians from the typical Bystander Effect experiment subject. It remains to establish the relevance of the Bystander Effect to medical consultants’ behavior.

In the context of medical consult provision, the core predictions of the Diminishing Marginal Productivity and Bystander Effect theories are the same: as the numbers of consults already rendered to a patient or of consultants already involved in a patient’s case increase, the probability the next consultant will continue to render additional consults and provide active management support decrease. (The All Hands on Deck framework generates the opposite prediction.) What distinguishes these two theories is the Bystander Effect’s prediction regarding the concentration of provided consults across involved consultants, conditional on the number of each.

The principal prediction of the Bystander Effect pertains to consultants’ behavior when it is unclear whether another consultant is engaging in active management. In addition, when there is clearer evidence one or more other consultants have already done so, the Bystander Effect implies that consultants will be less willing to provide active management. Thus, as the distributions of consults across a fixed number of consultants becomes more concentrated, reflecting greater investment by a few consultants in the patient’s case, the next consultant’s incentive to intervene and provide active management care weakens. Indeed, following Srivastava’s (2013) hypothesis of deference, the Bystander Effect holds that subsequent consultants will look upon this evidence of a previous consultant’s active management as an indication that they should sign off quickly rather than provide secondary active management, even if it is needed.

By contrast, what the Diminishing Marginal Productivity framework predicts about the effects of an increasing concentration of consults on subsequent consultants’ behavior is ambiguous. Assuming consultants are well aware of their secondary role as active managers of inpatients’ care, then the Diminishing Marginal Productivity framework would hold that new consultants joining cases with concentrated consult distributions would provide fewer consults, as they could expect only to serve the patient through specialty-specific input, not active management support. On the other hand, Diminishing Marginal Productivity theory also holds that the marginal productivity of consults may diminish more rapidly within individual consultants than across multiple consultants, whose differences of perspectives may prove valuable to the patient. In other words, as the distribution of consults across consultants becomes more concentrated, the more significantly involved consultants' last consults may be less productive than a new consultant's consults would be. Therefore, new consultants joining cases with especially concentrated consult distributions may provide more consults than consultants joining cases with less concentrated consult distributions.

Hypotheses

In this section I summarize the predictions of the All Hands on Deck, Diminishing Marginal Productivity, and Bystander Effect theories and describe how they align and conflict. This information is also presented in Table 9.

After a physician completes her initial consult, including a review of the patient's medical chart and all notes made by previous consultants, the consultant decides whether to "sign off" or to provide additional consults and active management care.[9] Suppose two patient cases are identical except that case A has one additional previous consultant or consult than case B. While the All Hands on Deck theory suggests that the consultant is more likely to provide additional consults and active management care for case A, both the Diminishing Marginal Productivity and Bystander Effect theories predict the opposite.

Now suppose two patient cases are identical, including with respect to the numbers of consults rendered and consultants involved, except that case C's distribution of consults is

[9] While the decision to sign off ultimately belongs to the consulting physician, in some hospitals it may be common for consulting physicians to communicate one-on-one with the patient's attending physician, and they may discuss together whether or not the consulting physician should sign off. Anecdotal evidence suggests that nearly all conversations between the attending physician and consultants are likely to center on the consulting physician's specialty-specific input and would include discussion of the patient's overall management or other specialists' consults only rarely. As such, the attending physician is unlikely to play a meaningful role in the consulting physician's decision to provide active management.

more concentrated than case D's. The All Hands on Deck theory offers no predictions for the response of the new consultant to this difference. If the Diminishing Marginal Productivity theory holds, it is not clear whether the consultant will be more or less inclined to provide additional consults and active management care. However, if the Bystander Effect theory holds, the consultant should provide fewer consults and should be less likely to provide active management care.

Table 9: Theoretical Predictions for New Consultant's Behavior, by Theoretical Framework

Medical Chart Reflects…	All Hands on Deck	Diminishing Marginal Productivity	The Bystander Effect
Additional consultants/ consults	More consults; greater probability of providing A/M care	Fewer consults; reduced probability of providing A/M care	Fewer consults; reduced probability of providing A/M care
More concentrated distribution of consults	No prediction	Ambiguous predictions	Fewer consults; reduced probability of providing A/M care

* A/M = active management

It is possible that the effects of Diminishing Marginal Productivity and the Bystander Effect are coincident in consultants' decision-making. As such, small negative effect estimates of differences in consult distribution concentrations should be interpreted as evidence of Diminishing Marginal Productivity as the dominant mechanism (the Bystander Effect might or might not play a meaningful role), and large negative effect estimates should be interpreted as evidence of the Bystander Effect as the dominant mechanism (Diminishing Marginal Productivity might or might not play a meaningful role). But finding either framework as dominant does not obviate the other framework entirely. Ultimately, findings of any consistent relationship between other consultants' decisions and the next consultant's decisions would constitute strong support for the identification of consultants' role as active managers of care above and beyond the role of providing specialty-specific input.

I describe my data and empirical framework for testing these hypotheses in the following section.

Data and Empirical Framework

Because elderly surgical patients tend to be highly vulnerable and in need of greater active management than other populations, I analyze the decision-making of consultants in the context of perioperative consults for Medicare beneficiaries. In particular, I consider the care provided to Medicare patients undergoing coronary artery bypass graft (CABG) or colectomy procedures—two relatively common, high-risk surgical procedures for patients that commonly exhibit multiple comorbid conditions and present with complications—as identified using 100% MedPAR (hospital inpatient services) files for 2007 through 2010 and all Medicare Part B claims (Carrier files) for the same patients with dates of services between the date of admission and the date of discharge. To further homogenize these patient samples, I restricted these samples to CABG patients not also undergoing valve replacement or percutaneous coronary intervention procedures and colectomy patients who also exhibited diagnoses of colon cancer on their inpatient hospital claims. In addition, I use the corresponding Beneficiary Summary files and the 2008 American Hospital Association survey to identify additional beneficiary and hospital characteristics, respectively.

Patients are excluded from my analytic samples if they were younger than age 65 or older than age 100, lacked Part B coverage, received zero consults during their hospital stay, had been hospitalized for the same procedure earlier in the same year, had their procedures performed at federal, Veterans Administration, or non-acute care hospitals or hospitals that could not be matched to AHA data or were outside the fifty states and the District of Columbia, or were otherwise missing data. Because Part B data were not available for all time periods and because of concerns about potential changes in consult coding practices between years (especially between 2009 and 2010, when certain consultation Current Procedural Terminology [CPT] codes were no longer accepted on Medicare claims), inpatient hospital stays spanning more than one calendar year (e.g., including December 31, 2007 and January 1, 2008) are excluded from these data. Without these year-spanning cases (approximately 0.6%), the remaining sample has a slightly shorter average length of stay than the full sample as a result of this exclusion, though this should not meaningfully affect study validity.

I identify the relevant pool of consulting physicians for my analyses using unique physician ID numbers (Carrier Line Performing Profiling Identification Number) as represented on Medicare Carrier File claim lines with first dates of service between the patient's date of admission and date of discharge.[10] I exclude from the pool of physicians to be analyzed the surgeons and anesthesiologists involved in the patients' principal procedures. In addition, to control for any role the surgeon or anesthesiologist may play in the patient's management post-surgery, I include among my models' regressors patient-level dummy variables indicating whether or not either billed for a consult at least once post-surgery. While I am not able to distinguish attending physicians from other consulting physicians using available Medicare claims data sets, I include among my sensitivity analyses regressions that identify effects separately among generalist consultants versus among interventionist and non-interventionist specialist consultants.

I model consultants' decision-making at the patient-physician dyad level, the level at which my theoretical frameworks are operative. This level of analysis permits identification based on differences in patient cases at the time of their consultants' initial consults. My identification strategy leverages the fact that individual consultants typically render their initial consults when requested with little negotiation or withholding and regardless of the number of previous consults or involved consultants.

The decision of interest in this study is the consultant's decision to provide additional consults and active management or to sign off following the initial consult. Because active management is not recorded explicitly in Medicare claims data, I construct two claims-derived proxy measures pertaining to the intensive margin of consult provision. These measures are (1)

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[10] While this approach may not uniquely identify a single care provider if residents, physician assistants, nurse practitioners, or other clinical staff render consults and employ "incident-to" billing for the physician identified with the ID, such billing practices may be less common in the inpatient setting than in outpatient hospital or office clinics. Moreover, because of the terms of incident-to billing, the provision of these services by allied health professionals would indicate extended engagement by the physician, the likes of which I seek to capture with my analysis. As such, interpretations of my results should not be significantly affected by this choice to identify physicians uniquely using Medicare billing ID numbers.

whether or not the individual consultant provides consulting care across two or more days and (2) the consultant's total number of days consulting. These two measures capture necessary conditions for active management by a consultant; without detailed electronic medical record data, it is not possible to determine the extent to which they are sufficient. These measures are also different in that the first captures the consultant's determination at the time of the initial consult, while the second incorporates additional information gathered by the consultant at later points in time.

In the first of my two principal analyses, I estimate the patient-physician dyad-level model of Equation (1), regressing consultant *i*'s decision to provide active management (AM_{piht}) for patient *p* in hospital *h* in the year *t* on two measures of other consultants' care before the date of *i*'s first consult: N_{pi}, the number of physicians rendering consults for patient *p*, and $AMPREV_{pi}$, an indicator of whether another consulting physician has provided active management care (here, consults over two or more days).

$$AM_{piht} = \alpha + \beta_1 N_{pi} + \beta_1' AMPREV_{pi} + \beta_2 X_p + \beta_3 X_i + \beta_4 X_{pi} + \beta_5 X_h + R_h + y_t + \omega_{piht} \quad (1)$$

In this equation, β_1 and β'_1 represent my parameters of interest: β_1 can be taken to reflect equally evidence of the Diminishing Marginal Product and Bystander Effect theoretical frameworks, while β'_1, which partly reflects the concentration of consults across consultants, offers more evidence of the Bystander Effect's hypothesis than that of Diminishing Marginal Product theory.

I include numerous patient-level, physician-level, and patient-physician dyad-level controls (X_p, X_i, and X_{pi}, respectively) to account for differences in patient severity and comorbidity, differences in average patterns of consults rendered by physicians like *i*, and observed care patterns on behalf of patient p. The patient-level controls include the total number of consultants involved in the case by discharge, first- and second-order age terms, sex, race category indicators, 29 indicators of comorbid conditions as identified using the Elixhauser comorbidity index (Elixhauser et al., 1998), a dummy variable indicating whether the surgical procedure was elective, and length of stay. I also include dummy variables for the days of the week of the patient's admission and of the patient's surgery—in case the timing and patterns of consults should be affected by weekends—and for the presence of a consultation by the patient's surgeon or anesthesiologist, which likely reflects a complication that would lead other clinicians to defer to surgeon or anesthesiologist in managing the patient. The physician-level controls include 19 indicators of physician *i*'s specialty and two dummy variables reflecting whether physician *i*'s initial consult fell within three or five days of the patient's death or discharge (given that the attending physician's expectations for the patient's death or discharge might be communicated to the consultant at this time). And the patient-physician dyad-level controls include dummies for each of 19 specialties indicating whether a consultant of that specialty had rendered a consult by the date of *i*'s first consult.

My hospital-level controls include teaching status, for-profit status, size (bed counts), nurse-to-patient ratio, and Medicaid fraction. The α term is a constant, and R_h and y_t represent region (of the hospital) and year fixed effects. I include these fixed effects to control for broad cultural differences across physician populations and differences in billing practices or medical technology diffusion. In all regressions, I cluster standard errors at the hospital level to account for any heteroskedasticity across hospitals.

In my second principal analysis, I estimate the patient-physician dyad-level model shown in Equation (2), regressing consultant *i*'s active management decision on a measure HHI_{pi} identifying how concentrated the distribution of consulting days has been across other consultants before the date of *i*'s first consult. This measure is constructed in the same way as the well-known Herfindahl-Hirschman Index (HHI): the sum of the squares of all previous consultants' shares of consulting days, with shares expressed as fractions multiplied by 100. All controls and fixed effects in Equation (1) are included in this equation as well, with the addition of $DAYS_{pi}$, the total number of consulting days before the date of *i*'s first consult.

$$AM_{piht} = \gamma + \beta_1 HHI_{pi} + \beta_1' DAYS_{pi} + \beta_2 X_p + \beta_3 X_i + \beta_4 X_{pi} + \beta_5 X_h + R_h + y_t + \omega_{piht} \quad (2)$$

To ensure that HHI_{pi} is well-defined, this analysis is limited to the experiences of consultants whose first consult took place at least one day after the patient's first consult overall.

This study protocol was approved by the University of Michigan Health Sciences and Behavioral Sciences Institutional Review Board under expedited review.

Results

After applying all inclusion and exclusion criteria, my main analytic samples consist of 253,209 consultants for 61,785 CABG patients and 115,853 consultants for 33,460 colectomy patients. In Table 10 I present select descriptive statistics characterizing these samples. (Corresponding patient-level descriptive statistics are presented in the Chapter Two Appendix.) As defined, both samples' patients are elderly, relatively sick, and complex. There are some meaningful differences in these groups' demographic characteristics: CABG patients are more likely to be male, a few years younger, diabetic, hypertensive, and treated in an academic hospital. Their consulting physicians are also somewhat more likely to be medical specialists, interventionist or non-interventionist, and to render their initial consults within three or five days of the patient's discharge. While both groups consist of vulnerable, complex patients for whom active management care may be valuable, they appear to be sufficiently distinct that findings found consistently for both samples may be considered generalizable to other vulnerable populations, particularly among Medicare beneficiaries.

Table 10: Descriptive Statistics for CABG and Colectomy Patient-Physician Dyad-Level Samples, 2007-2010

	CABG		**Colectomy**	
Variable	Mean or %	SD	Mean or %	SD
Active Management				
2+ days consulting	64.3%		66.0%	
Days consulting	3.17	3.32	3.57	3.87
Explanatory Variables				
Prior consulting physicians	2.97	3.72	2.90	3.49
Prior MD had 2+ days	64.3%		66.0%	
Select Control Variables				
Male	63.5%		44.3%	
Age	73.71	6.10	79.57	7.71
Black	7.5%		9.6%	
Other race (non-white)	5.1%		3.6%	
Length of stay	13.82	9.45	15.35	9.26
Post-op consult by surgeon	3.3%		4.9%	
Post-op consult by anes.	11.6%		17.6%	
Uncomplicated diabetes	42.3%		16.5%	
Congestive heart failure	3.3%		20.9%	
Hypertension	72.4%		48.6%	
Depression	2.6%		2.6%	
Elective procedure	40.5%		37.6%	
Academic hospital	26.9%		15.2%	
For-profit hospital	14.2%		12.2%	
Nurse-occupancy ratio	6.80	2.27	6.47	2.20
Medicaid share	15.83	8.48	15.79	9.13
Within 3 days of discharge	19.8%		17.3%	
Within 5 days of discharge	27.8%		25.6%	
Generalist physician	19.1%		36.5%	
Non-interventionist specialist	16.8%		8.9%	
Interventionist specialist	50.3%		43.7%	
n	253,209		115,853	

The results of my first patient-physician dyad-level analyses, representing the dependent variable of active management as the probability the physician renders consults over at least two days and the physician's total number of days consulting, are presented in Table 11 and Table 12, respectively. These tables' results are highly consistent with one another, across samples, and with the theoretical frameworks of Diminishing Marginal Product and the Bystander Effect. As such, they are also consistent with the understanding of consultants as providers of both specialty-specific input and active management care.

As shown in these tables, for each additional physician consulting for a complex CABG or colectomy patient before the index physician renders her first consult, the index physician's probability of providing two or more days consulting falls between 0.8 and 1.1 percentage points (1.2 to 1.7 percent of sample means), and her total days consulting fall approximately 0.25 days (7.1 to 7.4 percent). I also find that if one of the preceding consultants rendered consults across two or more days (i.e., provided active management), the index physician's probability of providing two or more days consulting falls between 13.2 and 14.2 percentage points (20.6 to 21.5 percent), and her total days consulting fall 0.49 to 0.95 days (15.5 to 26.6 percent). With these large, negative effect estimates, we can reject the hypotheses of the All Hands on Deck theoretical framework. Moreover, if these results are biased positively by unmeasured health status—other researchers have found this to be an important issue in studying consult use (Auerbach et al., 2007; Thilen et al., 2013a)—despite the efforts I have made to homogenize the sample and to control for observable health status differences, the true effects may be larger still.

Table 11: Patient-physician Dyad-level Models of Active Management, 2+ Days Consulting, Select Parameter Estimates, 2007-2010

	CABG		**Colectomy**	
Variable	Estimate	SE	Estimate	SE
Prior consulting physicians	**-0.0080**	**0.0008****	**-0.0113**	**0.0010****
Prior MD had 2+ days consulting	**-0.1324**	**0.0059****	**-0.1419**	**0.0053****
Total consulting physicians	-0.0049	0.0006**	-0.0037	0.0006**
Length of stay	0.0048	0.0004**	0.0045	0.0003**
Elective procedure	0.0529	0.0035**	0.0178	0.0036**
Init. consult < 3 days from disc.	-0.2111	0.0043**	-0.2016	0.0058**
Init. consult < 5 days from disc.	-0.0092	0.0044*	-0.0343	0.0052**
Prior post-op consult by surgeon	-0.0001	0.0058	0.0042	0.0070
Prior post-op consult by anes.	0.0023	0.0042	-0.0036	0.0042
Male	-0.0002	0.0021	0.0006	0.0028
Age	0.0044	0.0037	0.0019	0.0034
Black	0.0068	0.0054	0.0073	0.0054
Other race (non-white)	0.0170	0.0061**	0.0252	0.0079**
Academic hospital	-0.0352	0.0099**	-0.0349	0.0085**
Investor-owned hospital	0.0366	0.0101**	0.0357	0.0061**
Nurse-occupancy ratio	-0.0045	0.0013**	-0.0065	0.0011**
Medicaid share	-0.0008	0.0004	-0.0007	0.0002**
n	*253,209*		*115,853*	

Notes: **: Statistically significant at $p < 0.01$. *: Statistically significant at $p < 0.05$. Other control variables (results not presented) include age^2, 29 Elixhauser comorbid condition indicators, indicators for the day of the week on which the index surgery took place (Monday refs.), 19 indicators of the index consultant's specialty, indicators of whether a consultant had previously rendered a consult for each of 19 specialties, other profit status (neither discernibly investor-owned nor non-for-profit), indicators for hospital bed counts 200-349, 350-499, and 500+ (< 200 ref.), and region and year fixed effects. Standard errors are clustered at the hospital level.

Table 12: Patient-physician Dyad-level Models of Active Management, Total Days Consulting, Select Parameter Estimates, 2007-2010

	CABG		**Colectomy**	
Variable	Estimate	SE	Estimate	SE
Prior consulting physicians	**-0.2351**	**0.0109****	**-0.2546**	**0.0123****
Prior MD had 2+ days consulting	**-0.4901**	**0.0236****	**-0.9485**	**0.0336****
Total consulting physicians	0.0453	0.0073**	0.0301	0.0073**
Length of stay	0.1243	0.0056**	0.1418	0.0060**
Elective procedure	0.1228	0.0221**	-0.2708	0.0295**
Init. consult < 3 days from disc.	-0.4468	0.0166**	-0.4127	0.0221**
Init. consult < 5 days from disc.	-0.2515	0.0222**	-0.4192	0.0296**
Prior post-op consult by surgeon	-0.1003	0.0517	0.1683	0.0662*
Prior post-op consult by anes.	0.1450	0.0427**	-0.1508	0.0409**
Male	-0.0263	0.0162	0.0462	0.0232*
Age	-0.0180	0.0277	0.0599	0.0267
Black	0.0913	0.0457*	0.1993	0.0535**
Other race (non-white)	0.3080	0.0601**	0.4247	0.1005**
Academic hospital	-0.2789	0.0789**	-0.3942	0.0828**
Investor-owned hospital	0.3787	0.0792**	0.3954	0.0643**
Nurse-occupancy ratio	-0.0636	0.0136**	-0.0807	0.0114**
Medicaid share	-0.0083	0.0034*	-0.0055	0.0025*
n	*253,197*		*115,853*	

Notes: **: Statistically significant at $p < 0.01$. *: Statistically significant at $p < 0.05$. Other control variables (results not presented) include age^2, 29 Elixhauser comorbid condition indicators, indicators for the day of the week on which the index surgery took place (Monday refs.), 19 indicators of the index consultant's specialty, indicators of whether a consultant had previously rendered a consult for each of 19 specialties, other profit status (neither discernibly investor-owned nor non-for-profit), indicators for hospital bed counts 200-349, 350-499, and 500+ (< 200 ref.), and region and year fixed effects. Twelve observations are dropped from the CABG model's full sample of 253,209 observations due to conflicting billing dates and discharge dates. Standard errors are clustered at the hospital level.

The models described in Equation 2 differentiate the effects of Diminishing Marginal Productivity and the Bystander Effect; their results are presented in Table 13 and Table 14. The key parameter estimates from these models pertain to the consult share HHI measure. This measure is scaled so that a one-unit change in the variable corresponds to an increase in the concentration of consult-day shares across consultants by 2,500 (equivalent to the difference in concentrations between a set of consult-days distributed equally among four consultants and a set of consult-days shared equally between two consultants), a large change in consult-day concentrations. I find that when the index consultant observes consults have been more concentrated by the time of her first consult, her probability of providing two or more days consulting increases by 1.9 to 2.0 percentage points (2.9 to 3.1 percent), and her total days consulting rise 0.19 to 0.21 days (5.8 to 6.1 percent).

Table 13: Models of Active Management, 2+ Days Consulting, Select Parameter Estimates Including Consult-share HHI, 2007-2010

	CABG		Colectomy	
Variable	Estimate	SE	Estimate	SE
Consult-share HHI (/2,500)	**0.0185**	**0.0018****	**0.0202**	**0.0021****
Total previous consults	-0.0018	0.0001**	-0.0020	0.0002**
Total consulting physicians	-0.0006	0.0006	0.0002	0.0006
Length of stay	0.0040	0.0004**	0.0037	0.0003**
Elective procedure	0.0197	0.0035**	-0.0002	0.0042
Init. consult < 3 days from disc.	-0.2158	0.0044**	-0.2095	0.0061**
Init. consult < 5 days from disc.	-0.0213	0.0043**	-0.0412	0.0056**
Prior post-op consult by surgeon	0.0125	0.0064	0.0042	0.0081
Prior post-op consult by anes.	0.0020	0.0044	0.0018	0.0049
Male	-0.0042	0.0024	-0.0039	0.0035
Age	0.0021	0.0043	0.0003	0.0040
Black	-0.0008	0.0062	0.0128	0.0063*
Other race (non-white)	0.0115	0.0067	0.0277	0.0097**
Academic hospital	-0.0338	0.0098**	-0.0420	0.0089**
Investor-owned hospital	0.0301	0.0104**	0.0351	0.0068**
Nurse-occupancy ratio	-0.0038	0.0016*	-0.0054	0.0010**
Medicaid share	-0.0004	0.0004	-0.0005	0.0003
n	*176,313*		*80,507*	

Notes: **: Statistically significant at $p < 0.01$. *: Statistically significant at $p < 0.05$. Other control variables (results not presented) include age^2, 29 Elixhauser comorbid condition indicators, indicators for the day of the week on which the index surgery took place (Monday refs.), 19 indicators of the index consultant's specialty, indicators of whether a consultant had previously rendered a consult for each of 19 specialties, other profit status (neither discernibly investor-owned nor non-for-profit), indicators for hospital bed counts 200-349, 350-499, and 500+ (< 200 ref.), and region and year fixed effects. Standard errors are clustered at the hospital level.

Table 14: Models of Active Management, Total Days Consulting, Select Parameter Estimates Including Consult-share HHI, 2007-2010

	CABG		**Colectomy**	
Variable	Estimate	SE	Estimate	SE
Consult-share HHI (/2,500)	**0.1923**	**0.0132****	**0.2083**	**0.0147****
Total previous consults	-0.0426	0.0018**	-0.0453	0.0023**
Total consulting physicians	0.0280	0.0069**	0.0272	0.0065**
Length of stay	0.1109	0.0057**	0.1068	0.0057**
Elective procedure	0.0666	0.0215**	-0.1569	0.0284**
Init. consult < 3 days from disc.	-0.4821	0.0159**	-0.5140	0.0204**
Init. consult < 5 days from disc.	-0.3333	0.0234**	-0.4912	0.0306**
Prior post-op consult by surgeon	-0.0257	0.0603	0.0837	0.0662
Prior post-op consult by anes.	0.1455	0.0456**	-0.0437	0.0412
Male	-0.0097	0.0189	0.0433	0.0248
Age	-0.0349	0.0314	0.0648	0.0284*
Black	0.0049	0.0450	0.1883	0.0544**
Other race (non-white)	0.1770	0.0566**	0.2972	0.0826**
Academic hospital	-0.2602	0.0717**	-0.3434	0.0739**
Investor-owned hospital	0.2946	0.0674**	0.2987	0.0572**
Nurse-occupancy ratio	-0.0488	0.0106**	-0.0506	0.0099**
Medicaid share	-0.0062	0.0030*	-0.0033	0.0023
n	*176,313*		*80,507*	

Notes: **: Statistically significant at $p < 0.01$. *: Statistically significant at $p < 0.05$. Other control variables (results not presented) include age^2, 29 Elixhauser comorbid condition indicators, indicators for the day of the week on which the index surgery took place (Monday refs.), 19 indicators of the index consultant's specialty, indicators of whether a consultant had previously rendered a consult for each of 19 specialties, other profit status (neither discernibly investor-owned nor non-for-profit), indicators for hospital bed counts 200-349, 350-499, and 500+ (< 200 ref.), and region and year fixed effects. Standard errors are clustered at the hospital level.

The 95 percent confidence intervals for these estimates are sufficiently tight that negative estimates are ruled out. This result is not consistent with the Bystander Effect hypothesis of a negative effect. Thus my results appear to be most consistent with the predictions of the Diminishing Marginal Productivity framework. However, if there is substantial residual positive bias in my results due to unmeasured health status, the true effect of increasing concentration in consult distributions may be small and negative, potentially consistent with the Bystander Effect. Ultimately, while I find no strong evidence to support the Bystander Effect, I cannot rule it out definitively.

Sensitivity and Robustness

In this section I describe important ways in which my analyses may be modified simply to address corollary hypotheses or to test the sensitivity of my findings to changes of assumptions or specifications. I make these modifications and present findings in Table 15 and Table 16. The consistency of these estimates across specifications and subsamples can be taken as strong evidence in support of the role of consultants as active managers.

Table 15: Patient-physician Dyad-level Models, Supplemental and Sensitivity Analyses, 2007-2010

	Modeling Consult Provision Over 2+ Days				Modeling Total Days Consulting			
	CABG		**Colectomy**		**CABG**		**Colectomy**	
Variable	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Baseline Pt-MD Dyad-level Models								
Prior consulting physicians	-0.0080	0.0008**	-0.0113	0.0010**	-0.2351	0.0109**	-0.2546	0.0123**
Prior MD had 2+ days consulting	-0.1324	0.0059**	-0.1419	0.0053**	-0.4901	0.0236**	-0.9485	0.0336**
i. Intensive Care Consult Within 3 Days								
Prior consulting physicians	-0.0069	0.0012**	-0.0088	0.0022**	-0.2301	0.0136**	-0.2206	0.0219**
Prior MD had 2+ days consulting	-0.0037	0.0087	0.0283	0.0134*	0.0241	0.0513	-0.2991	0.0994**
ii. 6 Comorbid Conditions								
Prior consulting physicians	-0.0236	0.0100*	-0.0176	0.0068*	-0.1770	0.0460**	-0.2559	0.0454**
Prior MD had 2+ days consulting	-0.1388	0.0310**	-0.1023	0.0226**	-0.3066	0.1698	-0.7543	0.1514**
iii. For-profit Hospitals Only								
Prior consulting physicians	-0.0061	0.0021**	-0.0133	0.0033**	-0.3071	0.0281**	-0.3466	0.0498**
Prior MD had 2+ days consulting	-0.1236	0.0143**	-0.1322	0.0122**	-0.5438	0.0693**	-1.2012	0.1047**
iv. Academic Hospitals Only								
Prior consulting physicians	-0.0073	0.0014**	-0.0115	0.0022**	-0.2127	0.0197**	-0.2268	0.0255**
Prior MD had 2+ days consulting	-0.1508	0.0130**	-0.1948	0.0133**	-0.5036	0.0436**	-0.7650	0.0861**
v. Lagged Probability of General Medicine Co-management								
Low Co-mgmt								
Prior consulting physicians	-0.0012	0.0010	-0.0021	0.0014	-0.2068	0.0123**	-0.2506	0.0150**
Prior MD had 2+ days consulting	-0.1528	0.0074**	-0.1818	0.0090**	-0.3034	0.0324**	-0.6021	0.0602**
High Co-mgmt vs. Low Co-mgmt								
Prior consulting physicians	-0.0270	0.0030**	-0.0220	0.0026	-0.0676	0.0231**	0.0023	0.0214
Prior MD had 2+ days consulting	0.1202	0.0178**	0.1102	0.0174**	-1.0387	0.1426**	-0.8729	0.1374**
vi. One Randomly Selected Consultant per Patient								
Prior consulting physicians	-0.0016	0.0023	-0.0003	0.0005	-0.1833	0.0168**	-0.2457	0.0252**
Prior MD had 2+ days consulting	-0.3338	0.0094**	-0.0129	0.0023**	-1.0068	0.0333**	-1.4181	0.0468**

Notes: **: Statistically significant at $p < 0.01$. *: Statistically significant at $p < 0.05$. Control variables (results not presented) include age, age^2, black, other race (white ref.), 29 Elixhauser comorbid condition indicators, elective admission status, length of stay, indicators of initial consult within 3 or 5 days of patient discharge, indicators for the day of the week on which the initial consult took place (Monday ref.), 19 specialty indicators, indicators of prior post-operative consult by surgeon or anesthesiologist, teaching status, for-profit status, other profit status (neither discernibly for-profit nor non-for-profit), nurse-occupancy ratio, Medicaid patient share, indicators for hospital bed counts 200-349, 350-499, and 500+ (< 200 ref.), and region and year fixed effects. Standard errors clustered at the hospital level.

Table 16: Patient-physician Dyad-level Models Including Consult-share HHI Measure, Supplemental and Sensitivity Analyses, 2007-2010

	Modeling Consult Provision Over 2+ Days				Modeling Total Days Consulting			
	CABG		**Colectomy**		**CABG**		**Colectomy**	
Variable	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Baseline Pt-MD Dyad-level Models	0.0185	0.0018**	0.0202	0.0021**	0.1923	0.0132**	0.2083	0.0147**
i. Intensive Care Consult Within 3 Days	0.0194	0.0039**	0.0090	0.0063	0.2270	0.0362**	0.1857	0.0487**
ii. 6 Comorbid Conditions	0.0069	0.0148	0.0253	0.0121*	0.2234	0.0797**	0.2607	0.0769**
iii. For-profit Hospitals Only	0.0251	0.0042**	0.0183	0.0058**	0.2777	0.0330**	0.1854	0.0439**
iv. Academic Hospitals Only	0.0027	0.0035	0.0138	0.0052**	0.1429	0.0233**	0.2173	0.0381**
v. Lagged Probability of General Medicine Co-management								
Low Co-mgmt	0.0109	0.0023**	0.0136	0.0031**	0.1254	0.0138**	0.1711	0.0208**
High Co-mgmt vs. Low Co-mgmt	0.0462	0.0060**	0.0163	0.0060**	0.2418	0.0420**	0.0407	0.0415
vi. One Randomly Selected Consultant per Patient	0.0225	0.0033**	0.0258	0.0050**	0.1644	0.0165**	0.1793	0.0273**

Notes: **: Statistically significant at $p < 0.01$. *: Statistically significant at $p < 0.05$. Control variables (results not presented) include age, age^2, black, other race (white ref.), 29 Elixhauser comorbid condition indicators, elective admission status, length of stay, indicators of initial consult within 3 or 5 days of patient discharge, indicators for the day of the week on which the initial consult took place (Monday ref.), 19 specialty indicators, indicators of prior post-operative consult by surgeon or anesthesiologist, teaching status, for-profit status, other profit status (neither discernibly for-profit nor non-for-profit), nurse-occupancy ratio, Medicaid patient share, indicators for hospital bed counts 200-349, 350-499, and 500+ (< 200 ref.), and region and year fixed effects. Standard errors clustered at the hospital level.

In my main analyses, patient samples are restricted to those who have exactly three comorbid conditions identified on their hospital stay records. The value of active management should be greater for more complex patients. The predictions of the All Hands on Deck framework may be more likely to hold for more complex patients if their consultants recognize the need for greater active management and "pitch in" more to meet it. In addition, the predictions of the Diminishing Marginal Productivity and Bystander Effect frameworks may be less likely to hold for these patients if the marginal benefits of their consults are more difficult to estimate and if it is less clear that a single, previous consultant's active management care should be sufficient to meet the patient's needs, respectively.

To assess these possibilities, I re-estimate my models for patients with both three comorbid conditions and at least one consult in an intensive care unit within the first three days of the hospital stay (with a length of stay of at least six days) and, separately, for patients with exactly six identified comorbid conditions. In general, results for the sample of patients with an intensive care consult are similar to those I estimate for the base sample, though my estimates are smaller and less statistically significant in some cases pertaining to whether a previous consultant rendered consults across two or more days. This is likely the result of estimating the models on smaller samples (N = 51,499 CABG patient-physician dyads and N = 14,114 colectomy dyads for the intensive care consult models presented in Table 15). Estimates for the sample with six comorbid conditions are likewise comparable to estimates for the base sample.

There may be unmeasured hospital-level traits that bias my results as a function of their associations with the provision of additional consults, as through financial or other incentives for consulting physicians, or through differences in patients' health status. While I include select hospital-level controls in my regressions, doing so will not aid in detecting heterogeneous effects across hospital types. The All Hands on Deck framework may find greater support in an analysis of a sample of patient-physician dyads at an investor-owned hospital, for example, if consultants take a greater number of previously involved consultants as an indication of an opportunity to bill for more consultations themselves.

To determine how the hospital's investor-owned status and academic status affects these hypotheses, I re-estimate my models using samples restricted to patients who attended teaching hospitals or investor-owned hospitals. I find that my estimates for both of these samples are similar to those for the base sample. There is one noteworthy difference in my estimates of the effects of prior consultants' decisions to more actively manage a patient's case on the index consultant's active management decisions. These estimates remain negative for the investor-owned subsample, but they are significantly larger in magnitude than they are for the overall sample. These analyses yield no additional evidence to support the All Hands on Deck or Diminishing Marginal Productivity frameworks.

The Bystander Effect may also be distinguishable from Diminishing Marginal Productivity based on the effects of a hospital's norms regarding active management care. In hospitals with a more established record of "co-management," a strong form of active management in which a physician provide consults on at least 70% of patient days (Sharma et al., 2010), evidence that another physician has taken on active management responsibilities may be a strong indicator that the patient's active management need will be met. Thus, if the Bystander Effect holds in general, it should hold more strongly in these hospitals, as the index consultant may be particularly unlikely to provide active management care upon observing this strong indicator of active management (or co-management) already underway. The predictions of Diminishing Marginal Productivity should not be affected meaningfully by the hospital's co-management norms or policies.

I test this hypothesis by including in my main regressions a hospital-level variable measuring the average probability of like patients experiencing co-management in the previous calendar year and terms interacting this co-management probability variable with my measures of active management. In Table 15 and Table 16, I present the main parameter estimates for my active management measures as the estimates for "low co-management" hospitals, and I present the interaction effect estimates as the estimates for comparing "high co-management versus low co-management" hospitals. The co-management variables are scaled so that a one unit difference corresponds to the difference between hospitals where zero patients were co-managed and hospitals were all patients were co-managed the previous year. As shown in Table 15, the effects of prior consultants' active management on the index consultant's provision of consults over two or more days are typically much closer to zero in high co-management hospitals versus low co-management hospitals, while the effects of prior consultants' active management on the index consultant's total days consulting are negative and greater in magnitude in high co-management hospitals versus low co-management hospitals. In Table 16, I show that the effects of a more concentrated distribution of consults before the index consultant's first consult are positive and significantly larger in high co-management hospitals versus low co-management hospitals. Overall, the evidence yielded by these estimates is mixed, but, as in my main analyses, my results appear to support the Diminishing Marginal Productivity framework more than the Bystander Effect framework.

A potential concern about my patient-physician dyad-level analysis is that the results are disproportionately weighted to reflect the experiences of more complex patients in my samples or hospitals where consult provision is more frequent by the inclusion of one record for each patient-physician dyad: that is, patients and hospitals with more consulting physicians are reflected in additional data records. Thus my results may be positively biased. To address this concern, I also re-estimate my models using a data set containing only a single randomly selected dyad record for each hospital stay. The estimates I derive in this analysis vary somewhat about those I derive in my main analysis, both more positive and more negative. No estimates change signs, however, and so this analysis does not yield support for the All Hands on Deck framework. The estimated effects of the consult-share HHI measure remain relatively stable, and so this analysis also does not support further differentiating the Diminishing Marginal Productivity and Bystander Effect frameworks.

Conclusions and Future Directions

Observing the high and rising costs and unknown benefits of consults, many health care system stakeholders have dedicated efforts to develop new strategies and tools for reducing costs and improving quality in consulting care. The use of these tools and strategies, including e-consults, inpatient telemedicine services, co-management programs, and bundled payments for hospital and inpatient physician services, has become increasingly widespread in recent years as well (Kuo et al., 2009; Society of Hospital Medicine, 2011; George et al., 2012; Futurescan, 2014; Orlander, 2014). These policies and care delivery strategies can be designed and implemented more effectively with a more complete understanding of what consultants do and why.

In this study, I analyze how inpatient medical consultants' decisions about how many consults to provide a given patient are affected by the decisions of other medical consultants when caring for complex surgical inpatients. Given the magnitudes and regularity of these statistical relationships, I conclude that consultants are providing care that extends beyond providing specialty-specific insights and answers, which researchers typically understand to be the scope of their services. They appear to also provide active management support to help oversee and manage the patient's case. When I review the patterns of consultants' decision-making conditional on other consultants' behavior, I find these patterns to be inconsistent with an All Hands on Deck framework, whereby consultants observe their peers becoming more extensively involved in a patient's case and step in to ensure these other consultants' care is well-coordinated and that their own specialty's perspective is represented. And I find little evidence to support that these patterns follow the predictions of the Bystander Effect theory proposed by Stavert and Lott (2013). Rather the evidence is most consistent with a Diminishing Marginal Productivity framework: consultants provide approximately 20 percent fewer days consulting when others are already providing active management, but they provide approximately 6 percent more days consulting when the distribution of others' consults are more concentrated.

These findings, which are robust to several alternative specifications, indicate that administrators seeking to increase use of e-consults and telemedicine services should be mindful of the potential for these tools to interfere with the active management responsibilities of consultants. For example, they might consider instituting patient-centered initiatives such as coordinated co-management programs or like policies to ensure that there are resources available to attending physicians in need of additional support when overseeing the care of vulnerable, complex patients. Moreover, that consultants' patterns of care are consistent with a Diminishing Marginal Productivity framework suggests that many consultants are aware of this role of active management and calibrate the intensity of their consult provision to meet the patient's needs, given the mix of consultants already involved in the case. Whether consultants overestimate how rapidly the returns of their consults diminish and how well the active involvement of one or more consultants on a patient's case proxies for the effectiveness with which the patient's case is being managed, as Srivastava intimated (2013), remains an important open question. If these decisions are not made to optimize patient benefit, it may be possible to increase the appropriateness of consultants' decisions about their roles as active managers of care by ensuring the case information available to them at the time of their initial involvement is as complete as possible.

This analysis has a few important limitations. First, because this study relies on Medicare claims data, it identifies consultants' active management of patient cases using imperfect proxy measures. Consultants may be more actively involved—providing "curbside" consults and not billing for them (Weinberg et al., 1981; Burden et al., 2013)—or less active involved—billing for consults when their actual investment in the case is minimal—than is reflected in administrative records. The provision of more or fewer consults, as measured in this study, is a tangible reflection of active management, but measurement error in capturing active management using claims data may confound my estimates. Data gathered in qualitative interviews, surveys of consultants, or physicians' notes in electronic medical record systems may be valuable in identifying to which physicians consultants attributed the primary responsibilities for managing patient cases.

My measures of active management may also reflect other unrelated dimensions of the patients, consultants, or hospitals involved. I have used clinical indicators to substantially homogenize my patient samples, and I have included numerous patient-, physician-, and hospital-level controls in my analysis to address these concerns. While these controls are more extensive than are included in most studies of care coordination and physician decision-making, my results may be partially confounded by omitted variable bias due to unmeasured health status and severity differences or other factors. If unmeasured health status differences are the most significant of these omitted factors, the associated bias in my main analyses (models as described in Equation 1) would be positive, and so I would be less likely to observe results consistent with consultants' roles as active managers and with the Diminishing Marginal Product or Bystander Effect frameworks. It is not clear how unmeasured health status would be correlated with the concentration of consults across consultants. In future work, large, detailed electronic health record system data sets may support capturing more detailed information about the patient's health status at each point during the hospital stay, mitigating this concern. Such data may also be valuable in developing unbiased estimates of the effects consultants' services have on patient outcomes of broad interest, such as mortality, length of stay, and readmissions as well as more intermediate outcomes over which active care managers may have some greater influence (e.g., delayed charting, dangerous drug interactions, nurse ratings of communication or confusion at the unit level, and inadequate information transfer between physicians in the hospital or to the patient at discharge).

Finally, although I was able to construct my analyses for two distinct samples of patients undergoing different surgical procedures—CABG and colectomy—it is not clear that my findings are generalizable to all patients undergoing other major surgeries, other, similarly complex nonsurgical inpatients (e.g., patients with pneumonia, uncontrolled diabetes, or severe mental illness), or non-Medicare patients. Additional studies of medical consultants' decision-making in the care of other populations of interest may further substantiate the generalizability of my study's findings.

This study highlights the active management role of consultants and clarifies how consultants interact with their peers in deciding whether to provide active management support. The recognition that medical consultants provide this active management support as well as specialty-specific input is an important step toward designing effective policies and incentives to improve the quality and efficiency of their care.

Chapter Two Appendix

In Table 17, I present patient-level descriptive statistics for my analytic samples.

Table 17: CABG and Colectomy Patient-Level Samples, 2007-2010, Descriptive Statistics

	CABG		Colectomy	
Variable	Mean or %	SD	Mean or %	SD
Active Management				
2+ days consulting (any MD)	80.1%		69.6%	
Avg. days consulting (per MD)	2.88	1.63	3.21	1.92
Explanatory Variables				
Consulting physicians	4.10	3.71	3.46	3.64
Consulting specialties	2.48	1.85	2.23	2.01
Select Control Variables				
Male	64.8%		42.5%	
Age	73.45	5.89	78.51	7.58
Black	6.1%		9.1%	
Other race (non-white)	4.9%		3.9%	
Length of stay	10.33	5.90	10.92	6.55
Post-op consult by surgeon	2.9%		3.4%	
Post-op consult by anes.	6.4%		14.3%	
Uncomplicated diabetes	42.3%		23.4%	
Congestive heart failure	2.7%		13.4%	
Hypertension	80.3%		62.9%	
Elective procedure	52.4%		58.9%	
Academic hospital	25.5%		16.8%	
For-profit hospital	15.4%		11.6%	
Nurse-occupancy ratio	6.96	2.58	6.71	2.35
Medicaid share	15.99	8.66	16.39	9.65
n	61,785		33,460	

Chapter Three

Variation in the Quality of Diabetes Care for Veterans

The literature on geographic variation in health care has focused principally on the outcomes of use and expenditures, on care rendered to Medicare or privately insured patients, on low-value or "discretionary" services, and on the effects of financial incentives. While this work has been valuable for deepening our understanding of heterogeneity in decision-making among health care providers, it has also left many stones unturned. In particular, the literature on geographic variation in quality is substantially underdeveloped, and very little is known about the role of non-financial—that is, organizational or structural—factors in mediating such variation. Perhaps the most significant reason for this imbalance is the absence of data elements useful for quantifying quality in Medicare's and private insurers' administrative claims data. Specifically, these data systems lack patient health outcomes, patient health status indicators, and other clinical characteristics (e.g., lab values) important for clinicians' decisions about medical care. The measures of quality constructed using administrative claims data often fall short of precisely assessing guideline adherence in medical care, the gold standard of measured quality, and so the quality of care measured may poorly reflect the true quality of care patients receive. Moreover, it has been argued that these measures are insufficiently patient-centered and evidence-based (Kerr et al., 2001). As a consequence, studies that have sought to identify geographic variation in quality using such measures likewise produce imprecise estimates of true care quality and variation therein.

The same limitations hamper research on quality variation in the veteran population despite the availability of the data elements required to more precisely assess guidelines adherence in the Veterans Health Administration's (VA) Clinical Data Warehouse (CDW). It would be natural to expect more sophisticated research on diabetes care quality in particular in this setting, as nearly one fourth of veterans have been diagnosed with diabetes (VHA, 2013), and the VA's medical care use and costs associated with the condition are also very significant (Ashton et al., 2003; Maciejewski & Maynard, 2004). Yet historically, studies have typically measured diabetes care quality in the VA using the same administrative data-driven, limited process measures that appear in the Health Plan and Employer Data Information Set (HEDIS) and are used regularly outside the VA. Since 2000, such studies have regularly shown that the VA's quality of this care is quite high on average and often higher than is observed outside the VA (Jha et al., 2003; Asch et al., 2004; Kerr et al., 2004; Singh & Kalavar, 2004; Ward et al., 2004; Perlin & Pogach, 2006; Powers et al., 2009); however, the limitations of the measures used call these findings into question.

Studies of variation in diabetes care quality in this setting are further hampered by the fact that the process measures used have been included in the External Peer Review Program (EPRP), the VA's longstanding performance measurement program. As a consequence, the measured distribution of quality across VA facilities will be compressed due to Hawthorne and ceiling effects.

In this paper, I leverage the VA's clinically rich CDW data using a new, ordinal measure of blood pressure (BP) management among patients with diabetes to describe the variation in diabetes care quality across the VA. This ordinal measure is an innovative extension of the "tightly-linked clinical action measure" of BP control developed by Kerr and colleagues (2012), a measure which itself was not used in any capacity in the VA (performance measurement, public reporting, research, etc.) until 2011, the final few months of my four-year study period. In addition, I explore—using cross-sectional and clinician-level panel data analyses unique in the literature—to what extent organizational and structural characteristics of VA facilities can explain the patterns of diabetes care quality I observe. My analyses are informed by two theoretical frameworks adopted from the geographic variation literature: these are the framework of Resource Availability and Coordination and the framework of Physician Learning and Peer Effects.

I find moderate variation in this ordinal BP control quality measure across VA facilities, less than has been observed outside the VA and using other quality measures. In my analyses of the effects of available resources and coordination structures on diabetes care quality, I find no evidence of consistent relationships among these organizational features. However, I find strong evidence of large peer effects among physicians, particularly when using my novel identification strategy of following physicians who move between VA facilities during my study period. These findings help to fill important gaps in the geographic variation literature and offer valuable insights to VA administrators evaluating alternative strategies for improving diabetes care quality both within individual facilities and across the VA health care system.

Existing Literature on Geographic Variation in VA Quality

The existing literature on geographic variation in the quality of VA health care for veterans with diabetes is methodologically heterogeneous but uniformly limited in its applications of enriched clinical data, as described above. Most studies employ a cross-sectional design (Krein et al., 2001; Ward et al., 2004; Jackson et al., 2005; Kirsh et al., 2012), correlating cross-sectional survey data with contemporary performance on quality measures. One study employed a limited longitudinal design with quality improvement as its outcome of interest (Thompson et al., 2005), but no studies present evidence from multiple alternative frameworks side-by-side—as I do in this study—or replicate another paper's findings using alternative methods. Consequently, all preceding study findings have been characterized as associations: authors do not claim causal inference in their conclusions. This is an important limitation for a literature seeking to identify opportunities for quality improvement in diabetes care. In addition, all previous studies have relied on the limited, standard EPRP or HEDIS measures or the standard threshold values for common diagnostic or lab test results (e.g., 130/80 mm Hg for BP control) on which those measures are based. Examples of studies that supplement their use of such measures—as with partially clinically enriched process measures (Ward et al., 2004) or resource use measures (Krein et al., 2001)—are few.

Two key findings from this literature substantiate my approach in this study. First, my choice to analyze variation in diabetes care quality principally at the facility level is supported by the findings of Krein and colleagues (2001), who assessed diabetes care quality variation at the physician, provider group, and facility levels. Based on the results of their multilevel model, the authors concluded that quality measurement and improvement interventions should be directed at the facility-level, given that this is where they observed the greatest variation in their cross-section. Thompson and colleagues (2005) likewise found that some facility-level factors could be very important in determining average organizational quality measure performance through an examination of changes in facility performance over time. Other studies have followed this approach, concentrating their analyses at the facility level (Ward et al., 2004; Jackson et al. 2005; Kirsh et al., 2012). A few studies have found evidence suggesting that, in addition to facility-level variation, there exists important, if lesser, variation in diabetes care quality within facilities at the individual clinician level or at the region level (Egede et al., 2011; Trivedi et al., 2011). Detailed analysis of this secondary variation is beyond this study's scope.

The second key finding of this literature concerns the content of the facility characteristics identified as differentially associated with facilities demonstrating high-quality and low-quality diabetes care. Kirsh and colleagues (2012), comparing "high-performing" and "low-performing" facilities in their analysis of structured qualitative interview data, found that high-performing facilities' interviewees were more likely to cite sufficient and well-allocated clinical care resources (e.g., support staff) and resources to support patient engagement in care as well as well-coordinated collaborative and team-based care models. Jackson and colleagues (2005), likewise identified resources—specifically information systems and decision support tools—and well-coordinated team-based care principles and patient engagement as associated with improved hemoglobin A1c control at the facility level. Similarly, Ward and colleagues (2004) identified coordinated efforts to emphasize guideline adherence in practice, performance metrics monitoring, and a culture of engaged quality improvement as associated with high performance among VA facilities. Collectively, the findings of Kirsh and colleagues (2012), Ward and colleagues (2004), and Jackson and colleagues (2005), among others, are consistent with my own hypotheses of resource availability and coordination. I generate these hypotheses through the corresponding theoretical framework I describe in the following section.

Theoretical Frameworks

In this paper, I develop intuition, generate hypotheses, and select independent variables of interest using two theoretical frameworks drawn from the geographic variation literature. First I discuss the interplay of resource availability and coordination in determining facility outcomes, and second I discuss how a model of physician learning and peer effects can also be used to identify the effects of differences across provider facilities.

Resource Availability and Coordination

In a study concerned with physician supply and specialization and effects on the quality of care delivered to Medicare beneficiaries, Baicker and Chandra (2004b) laid out succinctly the intuition of the resource availability and coordination theoretical framework used commonly in the geographic variation literature. The authors set up their analysis by observing that in areas with greater physician specialization, patients see more doctors. It was unclear, however, whether the increased access to these care resources necessarily reflected "better care." Baicker and Chandra suggested this might not be the case if increasing physician volumes begat increasing coordination costs and "the potential for increased coordination failures;" such failures may result from specialist physicians inadequately internalizing "the coordination cost they impose on other physicians."

More generally, this framework may be stated in terms of the negative spillover effects of resource volume. Increases in a health care provider organization's capacity to provide services and care for patients enable the organization to avoid the hazards of "undertreatment" (e.g., failing to prescribe a blood pressure medication for a hypertensive patient), while a more resource-constrained facility may be unable to avoid such hazards. This understanding is consistent with findings in many different health care settings, including the VA (Wells & Sturm, 1995; Ayanian et al., 2002; Soban & Yano, 2005; Yano et al., 2007; Chang et al., 2011). However, an unintended consequence of increasing capacity is the increasing difficulty of ensuring all care resources are well-coordinated and allocated efficiently. In this environment, the resulting poor coordination or coordination failures may lead to "overtreatment" (e.g., risking hypotension in a previously hypertensive patient through excessive medication). Indeed, as coordination difficulties mount, the net marginal benefits of additional care resources may decline and even become negative as a facility's propensity to avoid undertreatment rises, but its propensity to overtreat rises more. Numerous studies have also identified this relationship in different health care settings (Fisher et al., 2003; Baicker & Chandra, 2004a; Soban & Yano, 2005; Yano et al., 2007; Skinner, Staiger, & Fisher, 2010; Chang), though it has been suggested these findings may be in part explained by differences in health status in some cases (Skinner, Staiger, & Fisher, 2006; CBO, 2008).

H1. Higher Resource Availability → Less Undertreatment

H2. Higher Resource Availability → More Overtreatment

It is useful to refine our understanding of "coordination" and what is meant by this term. In Baicker and Chandra's (2004b) framework, "coordination" signifies efforts (e.g., communication, information sharing) to prevent conflicts in delivered care modalities, redundancies in care, and unnecessary service use. In other words, the purpose of these coordination efforts is to constrain the use or misuse of some care resources. Such coordination efforts, which may effectively reduce the quantity of care resources used, may be termed "coordination as management."

However, in the quality improvement literature, the term "coordination" has been applied to a diverse array of organizational structures and practices extending beyond coordination as management structures (Baggs et al., 1992; Wheelan, Burchill, & Tilin, 2003; Katon et al., 2010). In another context, a facility manager, perceiving that certain facility resources are underutilized, might encourage its providers to build relationships and more efficiently leverage one another's capabilities to ensure patients get needed care. In other words, the purpose of these efforts to coordinate care patterns and delivery structures is to use more of its existing resources. Coordination efforts of this form, which may effectively increase the quantity of care resources used, may be termed "coordination as facilitation."

Importantly for this study, facilities may employ many coordination efforts that at different times may seek both to encourage and to discourage use of certain resources by physicians. When it cannot be identified whether these coordination efforts are principally of the coordination as management or coordination as facilitation varieties, it may be convenient to term the efforts "coordination as both." Given the historical focus at VA facilities on EPRP measures, which have incentivized greater use of resources—inadvertently rewarding overtreatment to prevent undertreatment—it is likely these coordination as both structures have been used most often to facilitate greater use of resources, much like "coordination as facilitation" structures.

Ultimately, how the quantity of available care resources at a facility affects the facility's quality of care—measured in terms of the underuse and overuse of services—may be mediated by the facility's efforts to coordinate those resources, that is, to manage or facilitate their use. This dual interpretation of coordination practices is not well-appreciated in the geographic variation literature or in the quality of care literature.

H3. *Higher Resource Availability with Coordination as Management → More Undertreatment than Higher Resource Availability without Coordination as Management*

H4. *Higher Resource Availability with Coordination as Management → Less Overtreatment than Higher Resource Availability without Coordination as Management*

H5. *Higher Resource Availability with Coordination as Facilitation → Less Undertreatment than Higher Resource Availability without Coordination as Facilitation*

H6. *Higher Resource Availability with Coordination as Facilitation → More Overtreatment than Higher Resource Availability without Coordination as Facilitation*

Physician Learning and Peer Effects

This paper aims to support a fuller understanding of the interplay of available resources with coordination mechanisms and how it affects the quality of patient care. Such information will be of greater use to VA and other organizational administrators if my findings can be validated using two alternative study designs and also if it can be shown that changes in clinical environments and care norms can drive improvement in care delivery.

To this end, I introduce a second geographic variation literature-derived framework on physician learning and peer effects. Initially laid out by Phelps and Mooney (1993) and reformulated by Epstein and Nicholson (2009), this framework describes how a physician's practice patterns may evolve over time as she adopts the practice patterns of her peers. In the context of a given treatment approach and its perceived efficacy (both papers are concerned with Caesarian sections), Phelps and Mooney's simple model holds that a physician's initial (prior) beliefs are acquired during training and then are updated by observing peers' practices. The physician's average practices, then, are a blend of her initial beliefs and later learnings, asymptotically approaching her peers' average practices over time as the weight given to initial beliefs decrease and the weight given to later learnings increase. Moreover, if a physician's peers change their practices, her practice will evolve likewise. Epstein and Nicholson (2009) produced evidence that physicians' patterns of practice do evolve and become more like their peers', if only very slowly. Phelps and Mooney (1993) suggest this pattern of internalizing local practice norms is attributable to physicians' inclinations to conform rather than flout their peers' examples. They also suggest that conformity may confer benefits of reduced risk of malpractice litigation, since, when an adverse health event befalls a patient, the involved physician could well claim no other local physician would have practiced differently.[11]

[11] This explanation suggests that local practice patterns beyond the walls of the VA facilities where clinicians practice may play a meaningful role in driving their care patterns. This subject may be worthy of further study, though it is beyond the scope of this work. Geographic variation studies have presented evidence that overall patterns of practice in the care of one population in a region do not predict patterns of care for a second

H7. More Undertreatment (Overtreatment) Among Peer Physicians → More Undertreatment (Overtreatment) by Individual Physician

If this prediction holds, it also serves to help explain the persistence of variation in quality of care despite national efforts to constrain such variation. Whatever incentives or constraints are in place (at the physician staff, facility, and patient population levels), the Physician Learning and Peer Effects framework predicts that physicians are compelled to practice as their peers do or in accordance with established practice norms.

Differential resource availability or coordination mechanisms across facilities may also influence whether and how quickly physicians' practice patterns evolve to become like their peers'. In particular, binding resource constraints (i.e., where there are fewer available resources or where coordination as management is strong relative to coordination as facilitation) could restrict physician practices to a particular pattern and limit physician discretion. For example, if a site has few allied health professionals on staff, all physicians might be disinclined to encourage their patients with diabetes to visit the facility regularly to have their medications re-calibrated, whereas at a site with more allied health professionals on staff, physicians might have more discretion in determining how much follow-up care to recommend. If this is the case, then physicians' practice patterns may be more likely to approach local patterns when resources are newly constrained (or when physicians move to a resource-constrained facility) than when resources are less constrained (or when physicians move where resource constraints are less binding).

H8. Stronger Resource Constraints (e.g., Lower Resource Availability) → Stronger Peer Effects (H7)

In the following section, I describe my empirical framework for testing the hypotheses associated with these frameworks.

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population, though the evidence is not fully consistent (Chernew et al., 2010; Franzini, Mikhail, & Skinner, 2010; Rettenmaier & Saving, 2010; Franzini et al., 2011).

Methods

In the literature on variation in care quality, my methods are innovative principally in two ways. First, I measure quality using a unique ordinal measure of BP control among patients with diabetes that supports identifying almost certain evidence of both undertreatment and overtreatment. And, second, I employ both cross-sectional and longitudinal designs side-by-side to lend additional credence to my findings. To my knowledge, the longitudinal design I employ is also unique in the literature.

Measure of BP Control

The ordinal measure of BP control I use in this study is based on the work of Kerr and colleagues (2012) who developed a new clinical action measure of diabetes care quality targeting BP control. This measure identifies index diabetes care visits with documented BP measurement and, based on the patient's BP reading, credits the provider with appropriate clinical action if the patient's prescription medication mix and dosages post-visit are aligned with evidence-based guidelines. Because these guidelines identify multiple alternative care pathways as clinically appropriate, depending on various patient characteristics and histories, Kerr and colleagues' measure makes similar allowances. Thus their clinical action measure "better capture the complexity of clinical decision making" for clinicians monitoring patients with diabetes than a standard diabetes care quality measure, which typically focuses on a single threshold level (e.g., BP below 130/80 mm Hg) and is agnostic about the means by which the threshold level is achieved or whether there is a strong evidence basis for taking clinical actions that do not achieve this strict level. Kerr and colleagues' measure is also superior to the standard quality measure in that it supports categorizing care episodes into potential undertreatment, appropriate care, or potential overtreatment, while the standard measure does not support identifying the latter.

For this paper, I further enhance Kerr and colleagues' measure by more precisely categorizing individual care episodes into the following mutually exclusive categories: almost certain undertreatment, potential undertreatment, appropriate care, potential overtreatment, and almost certain overtreatment. These additional categories of almost certain undertreatment and almost certain overtreatment are derived from published clinical trials and evidence-based guidelines (Messerli et al., 2006; Anderson et al., 2011) and the accepted definition of Stage 2 hypertension (American Heart Association, 2014). A summary description of the criteria used to categorize care episodes is presented in Figure 7. Kerr and colleagues' measure of appropriate care corresponds to Category 3 versus Categories 2 and 1 in the new ordinal measure, and Kerr and colleagues' measure of potential overtreatment corresponds to Category 4 versus Categories 3, 2, and 1.

Figure 7: Dependent Variable: Ordinal, Categorical Measure of Diabetes Care Quality

Category	Criteria
(5) Almost certain overtreatment	DBP < 60
(4) Potential overtreatment	Not (5) + SBP ≤ 130 and DBP ≤ 65, AND 3+ antihypertensive medications OR active intensification of Rx
(3) Appropriate care	Not (4) or (5) + SBP < 140 and DBP < 90, OR SBP < 150 and DBP < 65, OR SBP < 150 and 3+ antihypertensive medications OR Other appropriate clinical action* within 90 days
(2) Potential undertreatment	Not (1), (3), (4) or (5)
(1) Almost certain undertreatment	SBP ≥ 160, OR DBP ≥ 100

SBP = Systolic blood pressure, DBP = Diastolic blood pressure, * patient has normal blood pressure at follow-up appointment, increased dosage, changed drug class, or new class of antihypertensive drug added to regimen

For most analyses in this paper, I present results both for the overall ordinal measure and for separate analyses of dummy variables identifying each of appropriate care (measure = 3), almost certain undertreatment (measure = 1), and almost certain overtreatment (measure = 5).

Kerr and colleagues' (2012) measure was not used in any capacity for quality or performance measurement activities within the VA until 2011 (the final few months of my study period), and even today it is not widely known and is not used for public reporting purposes. As such, my analyses of variation using an extension of their measure are considerably less likely to be contaminated by Hawthorne and ceiling effects than analyses of variation using standard HEDIS or EPRP measures.

Empirical Framework

My methods for describing variation in the quality of care delivered to veterans with diabetes are non-parametric and straightforward. First, I calculate the ordinal measure of BP control for all eligible patient episodes, and I describe the distributions of the facility-year-level average values of this overall measure and facility-year-level fractions of patients receiving appropriate care, almost certain undertreatment, and almost certain overtreatment. I also plot the distributions of almost certain undertreatment and almost certain overtreatment jointly to establish the appropriateness of analyzing factors contributing to variation in the quality of care at the facility level. Lastly, I present summary statistics of BP control quality at the region level for comparison across regions.

After constructing scales of resource availability and coordination as both structures, I present preliminary, non-parametric evidence of the relationships between these scales and BP control quality measures and their consistency with the geographic variation literature's Resource Availability and Coordination framework.

In my first pooled, cross-sectional analyses at the episode level, I estimate multiple parametric models to identify the relationship between episode-level quality and facility-level measures of available resources, testing Hypotheses *H1* and *H2*. Among these models are ordinary least squares (OLS) and ordered logit models of the overall BP control measure $BPCont_{vft}$—for the veteran v treated in facility f in the year t—as a function of the broad resource availability scale RA_f, a set of veteran-, facility-, and county-level controls X_{vft}, and year fixed effects Y_t. I estimate both models to take advantage of the strengths of each: OLS model is comparatively easy to interpret, while the ordered logit model recognizes and accounts for the structure of the dependent variable as a discrete, ordinal measure.

The controls X_{vft} are included in these models to account for differences in the difficulty of managing patients' BP levels; they include indicators of the patient's sex and age, the facility physicians' responsibilities in addition to outpatient care (making rounds, serving as attending physicians), facility clinicians' stress levels, the training of residents in primary care at the facility, and the local area's health professional shortage area status and continuous measures of the county's total diabetes case burden, veteran population density, veteran facility density, total primary care physician density, and diabetes care need (diabetes-related death rate during 2004-2006, Medicaid eligible population density, and per capita income). I include year fixed effects to control for national trends in EPRP measure use and changes in associated incentives as well as national trends in the emphasis of the Primary Care Management Module and other delivery models reforms across VA facilities.

So that each model may be simply presented as a single equation, I present the OLS model's estimating equation as Equation 1, and I present the ordered logit model's likelihood function maximized in estimation as Equation 2.

$$BPCont_{vft} = \beta_0 + \beta_1 RA_f + \beta_X X_{vft} + Y_t + \varepsilon_{BPCont,vft} \tag{1}$$

$$L = \prod_{i=1}^{N} [\Lambda(\delta_0 - \boldsymbol{X})^{\text{if eq1}_i} \times [\Lambda(\delta_1 - \boldsymbol{X}) - \Lambda(\delta_0 - \boldsymbol{X})]^{\text{if eq2}_i} \times [\Lambda(\delta_2 - \boldsymbol{X}) - \Lambda(\delta_1 - \boldsymbol{X})]^{\text{if eq3}_i} \times [\Lambda(\delta_3 - \boldsymbol{X}) - \Lambda(\delta_2 - \boldsymbol{X})]^{\text{if eq4}_i} \times [1 - \Lambda(\delta_3 - \boldsymbol{X})]^{\text{if eq5}_i}], \text{ where } \boldsymbol{X} = \beta_1 RA_f + \beta_X X_{vft} + Y_t \tag{2}$$

In Equation 1, β_0 represents the constant term and $\varepsilon_{BPcont,vft}$ is the error. And in Equation 2, L is the likelihood, N is the number of episode-level observations indexed by i, Λ represents the logistic cumulative distribution function, δ_0 through δ_3 are the model's four threshold values, and $eq1_i$ through $eq5_i$ are binary indicators of the observation i's overall BP control measure equaling 1, 2, 3, 4, or 5, respectively. Because my theorized mechanisms operate at the facility-level, I cluster my standard errors at the facility level. In sensitivity analyses, I cluster standard errors at the Veteran's Integrated Service Network (VISN) and region levels.[12] A map of the VISNs is presented for reference in the Chapter Three Appendix.

I supplement the intuition derived from these models and directly test Hypotheses *H1* and *H2* by estimating separate logit models of three of the overall BP control measures' outcomes: almost certain undertreatment, appropriate care, and almost certain overtreatment. These models are summarized in Equation 3.

$$(BPCont = x)_{vft} = \Lambda\big(\beta_0 + \beta_1 RA_f + \beta_X X_{vft} + Y_t\big) + \omega_{BPCont,x,vft}, \text{ for } x = 1, 3, \text{ or } 5 \qquad (3)$$

In this equation, $\omega_{BPcont,x,vft}$ is the error, and all other terms are as presented in Equations 1 and 2.

In further refining the intuition derived from these models (Equations 1, 2, and 3), I re-estimate the models, replacing RA_f with the component subscales and factors of resource availability I developed following approaches 2 and 3.

To identify in the cross-section how coordination structures mediate the effects of resource availability on quality, testing Hypotheses *H3*-*H6*, I estimate revised versions of the above equations that introduce interactions between resource availability and measures of different coordination structures C_f. These models are summarized in Equations 4, 5, and 6.

$$BPCont_{vft} = \beta_0 + \beta_1 RA_f + \beta_2 C_f + \beta_3 RA_f \times C_f + \beta_X X_{vft} + Y_t + \varepsilon'_{BPCont,vft} \qquad (4)$$

$$L = \prod_{i=1}^{N}[\Lambda(\delta_0 - \boldsymbol{X}')^{\text{if eq1}_i} \times [\Lambda(\delta_1 - \boldsymbol{X}') - \Lambda(\delta_0 - \boldsymbol{X}')]^{\text{if eq2}_i} \times [\Lambda(\delta_2 - \boldsymbol{X}') - \Lambda(\delta_1 - \boldsymbol{X}')]^{\text{if eq3}_i} \times [\Lambda(\delta_3 - \boldsymbol{X}') - \Lambda(\delta_2 - \boldsymbol{X}')]^{\text{if eq4}_i} \times [1 - \Lambda(\delta_3 - \boldsymbol{X}')]^{\text{if eq5}_i}],$$

$$\text{where } \boldsymbol{X}' = \beta_1 RA_f + \beta_2 C_f + \beta_3 RA_f \times C_f + \beta_X X_{vft} + Y_t \qquad (5)$$

$$(BPCont = x)_{vft} = \Lambda\big(\beta_0 + \beta_1 RA_f + \beta_2 C_f + \beta_3 RA_f \times C_f + \beta_X X_{vft} + Y_t\big) + \omega'_{BPCont,x,vft},$$
$$\text{for } x = 1, 3, \text{ or } 5 \qquad (6)$$

[12] I define regions in accordance with the definition provided by the Department of Veteran Affairs Field Research Advisory Committee: Northeast (VISNs 1, 2, and 3), Mid-Atlantic (VISNs 4, 5, 6, 9, and 10), South (VISNs 7, 8, 16, and 17), Midwest (VISNs 11, 12, 15, 19, and 23), and West (VISNs 18, 20, 21, and 22).

I also re-estimate these models without year fixed effects and test the differences in the key covariate coefficients between models with and without the fixed effects. Where the differences are insignificant (this is the case for all models estimated), I estimate and present the interaction effects using techniques described in Karaca-Mandic, Norton, and Dowd (2012).

To address potential bias due to reverse causality in the cross-sectional estimates and to support the investigation of Hypotheses *H7* and *H8*, derived from the Physician Learning and Peer Effects framework, I conduct longitudinal analyses at the physician-year level. Specifically, I examine the care patterns of physicians who relocate their practices from one VA facility to another from one year to the next. I use relatively restrictive criteria to identify moving physicians: those for whom at least 60% of diabetes care episodes took place at a single VA facility in a given year[13] and at least 60% of diabetes care episodes took place at a different VA facility in the following year, with a minimum of 10 episodes in each of these years. I allow physician-years to be included in this sample if the pre-move and post-move years were non-consecutive and the intervening year had insufficient data to assess whether the physician had moved. The VA's Data Access Request Tracker staff linked physician records using staff Social Security numbers to support the identification of physician movers using these criteria.

Using these physician movers' data, I construct linear fixed effects models that are analogous to the models represented in Equations 1, 3, 4, and 6. The ordered logit models in Equations 2 and 5 are not replicable at the physician-year level because the ordinal BP control measure $BPCont_{vft}$ is summarized as a physician-year-level mean $BPContmean_{pt}$ for the physician p in the year t; $BPCont_{vft}$ is a discrete measure, but $BPContmean_{pt}$ is not. Likewise, the dependent variables capturing whether the patient received almost certain undertreatment, appropriate care, or almost certain overtreatment are summarized as physician-year means: $Frac_{BPCont=1,pt}$, $Frac_{BPCont=3,pt}$, and $Frac_{BPCont=5,pt}$, respectively. I estimate fixed effects in these

[13] At least 60% of diabetes care episodes took place at a single VA facility for over 99% of physician-years in my sample, and at least 90% of diabetes care episodes took place at a single VA facility for over 95% of physician-years. These data suggest that only rarely do physicians practice at two or more different VA facilities in a given year, let alone move from one facility to another.

models by replacing all model variables with the same variables demeaned, subtracting within-physician means from the variable values in each physician-year observation.

The panel data models I estimate that are analogous to the models in Equations 1, 3, 4, and 6 are summarized in Equations 7, 8, 9, and 10, respectively. For each variable Y in the cross-sectional models, $\ddot{Y}$ represents the corresponding demeaned variable.

$$BPCo\ddot{n}tmean_{pt} = \beta_0 + \beta_1 R\ddot{A}_f + \beta_X \ddot{X}_{pft} + Y_t + \ddot{\varepsilon}_{BPContmean,pt} \quad (7)$$

$$Fr\ddot{a}c_{BPCont=x,pt} = \beta_0 + \beta_1 R\ddot{A}_f + \beta_X \ddot{X}_{pft} + Y_t + \ddot{\omega}_{FracBPCont,x,pt}, \text{ for } x = 1, 3, \text{ or } 5 \quad (8)$$

$$BPCo\ddot{n}tmean_{pt} = \beta_0 + \beta_1 R\ddot{A}_f + \beta_2 \ddot{C}_f + \beta_3 R\ddot{A}_f \times \ddot{C}_f + \beta_X \ddot{X}_{pft} + Y_t + \ddot{\varepsilon}'_{BPContmean,pt} \quad (9)$$

$$Fr\ddot{a}c_{BPCont=x,pt} = \beta_0 + \beta_1 R\ddot{A}_f + \beta_2 \ddot{C}_f + \beta_3 R\ddot{A}_f \times \ddot{C}_f + \beta_X \ddot{X}_{pft} + Y_t + \ddot{\omega}'_{FracBPCont,x,pt},$$
$$\text{for } x = 1, 3, \text{ or } 5 \quad (10)$$

These panel data models overcome the potential bias due to reverse causality in the corresponding cross-sectional models by identifying effects solely using differences in physicians' practices and their exposures to facility environments and patient mixes over time. This identification strategy depends on the assumption of exogenous changes in physician practice location. I discuss potential threats to this assumption in a later section.

While each of the models in Equations 1-10 implicitly tests a facility-level dimension of Hypotheses *H7* and *H8* concerning physician learning and peer effects by identifying the effects of facility-level factors on physician-level care patterns, I test these hypotheses more fully and explicitly in the models represented in Equations 11-14. These models relate physician-year-level quality measure performance to average facility-year-level quality measure performance using both cross-sectional and longitudinal frameworks. In the cross-sectional models (Equations 11 and 12), I regress the physician's BP control measure mean values in a given year $BPContmean_{pt}$ and $\mathrm{Frac}_{BPCont=x,pt}$ on the BP control measure mean values for the physician's modal facility (at least 60% of diabetes episodes at the facility) during the same year FAC_{pft} and $FAC_{x,pft}$. For each physician-year record, the facility's BP control measure mean values are constructed without the experience of the physician herself so as to avoid inducing correlations between physician-year-level and facility-year-level means arithmetically.

$$BPContmean_{pt} = \beta_0 + \beta_1 FAC_{pft} + \beta_X X_{vft} + Y_t + \sigma_{BPCont,vft} \quad (11)$$

$$Frac_{BPCont=x,pt} = \beta_0 + \beta_1 FAC_{x,pft} + \beta_X X_{pft} + Y_t + \eta_{FracBPCont,x,pt}, \text{ for } x = 1, 3, \text{ or } 5 \quad (12)$$

The goal of the panel data models is to identify effects based on the differences in average facility-year-level quality measure performance between physician movers' pre-move and post-move facilities. And so these differences $FAC\Delta_{pft}$ and $FAC\Delta_{x,pft}$—between the average performance of the physician's home facility in the current year and the average performance of the physician's home facility in the final year pre-move—serve as the key independent variables in the panel data models I estimate (Equations 13 and 14). Because these differences are computed relative to the pre-move year, any preceding physician-years for a moving physician are dropped from this analysis. Again, all facility-year averages are computed without the experience of the individual physician mover, and all variables are demeaned in the panel data models to estimate fixed effects regressions.

$$BPCon\ddot{t}mean_{pt} = \beta_0 + \beta_1 F\ddot{AC}\Delta_{pft} + \beta_X \ddot{X}_{pft} + Y_t + \ddot{\sigma}_{BPContmean,pt} \quad (13)$$

$$F\ddot{r}ac_{BPCont=x,pt} = \beta_0 + \beta_1 F\ddot{AC}\Delta_{x,pft} + \beta_X \ddot{X}_{pft} + Y_t + \ddot{\eta}_{FracBPCont,x,pt}, \text{ for } x = 1, 3, \text{ or } 5 \quad (14)$$

In the Equations 11-14, $\sigma_{BPCont,vft}$, $\eta_{FracBPCont,x,pt}$, $\ddot{\sigma}_{BPcont,vft}$, and $\ddot{\eta}_{FracBPCont,x,pt}$, represent the new residuals.

Such tests of physician learning and peer effects must be interpreted carefully due to the well-understood difficulties of identification and endogeneity in peer effects analyses (Mansky, 1993). In particular, without more clearly representing specific mechanisms by which these peer effects take place, one cannot infer directly from my analyses that the effects are a consequence purely of differences among the physicians themselves (e.g., preferred patterns of practice), among the facilities where they practice (e.g., organizational structures or incentive programs), or among the patient populations they serve (e.g., average difficulty with which patients' BP is managed). In the context of this study, it is unlikely that peer effects emerge because of differences in knowledge of the evidence about the proper way to manage blood pressure in patients with diabetes—the guidelines underlying the construction of this study's BP control measure date back to the late 1990s and early 2000s (Kerr et al., 2012), and the VA's national EPRP performance measurement system aids in homogenizing awareness of evidence-based care practices. In addition, my peer effects estimates for the probability of patients receiving appropriate care (measure = 3) are unlikely to emerge from differences in how easily patients can be managed; this is because of the controls I include in my models to address this concern and because the BP control measure scores of 2, 3, or 4 are assigned to patient cases purely in response to the appropriateness of clinical actions and account for potentially important differences in patient traits. As a result, it is most appropriate to interpret these results in terms of differences between facilities.

Finally, for the explicit test of Hypothesis *H8*, I add to the Equations 11-14 measures of the current-year facility's resource availability and interactions between these measures and $FAC\Delta_{pt}$ to determine whether physicians' peer effects are mediated by available facility resources.

I conduct all analyses using Stata/MP 13.1 analytic software.

Data & Study Sample

For these analyses I constructed a rich dataset by linking data from a variety of VA datasets and select non-VA data.

My principal analytic sample of diabetes care episodes and BP control information is generated using VA Clinical Data Warehouse (CDW) data. I identify all veterans ages 18 and older who, during FY2008-FY2011, met the eligibility criteria Kerr and colleagues (2012) used in defining their measures of BP control for diabetes patients—they present these detailed criteria in full. To summarize, these veterans must have records of care delivery encounters with select diabetes- and hypertension-related diagnosis codes and recorded BP levels during the index fiscal year as well as the year before. Veterans were excluded if were diagnosed with gestational diabetes, steroid-induced diabetes, or hyperglycemia, if there was evidence they had select terminal conditions, if they died during the index year, or if there were notations in their medical records of specific restrictions on the care they received. Before restricting the sample to records that could be merged with facility-level datasets, these data were comprised of approximately 3.5 million veteran-years with valid BP control measure values (one measure value per eligible veteran-year). The application of the exclusion criteria, the merging of these data with facility-level datasets, and the exclusion of records for sites with fewer than 10 cases in a year or with missing data values yielded a sample of 966,632 veteran-years. I used this sample of veteran-years to construct my conservatively-defined longitudinal sample of 1,016 physician-years.

Data on the facilities where veterans received care are derived from four sources. Two of these data sources are VA Clinical Practice Organization Surveys (CPOS) developed by researchers in the VA HSR&D Center of Excellence for the Study of Healthcare Provider Behavior and distributed to VA facilities during 2006 and 2007, immediately before my study period. The first of these CPOS modules was distributed to facilities' Chiefs of Staff ("COS module"; Yano et al., 2007a), and the second was distributed to facilities' Primary Care Directors ("PC module"; Yano et al., 2008). The PC module's survey sample included 250 VA facilities, including 153 VA medical centers and 97 large community-based outpatient clinics (CBOCs); the response rate was 90 percent. This survey "focused on primary care program features and practice arrangements." The COS module's survey sample included 129 sites with a VA hospital and an identifiable Chief of Staff. This survey achieved an 86 percent response rate and "focused on hospital characteristics and ambulatory care practice arrangements."

A third data source is the 2008-2009 VA Primary Care Survey (PCS), which, like the CPOS PC module, was developed by the VA HSR&D Center of Excellence for the Study of Healthcare Provider Behavior and distributed to Primary Care Directors at a larger sample (N = 248) of VA medical centers and CBOCs. This survey sought to identify primary care practices in the VA that were successful and practices in need of improvement. This survey's response rate was 92 percent. Information from both CPOS sources and the PCS is available for 84 VA facilities.

The fourth data source I relied on for obtaining information about the facilities where veterans with diabetes received care was, again, the VA CDW. I used these data to construct aggregated facility-year-level information about patients, staff, and average patterns of care.

Gathering information from each of these sources is desirable because they contain different types of information. The CPOS and PCS data contain more subjective, specific, largely time-invariant information about the sufficiency of select resources, whereas the CDW data consist of more objective, less specific, time-varying information about existing resources and their use. Combining such diverse data types in my analysis adds to its construct and external validity. Where information from different sources is duplicative (e.g., the same question is asked in different surveys in different years), I retain for each care episode the data from the source that most recently preceded it.

Additional data sources used in these analyses included Vital Status records—this is a VA data set that more precisely identifies veterans' dates of death than the CDW alone—records of VA facilities' resident training programs in outpatient care, and the Area Health Resource File to capture county characteristics where VA facilities are located; such characteristics include the local veteran population density, whether the area is designated a health professional shortage area, and measures of local diabetes care burden.

This study protocol was approved by the VA Research & Development Committee and Institutional Review Board.

Key Explanatory Variables: Resource Availability and Coordination

My key independent variables are measures of resource availability and coordination of resources at the facility level. To simplify analysis and interpretation of my data on resource availability and "coordination as both" structures, I construct and analyze the data in scales. This is an attractive approach because my analytic data set contains more diabetes care-relevant variables about these constructs than can be reasonably analyzed individually.

I develop the scales using three different approaches. My first approach is to construct broad scales of these concepts. These scales support straightforward analysis and interpretation of effects in the terms of this study's theoretical frameworks. However, they may not yield insights about which specific resources and coordination structures are most important in driving the observed relationships.

My second and third approaches involve the construction of narrower subscales, each approach meant to validate the other. I construct clinical and non-clinical subscales using subsets of data items that appear *ex ante* to be more homogeneous and focused on previously validated underlying component factors (Parchman, Noël, & Lee, 2005; Soban & Yano, 2005; Yano et al., 2007b; AHRQ, 2011; Jackson et al., 2011; Kilbourne et al., 2011; Rosland et al., 2013). And, third, I conduct a principal-factor analysis with varimax rotation of variables that allows the data to identify underlying component factors freely. For this final approach, I generate regression-based factor scores for all component factors retained with eigenvalues greater than one in concordance with the Kaiser criterion—I also generate Scree plots and use them in tandem with the Kaiser criterion to choose the factors to be retained. My second and third approaches are more complex methodologically but may be more helpful in identifying important mechanisms at work.

For each scale, I pre-standardize each included data item to have mean zero and standard deviation one in accordance with the standard practices of exploratory factor analysis, and I report Cronbach's α statistics to test the scales' internal consistency. Complete lists of the data items I use in constructing scales of resource availability and coordination as both structures are provided in the Chapter Three Appendix.

The CPOS and PCS data do not contain sufficient specific detail in their questions about most diabetes care-related coordination structures to identify them uniquely as reflective of coordination as management or coordination as facilitation. In this study I examine the mediating effects of these constructs using the few coordination structures for which such a designation can be made. For coordination as management, I analyze differences across facilities with respect to the existence of requirements that physicians obtain pre-authorization for specified medications. And for coordination as facilitation, I analyze differences across facilities with respect to two variables: any identified difficulties coordinating with endocrinology specialists (never or rarely versus more often) and the existence of service agreements between primary care and endocrinology or diabetes clinics for coordination purposes (fully or partially implemented versus none). Future explorations of the frameworks described in this study may benefit from more in-depth examinations of additional coordination structures more clearly identifiable as coordination as management or coordination as facilitation in their functions.

Control Variables

In analyses that include measures of coordination as management or coordination as facilitation, I also include my scale of coordination as both structures. The purpose of including this scale is to control for any disproportionate investment in coordination structures or a broad culture of collaborative coordination overall at any one facility, of which coordination as management or coordination as facilitation structures may be only a small part. Absent this control, my parameters of interest might be confounded by the simultaneous use of different types of coordination structures at a given facility.

The patient-level controls I include in all regressions—aggregated to the facility-year level in the longitudinal, physician-year-level analyses—are limited to sex and a set of age splines (provider-year-level average proportions of patients in age ranges 18-40, 41-65, 66-80, and ≥ 81 in longitudinal analyses). These controls are intended to proxy for patient comorbidities and complexity, which can affect how easily physicians manage their care in accordance with evidence-based guidelines. Because select complex patients are excluded from the Kerr and colleagues' (2012) BP control measure, it is unlikely the absence of other patient-level control variables (e.g., comorbid condition indicators) meaningfully affects my findings.

At the facility level, I include controls first for constraints on physicians' time. Such constraints may affect physicians' capacity to learn and follow clinical practice guideline developments and the amount of time they have to spend with each patient. I include variables reflecting whether at least some facility physicians have inpatient care responsibilities—making rounds with ward teams, working as attending physicians for inpatients—on top of their outpatient medical care responsibilities, whether local clinicians feel overwhelmed with stress and how busy their clinics are, and whether or not the facility formally trains residents or other trainees in outpatient care. The indicator for the presence of local training programs also serves as a proxy for the facility's academic affiliation. This control variable may be important if physicians who practice in facilities affiliated with academic medical centers are more likely to engage with their peers in knowledge-sharing interactions or otherwise influence one another's practices than physicians who practice in other settings. So and colleagues (2012) have also identified independent effects of academic affiliation on the quality of care delivered to veterans.

I also control for the density of the local veteran population and total diabetes care episodes at the facility in each year to capture both strain on local facility resources due to demand and also any unmeasured resources VISNs may allocate to certain facilities rather to others.

In addition, there may be other factors associated with the urban or rural location of a VA facility—as examples, difficulties working with large homeless or seriously mentally ill populations, or cultural issues working with Native American, African American, or Hispanic patients (Kirsh et al., 2012)—that affect the quality of care (Weeks, Yano, & Rubenstein, 2002). Such facilities may also be under-resourced for diabetes care if the local veteran population is disproportionately diabetic. For these reasons, I include as controls measures of local non-VA care resources (a health professional shortage area indicator and primary care physicians per 1,000 residents), a measure of diabetes prevalence (diabetes-related deaths during 2004-2006 per 1,000 deaths), and measures associated with other access concerns (per-capita income and estimated Medicaid eligible individuals per 1,000 residents).

Results

Descriptive statistics for my analytic samples are presented in Table 18. In these samples, the BP control measure average is slightly greater than 3, and the average proportions of episodes with measure value 5 (12.9%-14.2%) significantly exceeds the average proportions of episodes with measure value 1 (3.9%-5.0%). This suggests that, on average, veterans with diabetes and hypertension were given appropriate care for their hypertension during FY2008-FY2011. However, if they received care out of line with evidence-based guidelines, they were more likely to be almost certainly overtreated than almost certainly undertreated. The resource availability and coordination as both scales have means near zero as a result of their component data items' standardization (mean zero) prior to inclusion in the scales. The means of these samples' control variables tend to reflect the population of veterans with diabetes overall. In particular, sample veterans tend to be older and male. In my cross-sectional sample, two thirds of veteran-years took place at facilities where residents were trained on-site, nearly 86% of physicians expressed feeling overwhelmed at their practices in these same facilities, and just less than half of veteran-years took place in counties designated as health professional shortage areas. The longitudinal sample's physician-years took place in facilities that were somewhat smaller and in areas more likely to be designated health professional shortage areas with denser veteran populations.

Additional descriptive statistics for the individual variables used to construct my scales of resource availability and coordination are presented in the Chapter Three Appendix.

Table 18: Sample Descriptive Statistics, Episode-level and Provider-year-level

	Cross-sectional Sample (episode level)		*Longitudinal Sample (provider-year level)*	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Dependent Variables				
BP Control Measure Value (1 to 5)	3.18	(0.11)	3.12	(0.48)
Almost Certain Undertreatment (Measure = 1)	3.9%		5.0%	
Appropriate Care (Measure = 3)	69.0%		68.2%	
Almost Certain Overtreatment (Measure = 5)	14.2%		12.9%	
Key Explanatory Variables				
Resource Availability Scale	-0.03	(0.23)	0.01	(0.23)
Pre-Authorization for Select Rx	0.87	(0.33)	0.84	(0.37)
No Difficulties Coord. With Endocrinology	0.37	(0.48)	0.36	(0.48)
Service Agreement with Endocrinology	0.38	(0.49)	0.36	(0.48)
Coordination as Both Scale	0.04	(0.35)	-0.02	(0.33)
Patient-level Control Variables				
Female	3.6%		4.6%	
Age	67.0	(10.8)	66.8	(4.2)
Facility-level Control Variables				
PCPs Also Make Rounds	20.9%		21.2%	
PCPs Also Attending Physicians	69.2%		73.8%	
Clinicians Express Feeling Overwhelmed	85.9%		88.7%	
Residents Trained On-site (Academic)	67.1%		71.6%	
Total Episodes (1,000s)	4.0	(1.9)	3.0	(1.8)
County-level Control Variables				
Veteran Population, 2010*	60.2	(66.1)	95.9	(110.7)
Veteran Hospitals Beds, 2008*	13.0	(18.5)	11.1	(16.8)
Health Professional Shortage Area	48.3%		55.9%	
PCPs in Patient Care, 2010*	0.9	(0.3)	0.8	(0.3)
Diabetes Deaths, 2004-2006*	0.3	(0.1)	0.3	(0.1)
Per Capita Income, 2008 ($1,000s)	$39.9	($11.8)	$40.8	($10.1)
Medicaid-Eligibles, 2007*	208.5	(73.4)	223.6	(89.7)
Years				
FY 2008	24.8%		23.9%	
FY 2009	24.8%		26.0%	
FY 2010	25.1%		27.7%	
FY 2011	25.2%		22.4%	
n	*966,632*		*1,016*	

* Measured per 1,000 population

Variation in BP Control across VA Facilities

Figure 8 depicts the distributions of FY2011 (the most recent year in my sample) average ordinal measure values and rates of appropriate care, almost certain undertreatment, and almost certain overtreatment across facilities in my sample (N = 244,067). While this figure marks meaningful variation across facilities in the average measure value (panel i) and the fraction of patients receiving appropriate care (panel ii), this variation is somewhat narrow relative to distributions of quality shown outside the VA and for other quality measures. Both distributions are quite smooth in general. The average measure value distribution identifies a single high-outlier facility (average value above 3.4) and a handful of low-outlier facilities. By comparison, the appropriate care distribution identifies a single low-outlier facility (rate less than 0.6) and two high-outlier facilities (rate greater than 0.8), but these high-outlier facilities are not well-removed from other facilities with marginally lower rates.

Of greater interest are Figure 8's distributions of almost certain undertreatment (panel iii) and overtreatment (panel iv). The distribution of almost certain overtreatment is considerably wider—its range is approximately three times the range of the almost certain undertreatment distribution—in part because of its higher mean and lesser floor effects. While the distribution of almost certain undertreatment is concentrated about its mean, the distribution of almost certain overtreatment is less concentrated. In addition, both distributions identify a small number of high outliers and no distinct low outliers. Corresponding charts for previous years revealed similar patterns.

Figure 8: Average Values and Rates of Appropriate Care, Almost Certain Undertreatment, and Almost Certain Overtreatment by Facility, BP Control Ordinal Measure, FY2011

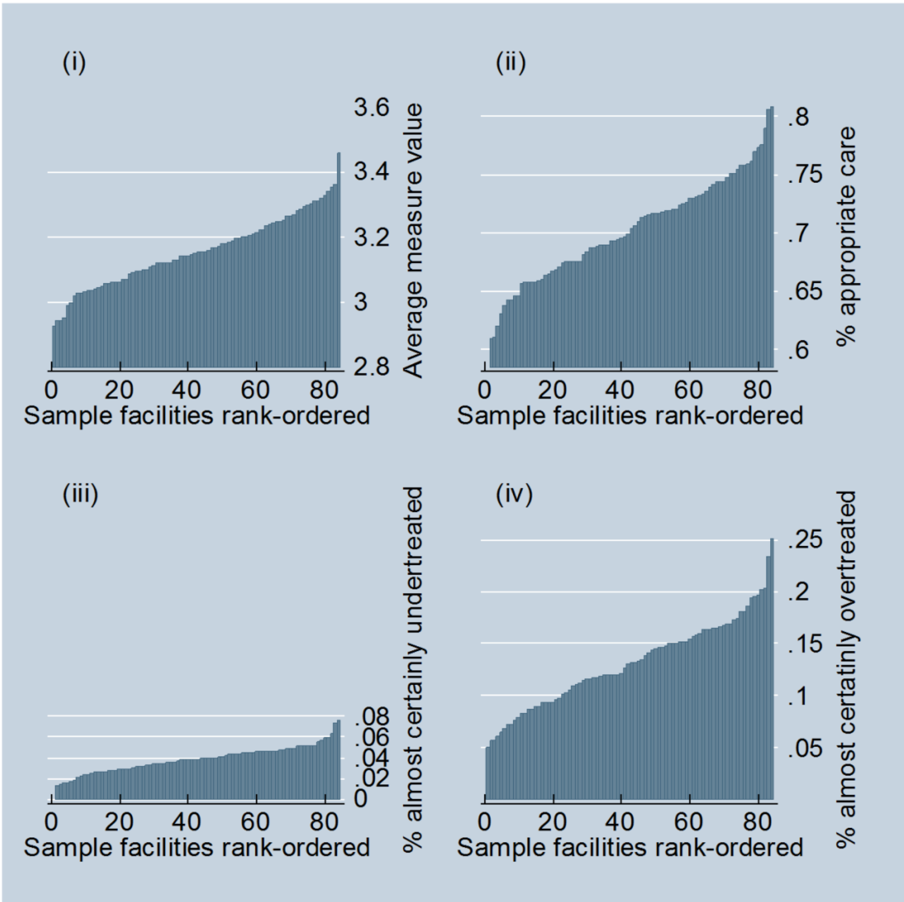
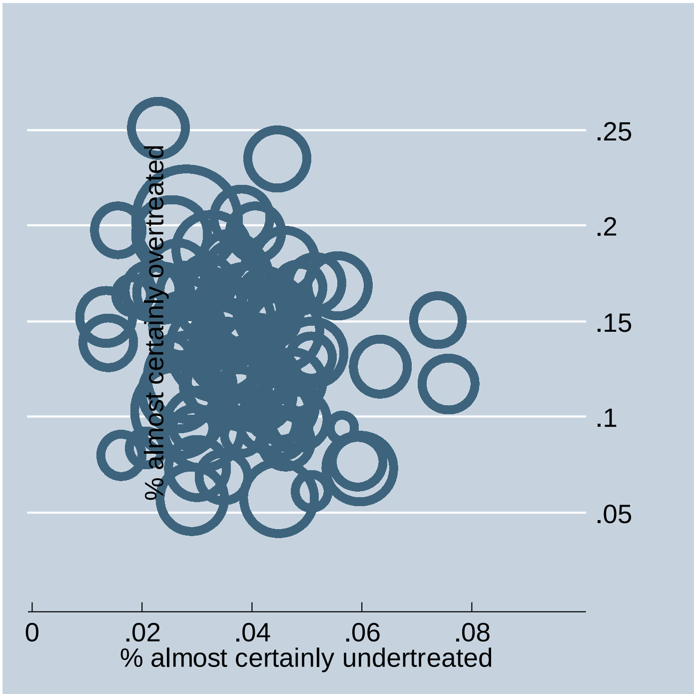


Figure 9 depicts a facility-level scatterplot of FY2011 rates of almost certain undertreatment and almost certain overtreatment to assess any unadjusted correlation between the two. In this figure, the sizes of the plotted circles are weighted by the number of episodes at the facility: larger circles identify facilities with larger samples of diabetes care episodes. There is considerable noise in this relationship, but there is a statistically significant, negative correlation between the two rates ($r(244{,}065) = -0.21$, $p < .001$). This negative correlation is stronger among larger facilities with more than 4,000 episodes during FY2011 ($r(102{,}780) = -0.47$, $p < .001$) than among smaller facilities ($r(141{,}283) = -0.14$, $p < .001$). Again, corresponding plots for previous years revealed similar patterns.

Figure 9: Almost Certain Undertreatment Rate versus Almost Certain Overtreatment Rate by Facility, BP Control Ordinal Measure, FY2011



The negative association between almost certainly undertreated and almost certainly overtreated patient fractions supports the choice of analyzing quality of care using this study's BP control measure at the facility level. However, the substantial noise about the trend in this figure suggests that numerous factors, perhaps at multiple levels, contribute to this variation.

Finally, in Table 19, I compare facility-level descriptive statistics by region for BP control measure values and key independent variables. While there is meaningful variation across regions in select independent variables, particularly between the West region and other regions, there is little variation in any of the BP control measures at this level.

Table 19: Facility-year-level Descriptive Statistics by Region, FY2008-FY2011

Variable	*Northeast Region*	*Mid-Atlantic Region*	*South Region*	*Midwest Region*	*West Region*
Dependent Variables					
BP Control Measure Value (1 to 5)	3.17	3.16	3.18	3.16	3.13
	(0.11)	(0.08)	(0.11)	(0.13)	(0.11)
Almost Certain Undertreatment (Measure = 1)	3.9%	4.0%	4.0%	4.1%	4.1%
	(1.0%)	(1.4%)	(1.2%)	(1.5%)	(1.4%)
Appropriate Care (Measure = 3)	68.9%	70.1%	68.8%	68.8%	70.7%
	(4.6%)	(4.3%)	(5.3%)	(4.5%)	(5.8%)
Almost Certain Overtreatment (Measure = 5)	13.0%	13.4%	14.3%	13.8%	12.4%
	(4.6%)	(3.3%)	(4.5%)	(4.7%)	(4.7%)
Key Explanatory Variables					
Resource Availability Scale	-0.01	-0.06	-0.02	-0.03	0.19
	(0.16)	(0.21)	(0.19)	(0.28)	(0.72)
Pre-Authorization for Select Rx	0.92	1.00	0.94	0.83	0.69
	(0.28)	(0.00)	(0.24)	(0.38)	(0.47)
No Difficulties Coord. With Endocrinology	0.17	0.35	0.31	0.52	0.31
	(0.38)	(0.48)	(0.47)	(0.50)	(0.47)
Service Agreement with Endocrinology	0.50	0.35	0.25	0.35	0.38
	(0.51)	(0.48)	(0.44)	(0.48)	(0.49)
Coordination as Both Scale	-0.08	0.05	0.23	-0.11	-0.05
	(0.40)	(0.34)	(0.29)	(0.37)	(0.32)
N (facility-years)	*48*	*80*	*64*	*92*	*52*

Note: Mean values are reported with standard deviations in parentheses.

Resource Availability and Coordination as Both Scale Construction and Descriptive Analysis

In Table 20 I provide summary statistics regarding the construction of my scale of resource availability following my first and second approaches. In accordance with my first approach, I constructed broad scales for each of resource availability and coordination as both. I used 16 variables to construct the resource availability scale. Based on its Cronbach's α statistic of 0.55, this scale is only marginally internally consistent. The resource availability subscales of clinical staff and non-clinical staff resources—with α = 0.36 and α = 0.67, respectively—indicate that what limited internal consistency the resource availability scale has comes from variables concerning non-clinical staff resources. These findings are not surprising given the array of resource types included in this analysis. The coordination as both scale, constructed using 11 variables, is not internally consistent (α = 0.38), and so I conduct sensitivity analyses in which I replace the coordination as both scale with the complete set of its component variables in my regressions.

Table 20: Constructing Scales of Resource Availability and Coordination as Both; Scale Summary Statistics at the Facility Level, FY2008-FY2011

	Component Variables		Scale Statistics†		
Scale	N	Cronbach's α	SD	Min	Max
Approach 1: Single, Broad Scale					
Resource Availability	16	0.55	0.36	-0.56	2.78
Coordination as Both	11	0.38	0.32	-0.79	0.69
Approach 2: Component Subscales					
Resource Availability					
Clinical Staff Resources	9	0.36	0.39	-1.04	0.86
Non-clinical Resources	7	0.67	0.58	-0.65	6.75

† All scales have mean 0 because all component variables are standardized with mean zero and standard deviation one before inclusion

Table 21 presents information on my principal-factor analyses of resource availability and coordination as both. With respect to resource availability, three factors were identified with eigenvalues greater than one. Ordered by rotated factor loadings, the top three variables for the first factor identify it with the non-clinical resources component subscale I formulated for my second approach. The second and third factors' top three variables are less clearly thematically aligned. Thus analyses of the first factor may be interpreted to reflect non-clinical resource effects, while analyses of the second and third factors—the second factor in particular, given two of its top variables have inverse impacts—may not be interpretable. For this reason, I focus my analysis on the first factor and on the scales developed through my first and second approaches.

Table 21: Principal-Factor Analyses of Resource Availability and Coordination as Both

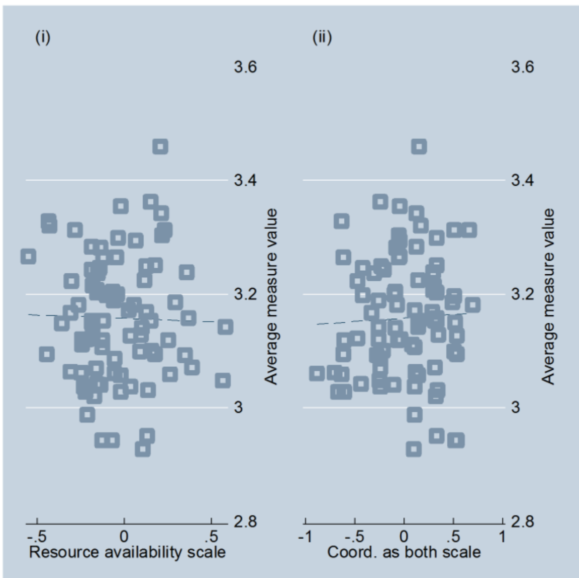
Variable Group	Eigenvalue	Variable 1†	Variable 2†	Variable 3†
Resource Availability				
Factor 1	2.99	FTE officers, administrators, supervisors	Exam rooms per PCP	FTE clerks and receptionists
Factor 2	1.40	Total primary care physicians at site*	Appropriately equipped exam rooms sufficient	Endocrinology/diabetology specialists onsite*
Factor 3	1.04	Endocrinology/diabetology specialists onsite	Medical informatics support sufficient	Total primary care physicians at site
Coordination as Both				
Factor 1	1.11	Visible support for guideline implementation	Teamwork in implementing guidelines	Cooperative culture

† Highest-relevance variables for factor, rank-ordered by rotated factor loadings, * inverse impact on factor

For each of the dependent variables of the average BP control measure value, appropriate care (measure = 3), almost certain undertreatment (measure = 1), and almost certain overtreatment (measure = 5), I present two scatterplots in Figure 10, Figure 11, Figure 12, and Figure 13, respectively. The panels (i) and (ii) in each figure are FY2011 facility-year-level scatterplots depicting the relationship between the dependent variable on the y-axis and my scales of resource availability and coordination as both, respectively, on the x-axis. Each scatterplot is also presented with its associated line of best fit. (Corresponding plots for previous years showed similar patterns.) Excluded from these figures is one outlier facility-year with a resource availability scale value of 2.41, the second highest value being 0.58.

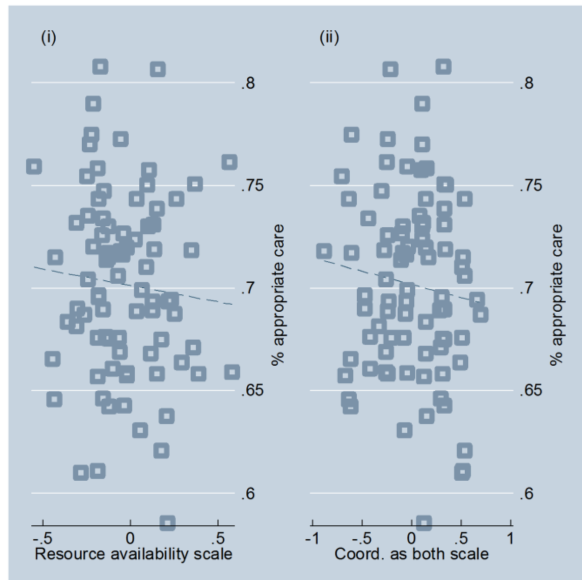
If coordination as both structures operate like coordination as facilitation structures because of the VA's historical focus on EPRP measure performance, then resource availability and coordination as both scales should be similarly associated with BP control measures. Based on these unadjusted scatterplots, this appears to be the case. Figure 11, Figure 12, and Figure 13 show parallel associations across panels: greater resource availability and coordination as both scales are associated with lower fractions of patients receiving appropriate care, higher fractions almost certainly undertreated, and higher fractions almost certainly overtreated. Given that most facilities' average BP control measure values are greater than 3, the appropriate care and overtreatment patterns are consistent and in line with expectations. The positive associations with undertreatment are contrary to my hypothesis. Finally, the relationships between the average BP control measure value and each of resource availability and coordination as both scales are indeterminate. All of these associations are statistically insignificant; in part this may be attributable to small sample sizes (n = 83), but there is substantial noise in these relationships as well.

Figure 10: Average BP Control Measure Value versus Resource Availability and Coordination as Both Scales, FY2011



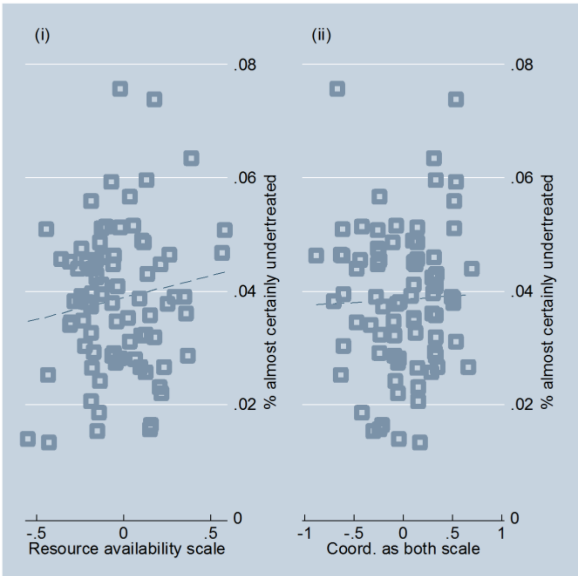
Lines of best fit: (i) β = -0.011 (p = 0.83) and (ii) β = 0.012 (p = 0.70)

Figure 11: % Appropriate Care (BP Control) versus Resource Availability and Coordination as Both Scales, FY2011



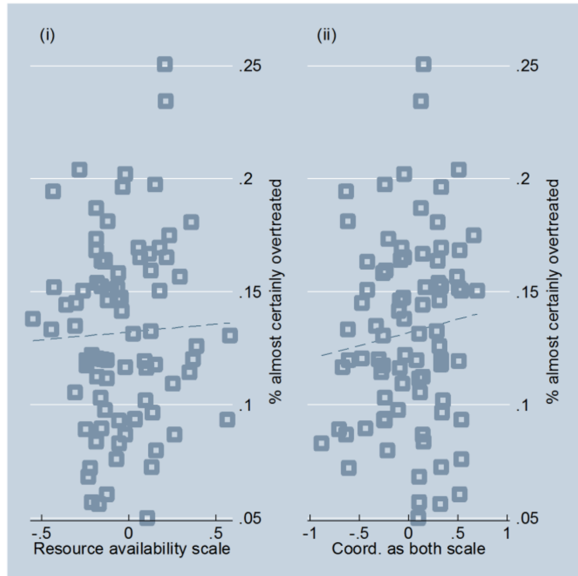
Lines of best fit: (i) β = -0.016 (p = 0.48) and (ii) β = -0.013 (p = 0.35)

Figure 12: % Almost Certainly Undertreated (BP Control) versus Resource Availability and Coordination as Both Scales, FY2011



Lines of best fit: (i) β = 0.008 (p = 0.21) and (ii) β = 0.001 (p = 0.77)

Figure 13: % Almost Certainly Overtreated (BP Control) versus Resource Availability and Coordination as Both Scales, FY2011



Lines of best fit: (i) β = 0.007 (p = 0.73) and (ii) β = 0.012 (p = 0.35)

Cross-sectional Analysis Results

In Table 22, I present the results of three OLS models of the overall BP control measure, as presented in Equation 1. These models differ in their specification of resource availability: as a broad scale, as a pair of component subscales (clinical staff resources and non-clinical resources), and using the three regression-based factor scales developed through principal factor analysis. Each of these variables was standardized with mean 0 and variance 1 prior to modeling. Only the coefficient estimate for the clinical resources subscale is statistically significant; this estimate suggests that a one standard deviation increase in clinical resources is associated with a measure reduction of 0.053 units, equivalent to 5.3 percent of the sample switching from appropriate care (3) to potential undertreatment (2). In total, five of the six estimates are negatively signed. These negative associations are contrary to the Resource Availability and Coordination framework's hypothesis.

Among the other variables in these models, all of the patient-level covariates are strongly statistically significant—this is not surprising given that the model is estimated at the episode level and the samples are large. There are also positive associations between the BP control measure and primary care physicians also serving as attending physicians at the facility as well as facility size based on the total number of measured diabetes episodes. There were no meaningful changes in these models' results when standard errors were clustered at the VISN (network) or region level.

Table 22: OLS Models of Overall BP Control Measure (1-5), Alternative Approaches for Specifying Resource Availability, Equation 1

	Approach 1 (Broad Scale)		Approach 2 (Comp. Subscales)		Approach 3 (Factor Scales)	
Variable	Est.	SE	Est.	SE	Est.	SE
Key Explanatory Variables						
Resource Availability Scale	-0.026	(0.039)				
Clinical Resources Subscale			-0.053	(0.024)**		
Non-clinical Resources Subscale			-0.009	(0.026)		
RA Factor 1					-0.079	(0.088)
RA Factor 2					-0.018	(0.018)
RA Factor 3					0.013	(0.013)
Patient-level Control Variables						
Female	0.045	(0.011)**	0.047	(0.010)**	0.047	(0.011)**
Age 18-40	-0.022	(0.001)**	-0.022	(0.001)**	-0.021	(0.001)**
Age 41-65	0.035	(0.002)**	0.035	(0.002)**	0.034	(0.002)**
Age 66-80	0.008	(0.001)**	0.008	(0.001)**	0.008	(0.001)**
Age 81+	-0.015	(0.001)**	-0.015	(0.001)**	-0.015	(0.001)**
Facility-level Control Variables						
PCPs Also Make Rounds	0.032	(0.034)	0.032	(0.033)	0.031	(0.033)
PCPs Also Attending Physicians	0.042	(0.023)*	0.043	(0.023)*	0.046	(0.024)*
Clinicians Express Feeling Overwhelmed	-0.055	(0.035)	-0.052	(0.034)	-0.050	(0.035)
Residents Trained On-site (Academic)	0.028	(0.021)	0.025	(0.020)	0.026	(0.022)
Total Episodes (1,000s)	0.018	(0.006)**	0.021	(0.006)**	0.021	(0.008)**
County-level Control Variables						
Veteran Population, 2010†	0.0002	(0.0001)	0.0003	(0.0001)*	0.0002	(0.0002)
Veteran Hospitals Beds, 2008†	0.0000	(0.0006)	0.0001	(0.0006)	-0.0001	(0.0006)
Health Professional Shortage Area	-0.016	(0.024)	-0.021	(0.024)	-0.020	(0.024)
PCPs in Patient Care, 2010†	-0.040	(0.039)	-0.022	(0.040)	-0.029	(0.043)
Diabetes Deaths, 2004-2006†	0.090	(0.134)	0.094	(0.132)	0.104	(0.123)
Per Capita Income, 2008 ($1,000s)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
Medicaid-Eligibles, 2007†	-0.0003	(0.0002)*	0.000	(0.000)	-(0.0003)	(0.0002)
Years						
FY 2008	(ref.)		(ref.)		(ref.)	
FY 2009	0.009	(0.007)	0.010	(0.007)	0.010	(0.007)
FY 2010	0.013	(0.009)	0.016	(0.009)*	0.015	(0.009)
FY 2011	-0.007	(0.010)	-0.004	(0.010)	-0.005	(0.010)
Constant	3.611	(0.097)**	3.569	(0.096)**	3.557	(0.100)**
n	*966,632*		*966,632*		*966,632*	

* $p < 0.10$. ** $p < 0.05$. † Measured per 1,000 population.

Table 23 presents the resource availability-specific estimates of two ordered logit models of the overall BP control measure and six logit models of almost certain undertreatment, appropriate care, and almost certain overtreatment. These models are as presented in Equations 2 and 3. The first set of estimates corresponds to models with resource availability specified as a broad scale, and the second and third sets correspond to models with resource availability specified as its two component subscales. I also estimated these models with resource availability specified using factor scales, with similar results. I present marginal effect estimates rather than coefficient estimates, and so the outcome-specific marginal effect estimates for the ordered logit models can be compared to the marginal effect estimates for the logits.

As in Table 22, the effect estimates of the broad scale of resource availability are not statistically significant, though these estimates are generally consistent in sign with the statistically significant effect estimates obtained for the clinical resources subscale. The ordered logit results suggest that, where levels of available clinical staff resources are one standard deviation higher, rates of almost certain overtreatment are 1.5 percentage points lower, rates of appropriate care are 0.6 percentage points higher, and rates of almost certain undertreatment are 0.5 percentage points higher. These are economically significant effects, particularly for almost certain overtreatment, and effects consistent with the results in Table 22.

Table 23: Marginal Effect Estimates of Almost Certain Undertreatment, Appropriate Care, and Almost Certain Overtreatment in BP Control, Ordered Logit and Logit Models, Equations 2 and 3

	Ordered Logit Model of Overall BP Control Measure (1-5)		*Logit Model of BP Control Measure = 1 (Undertreatment)*		*Logit Model of BP Control Measure = 3 (Appropriate Care)*		*Logit Model of BP Control Measure = 5 (Overtreatment)*	
Modeled Outcome Variable	Est.	SE	Est.	SE	Est.	SE	Est.	SE
Marginal Effects of Resource Avail. Scale								
BP Control Measure = 1 (Undertreatment)	0.002	(0.003)	0.004	(0.005)				
BP Control Measure = 3 (Appropriate Care)	0.004	(0.005)			-0.004	(0.019)		
BP Control Measure = 5 (Overtreatment)	-0.008	(0.011)					-0.002	(0.014)
Marginal Effs. of Clinical Resources Subscale								
BP Control Measure = 1 (Undertreatment)	0.005	(0.002)**	0.004	(0.156)				
BP Control Measure = 3 (Appropriate Care)	0.006	(0.003)**			0.011	(0.014)		
BP Control Measure = 5 (Overtreatment)	-0.015	(0.007)**					-0.018	(0.010)*
Marginal Effs. of Non-clinical Resources Subscale								
BP Control Measure = 1 (Undertreatment)	0.001	(0.002)	0.002	(0.002)				
BP Control Measure = 3 (Appropriate Care)	0.001	(0.003)			-0.008	(0.014)		
BP Control Measure = 5 (Overtreatment)	-0.003	(0.007)					0.002	(0.011)
n	*966,632*		*966,632*		*966,632*		*966,632*	

* p < 0.10. ** p < 0.05. Additional control variables included in models (results not shown) include Female, Age 18-40, Age 41-65, Age 66-80, Age 81+, Facility's PCPs Also Make Rounds, Facility's PCPs Also Attending Physicians, Facility's Clinicians Express Feeling Overwhelmed, Residents Trained On-site (Academic Facility), Total Episodes (1,000s) at Facility, County's Veteran Population in 2010, County's Veteran Hospital Beds in 2008, Health

Professional Shortage Area, County's PCPs in Patient Care in 2010, County's Diabetes Deaths in 2004-2006, County's Per Capita Income in 2008 ($1,000s), County's Medicaid Eligible Population in 2007, and year fixed effects.

In Table 24 I present select coefficient estimates from the models represented in Equation 4, which include measures of resource availability, coordination, and their interactions. None of these factors was found to be statistically significant, except for a positive estimate for the interaction between resource availability and the absence of difficulties primary care providers experience when coordinating with endocrinology departments. Thus veterans treated at facilities with more available resources may be more likely to be overtreated and less likely to be undertreated where primary care and endocrinology services are well coordinated, relative to where such services are not well coordinated. This represents limited, suggestive evidence consistent with the Resource Availability and Coordination framework hypothesis that coordination as facilitation structures may effectively increase the quantity of resources used in controlling the blood pressure of veterans with diabetes. Results were similar for alternative specifications of resource availability.

Table 24: Interactions of Resource Availability and Coordination, OLS Models of Overall BP Control Measure (1-5), Equation 4

	RA Interacted with Coordination as Management		*RA Interacted with Coordination as Facilitation*		*RA Interacted with Coordination as Both*	
Variable	Est.	SE	Est.	SE	Est.	SE
Key Explanatory Variables						
Resource Availability Scale (RA)	-0.046	(0.045)	-0.045	(0.047)	-0.049	(0.046)
Pre-Authorization for Select Rx (CM)	0.009	(0.013)	0.012	(0.012)	0.011	(0.013)
No Difficulties Coord. With Endocrinology (CF1)	-0.007	(0.012)	-0.006	(0.011)	-0.007	(0.011)
Service Agreement with Endocrinology (CF2)	0.011	(0.012)	0.015	(0.012)	0.012	(0.012)
Coordination as Both Scale (CB)	0.031	(0.031)	0.014	(0.030)	0.030	(0.033)
Interaction Terms						
RA × CM	0.017	(0.045)				
RA × CF1			0.098	(0.038)**		
RA × CF2			-0.037	(0.042)		
RA × CB					-0.003	(0.111)
n	*966,632*		*966,632*		*966,632*	

* $p < 0.10$. ** $p < 0.05$. Additional control variables included in models (results not shown) include Female, Age 18-40, Age 41-65, Age 66-80, Age 81+, Facility's PCPs Also Make Rounds, Facility's PCPs Also Attending Physicians, Facility's Clinicians Express Feeling Overwhelmed, Residents Trained On-site (Academic Facility), Total Episodes

(1,000s) at Facility, County's Veteran Population in 2010, County's Veteran Hospital Beds in 2008, Health Professional Shortage Area, County's PCPs in Patient Care in 2010, County's Diabetes Deaths in 2004-2006, County's Per Capita Income in 2008 ($1,000s), County's Medicaid Eligible Population in 2007, and year fixed effects.

In Table 25 I present interaction effect estimates for the logit models described in Equation 6; the very small and statistically insignificant estimates for the model of almost certain undertreatment are not presented. All effect estimates were generated using the coefficient estimates from the re-estimated versions of these models without year fixed effects (parameter estimates were found to be insignificantly different between the models with and without year fixed effects). The only statistically significant interaction effects are estimated for the clinical resources subscale of resource availability and my two measures of coordination as facilitation. These interaction effect estimates indicate that in facilities where primary care departments effectively coordinate and share service agreements with endocrinology departments (i.e., where effective coordination as facilitation structures are in place), higher levels of available clinical resources are associated with increases in the probability of patients receiving appropriate care and decreases in the probability of patients receiving almost certain overtreatment, relative to facilities with less effective coordination as facilitation structures. These findings contradict the hypothesis of the Resource Availability and Coordination framework. Findings were similar for regressions estimated using alternative specifications of resource availability and for the ordered logit model represented in Equation 5.

Table 25: Interactions of Resource Availability and Coordination, Logit Models of Appropriate Care and Almost Certain Overtreatment in BP Control, Equation 6

	Logit Models of BP Control Measure = 3 (Appropriate Care)		*Logit Models of BP Control Measure = 5 (Overtreatment)*	
Interaction Effects	Est.	SE	Est.	SE
RA × Pre-Authorization for Select Rx (CM)	-0.003	(0.011)	0.014	(0.044)
RA × No Difficulties Coord. With Endocrinology (CF1)	-0.012	(0.011)	0.061	(0.040)
RA × Service Agreement with Endocrinology (CF2)	0.004	(0.010)	-0.029	(0.033)
RA × Coordination as Both Scale (CB)	-0.018	(0.026)	0.023	(0.089)
RA Clinical Resources Subscale × CM	-0.019	(0.016)	0.055	(0.055)
RA Non-clinical Resources Subscale × CM	0.012	(0.014)	-0.048	(0.060)
RA Clinical Resources Subscale × CF1	0.028	(0.012)**	-0.076	(0.037)**
RA Non-clinical Resources Subscale × CF1	-0.017	(0.011)	0.073	(0.040)*
RA Clinical Resources Subscale × CF2	0.042	(0.014)**	-0.114	(0.044)**
RA Non-clinical Resources Subscale × CF2	-0.002	(0.009)	0.005	(0.030)
RA Clinical Resources Subscale × CB	0.001	(0.015)	-0.024	(0.043)
RA Non-clinical Resources Subscale × CB	0.001	(0.018)	-0.001	(0.055)
n	*966,632*		*966,632*	

* p < 0.10. ** p < 0.05. Additional control variables (results not shown) include Female, Age 18-40, Age 41-65, Age 66-80, Age 81+, Facility's PCPs Also Make Rounds, Facility's PCPs Also Attending Physicians, Facility's Clinicians Express Feeling Overwhelmed, Residents Trained On-site (Academic Facility), Total Episodes (1,000s) at Facility, County's Veteran Population in 2010, County's Veteran Hospital Beds in 2008, Health Professional Shortage Area, County's PCPs in Patient Care in 2010, County's Diabetes Deaths in 2004-2006, County's Per Capita Income in 2008 ($1,000s), County's Medicaid Eligible Population in 2007, and year fixed effects.

Panel Data Analysis Results

In Table 26 and Table 27 I present the results of the fixed effects models estimated to further test the Resource Availability and Coordination framework's relevance in the context of BP control for veterans with diabetes. Results for models of the overall BP control measure as well as almost certain undertreatment, appropriate care, and almost certain overtreatment are presented in both tables.

The results in Table 26 pertain to the models described in Equations 7 and 8, which include resource availability measures but no coordination measures among their independent variables; those in Table 27 pertain to the models described in Equations 9 and 10, which include both resource availability measures and coordination measures as well as their interactions. The results in Table 26—for models using broad scales, clinical and non-clinical subscales, and regression-based factor scales to specify resource availability—are inconsistent across specifications and models. The only (marginally) statistically significant estimates are the negative estimated effect of the non-clinical resources subscale on the probability of almost certain overtreatment and the large positive estimated effect of the first resource availability factor scale on the probability of appropriate care. Likewise, as shown in Table 27 for the clinical and non-clinical resource availability subscales, there is little evidence of a meaningful interaction effect of resource availability and coordination in models of different measures of BP control. Results were similar for other specifications of resource availability.

Like the cross-sectional model results presented above, these fixed effects model estimates offer no consistent evidence of meaningful relationships between resource availability and BP control or between resource availability and coordination. There is even less evidence of relationships consistent with those predicted in the Resource Availability and Coordination theoretical framework.

Table 26: Effects of Resource Availability on BP Control Measures, Fixed Effects Models, Equations 7 and 8

	Models of Overall BP Control Measure		*Models of BP Control Measure = 1 (Undertreatment)*		*Models of BP Control Measure = 3 (Appropriate Care)*		*Models of BP Control Measure = 5 (Overtreatment)*	
Variable	Est.	SE	Est.	SE	Est.	SE	Est.	SE
Resource Availability Scale	0.099	(0.108)	0.006	(0.021)	0.028	(0.092)	-0.002	(0.045)
Clinical Resources Subscale	0.102	(0.103)	-0.031	(0.024)	-0.028	(0.057)	0.005	(0.040)
Non-clinical Resources Subscale	-0.015	(0.058)	-0.016	(0.018)	0.051	(0.038)	-0.042	(0.025)*
RA Factor 1	0.147	(0.501)	-0.076	(0.120)	0.394	(0.223)*	-0.094	(0.136)
RA Factor 2	0.033	(0.080)	-0.032	(0.026)	0.003	(0.044)	-0.015	(0.021)
RA Factor 3	-0.046	(0.028)	0.009	(0.009)	-0.019	(0.023)	0.000	(0.010)
n	*1,016*		*1,016*		*1,016*		*1,016*	

* p < 0.10. ** p < 0.05. Additional control variables included in models (results not shown) include Female, Age 18-40, Age 41-65, Age 66-80, Age 81+, Facility's PCPs Also Make Rounds, Facility's PCPs Also Attending Physicians, Facility's Clinicians Express Feeling Overwhelmed, Residents Trained On-site (Academic Facility), Total Episodes (1,000s) at Facility, County's Veteran Population in 2010, County's Veteran Hospital Beds in 2008, Health Professional Shortage Area, County's PCPs in Patient Care in 2010, County's Diabetes Deaths in 2004-2006, County's Per Capita Income in 2008 ($1,000s), County's Medicaid Eligible Population in 2007, and year fixed effects.

Table 27: Effects of Resource Availability and Coordination on BP Control Measures, Fixed Effects Models, Equations 9 and 10

	Models of Overall BP Control Measure		*Models of BP Control Measure = 1*		*Models of BP Control Measure = 3 (Appropriate*		*Models of BP Control Measure = 5 (Overtreatment)*	
Interaction Effects	Est.	SE	Est.	SE	Est.	SE	Est.	SE
RA Clinical Resources Subscale × Pre-Authorization for Select Rx (CM)	0.109	(0.070)	-0.013	(0.015)	-0.021	(0.031)	0.035	(0.029)
RA Non-clinical Resources Subscale × Pre-Authorization for Select Rx (CM)	0.010	(0.026)	-0.007	(0.006)	0.013	(0.015)	-0.002	(0.010)
RA Clinical Resources Subscale × No Difficulties Coord. With Endocrinology (CF1)	0.022	(0.071)	0.006	(0.013)	-0.003	(0.020)	0.010	(0.023)
RA Non-clinical Resources Subscale × No Difficulties Coord. With Endocrinology (CF1)	0.050	(0.047)	-0.006	(0.005)	-0.048	(0.021)**	0.021	(0.018)
RA Clinical Resources Subscale × Service Agreement with Endocrinology (CF2)	-0.134	(0.104)	0.007	(0.015)	-0.005	(0.041)	-0.055	(0.039)
RA Non-clinical Resources Subscale × Service Agreement with Endocrinology (CF2)	-0.031	(0.027)	0.003	(0.004)	0.018	(0.017)	-0.017	(0.011)
RA Clinical Resources Subscale × Coordination as Both Scale (CB)	-0.219	(0.134)	0.018	(0.028)	0.053	(0.047)	-0.085	(0.049)
RA Non-clinical Resources Subscale × Coordination as Both Scale (CB)	-0.049	(0.132)	0.015	(0.021)	-0.020	(0.045)	-0.013	(0.056)

* p < 0.10. ** p < 0.05. In addition to the main effects of resource availability and coordination, these models also include provider-year-level averages of the following control variables: Female, Age 18-40, Age 41-65, Age 66-80, Age 81+, Facility's PCPs Also Make Rounds, Facility's PCPs Also Attending Physicians, Facility's Clinicians Express Feeling Overwhelmed, Residents Trained On-site (Academic Facility), Total Episodes (1,000s) at Facility, County's Veteran Population in 2010, County's Veteran Hospital Beds in 2008, Health Professional Shortage Area, County's PCPs in Patient Care in 2010, County's Diabetes Deaths in 2004-2006, County's Per Capita Income in 2008 ($1,000s), County's Medicaid Eligible Population in 2007, and year fixed effects. Results not shown.

The results presented in Table 28 pertain to the models described in Equations 11 through 14, which are intended to test the principal hypothesis of the Physician Learning and Peer Effects framework, hypothesis *H7*. I present in parallel the results of the cross-sectional models of physician-year-level BP control measure performance as a function of facility (index physician-exclusive) average BP control measure performance in the same year—for all physician-years in my sample (N = 90,984) and for all physician-years for physicians who moved between facilities during my study period (N = 1,945). I also present the corresponding results of the fixed effects models of physician-year-level BP control measure performance (among moving physicians, N = 1,261[14]) as a function of the difference in facility-year-level measure performance between the current facility-year and the last pre-move facility-year.

All results presented are consistent with hypothesis *H7* that physicians' performance on the BP control measures will track with the performance of their peers at the same facility. The fixed effects model results—shown in row (iii)—are the largest estimates of peers' influence on the index physicians' performance. These constitute my principal results in this analysis. The second of these estimates, for example, suggests that for every one percentage point increase in the physician's current facility's probability of almost certainly undertreating a patient in the index year, relative to the physician's pre-move facility's performance in the physician's pre-move year, the physician's own probability of almost certainly undertreating a patient rises 0.335 percentage points in the index year. This is a very strong peer effect, especially considering that these results are for physicians less than three years removed from their previous facility. Previous evidence has suggested that physician peer effects may be small initially and develop slowly over time (Epstein & Nicholson, 2009). Moreover, that my results are comparable in magnitude for the probability of appropriate care versus other measure specifications suggests that these estimates should be interpreted primarily in terms of differences in facility characteristics (e.g., organizational structures and incentive programs).

A comparison of rows (i) and (ii)—the results of the cross-sectional models of peer effects—indicates that the sample of physician movers may be more easily influenced by their care environments than the general population of physicians treating veterans with diabetes. Still, if average peer effects for all physicians were only as large as those estimated using the full sample of physicians, my results would constitute evidence of meaningful, if smaller, peer effects consistent with the predictions of the Physician Learning and Peer Effects framework.

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[14] This sample of 1,261 physician-years is larger than the sample of 1,016 physician-years used in previous fixed effects models. This is because the models with results presented in **Error! Reference source not found.** do not nclude the measures of resource availability and coordination that are not available for all facilities.

Table 28: Peer Effects in Quality of BP Control, OLS and Fixed Effects Models, Equations 11-14

Model		*N*	*Model of Overall BP Control Measure (1-5)* Est.	SE	*Model of BP Control Measure = 1 (Undertreatment)* Est.	SE	*Model of BP Control Measure = 3 (Appropriate Care)* Est.	SE	*Model of BP Control Measure = 5 (Overtreatment)* Est.	SE
(i)	Current Facility-year-level (self-exclusive) Measure Performance, All Physicians	*90,984*	0.092	(0.020)**	0.121	(0.029)**	0.096	(0.018)**	0.087	(0.020)**
(ii)	Current Facility-year-level (self-exclusive) Measure Performance, Moving Physicians	*1,945*	0.254	(0.066)**	0.264	(0.119)**	0.169	(0.091)*	0.181	(0.065)**
(iii)	Difference in Facility-year-level (self-exclusive) Measure Performance, Current Facility-year Minus Pre-move Facility-year	*1,261*	0.263	(0.101)**	0.335	(0.121)**	0.493	(0.109)**	0.394	(0.104)**

* $p < 0.10$. ** $p < 0.05$. Additional control variables used in models (results not shown) include provider-year-level averages of the following variables: Female, Age 18-40, Age 41-65, Age 66-80, and Age 81+. Other controls include Facility's PCPs Also Make Rounds, Facility's PCPs Also Attending Physicians, Facility's Clinicians Express Feeling Overwhelmed, Residents Trained On-site (Academic Facility), Total Episodes (1,000s) at Facility, County's Veteran Population in 2010, County's Veteran Hospital Beds in 2008, Health Professional Shortage Area, County's PCPs in Patient Care in 2010, County's Diabetes Deaths in 2004-2006, County's Per Capita Income in 2008 ($1,000s), County's Medicaid Eligible Population in 2007, and year fixed effects.

Finally, to support a direct test of hypothesis *H8*, I estimated regressions similar to those presented in Table 28 but with measures of resource availability added along with interactions between resource availability and self-exclusive facility BP control measure means. These models consistently showed statistically insignificant mediation of facility peer effects by resource availability (results not shown). It appears there are other facility-level factors substantially more important than resource availability driving the above results.

Discussion

The VA is engaged in many longstanding performance measurement and quality improvement efforts focused on standard quality measures, which typically target individual care processes (i.e., that should always or never be rendered) or individual biological measure thresholds. This study quantifies variation in the quality of care delivered in terms of evidence-based guideline adherence, as the ordinal BP control measure I use supports. I extend this exploration of variation in the VA's diabetes care quality in two ways, relying on the geographic variation literature to develop underlying theoretical frameworks. First, I use measures of resource availability and coordination to study how a facility's available resources affect care quality and how much coordination structures mediate this relationship. And second, I assess the extent to which these and other facility-level structures and peer effects affect local patterns of practice.

In my analyses of variation in BP control measures of diabetes care quality, I find meaningful variation across VA facilities, though this variation is relatively less overall than has been observed outside the VA or using other quality measures. In particular, I find remarkably little variation across regions in performance despite meaningful variation in other observable facility characteristics. While the BP control measure used in this study is distinct from the diabetes care quality measures used in the VA's EPRP performance measurement system, it is possible that the regular calculation and reporting of those EPRP measures over the last fifteen years has led many facilities and clinicians to emphasize diabetes care evidence based guidelines in their practices more than they would without the EPRP system. Such focus could have reduced the variation I observe; variation may be greater for quality measures less related to any existing EPRP measures. In addition, I note there is greater variation across VA facilities in rates of almost certain overtreatment of veterans than there is in almost certain undertreatment of veterans, though this is not unexpected given the negative correlation I find between these two measures and the greater likelihood that almost certain undertreatment rates will be compressed due to floor effects.

Throughout my analyses of facilities' available resources and coordination structures and their relationship to local physicians' BP control measure performance, the evidence I find is limited and inconsistent with the predictions of the framework of Resource Availability and Coordination. These findings persist across three specifications of resource availability—as a single broad scale, as two subscales of clinical and non-clinical resource availability, and as three regression-based factor scales developed through a principal factor analysis—across both cross-sectional and panel data models, and across four related measures of quality in BP control. I find similar inconsistencies for each set of coordination measures that I analyze—coordination as management, coordination as facilitation, and coordination as both—as well. I conclude that facility resources and coordination structures do not meaningfully affect the quality of BP control management for veterans with diabetes.

This conclusion appears to stand opposed to the conclusions drawn by Soban and Yano (2005) and Yano and colleagues (2007b), who found primary care practice resources were positively associated with performance on various preventive care quality measures. Soban and Yano, who studied effects of resources on multiple preventive care quality measures, did not find positive associations for all of the measures they studied, and they did not include BP control for veterans with diabetes among the measures they examined. As such, it not necessarily surprising that my work identifies one measure on which primary care-related resources have little effect. The sets of resource measures used in these three studies are distinct as well; this too may contribute to differences in our findings.

My examination of the Resource Availability and Coordination framework has three key limitations. First, the set of resource availability and coordination measures available for VA facilities is somewhat limited in that the measures are largely time-invariant and tend to reflect the subjective opinions of the facility's chief of staff or primary care director. More objective, regularly captured measures might be less subject to measurement error. Moreover, I selected a set of resource availability and coordination measures anticipated to be diabetes care-related for my analyses. This selection process may have overlooked important measures or included measures unrelated to diabetes care quality, further obscuring what relationships may exist.

The second key limitation of this analysis is the low internal consistency of the scales I use to condense the information in these resource availability and coordination measures into more consumable measures. The resource availability scales' low internal consistency, for example, makes it more difficult to ascribe my findings to the broader concept of resource availability to which the Resource Availability and Coordination framework refers. On the other hand, given how broad the concept of resource availability is in general, it is not surprising that the heterogeneous set of measures I use to represent it in this analysis should fall below the 0.70 threshold for Cronbach's α statistics commonly used in the social sciences. Moreover, that I have focused my analysis more on the scales with higher Cronbach's α statistics rather than all scales generated strengthens my inferences.

Finally, despite my large episode-level datasets, my analysis of the Resource Availability and Coordination framework's hypotheses is limited by the fact that much of the variation I use to identify the effects of resource availability and coordination on quality is derived from cross-sectional differences among 84 VA facilities. This limitation could lead to concerns of simultaneity bias in my cross-sectional model estimates. Both how decoupled the VA's resource allocation processes at the facility level were from facilities' diabetes care burdens during this study period and the consistency of my findings between these cross-sectional models and fixed effects models, which identify effects using differences in facility exposures for moving physicians, alleviate much of these concerns. However, a related concern that there is not enough variation among these 84 facilities to identify effects may be valid. Efforts to develop and use richer data sets consisting of time-varying, objectively measured facility characteristics or to employ other analytic approaches may be valuable in further testing the relationships between facility characteristics and quality measure performance.

My analyses of the Physician Learning and Peer Effects framework's hypotheses, by contrast, reveal a strong relationship between a physician's BP control quality measure performance and that of his peers at the same facility. This result is robust to analysis of different BP control measures (the overall measure and outcome specific measures of appropriate care, almost certain undertreatment, and almost certain overtreatment) and is consistently strong and positive in both cross-sectional and fixed effects models. This finding supports the validity of efforts to identify determinants of care quality at the facility level. It should also encourage future investigations of facility-level or physician team-level factors that may affect physician learning when physicians are exposed to new facilities or, perhaps, substantially new care delivery structures or incentive programs implemented at the same facility.

The potential for differences in findings in my fixed effects models, relative to cross-sectional estimates, due to selection bias is highlighted in this analysis. My cross-sectional peer effects model results for all physicians and for physician movers are significantly different from one another, but physician-level data to support exploring these differences in greater detail are not available. If physicians are more likely to move if they are uncomfortable with the constraints or practice norms in their pre-move facilities, or if they are younger and less fixed in their patterns of practice, then my fixed effects models may overestimate the magnitude of the positive peer effects I observe in diabetes care quality, and the true peer effects in this context may be more comparable to the smaller estimates I generate in my cross-sectional models. On the other hand, I may underestimate these peer effects if physicians are more likely to move, for example, when they are offered new responsibilities at other facilities that would divert their attentions from diabetes care. However, such transitions might also make these physicians less likely to be included in my sample, given my diabetes care episode minimum requirements. Other panel study designs relying on physician responses to within-facility changes over time (see, for example, Hysong et al., 2012) may be helpful in addressing some of these concerns if the changes were largely unforeseen, though such conditions are almost certainly uncommon.

The differences between the VA and non-VA health care sectors, which make the VA a useful setting in which to examine some statistical relationships between facility characteristics and care quality (e.g., largely homogeneous reimbursement structures and central governance within the VA), also make it difficult to assess how externally valid my findings are in non-VA settings. In particular, the robustness of the VA's performance measurement and quality improvement enterprises may affect the relationships among resource availability, coordination, and quality in ways that the non-VA health care sector cannot realize at present. However, as non-VA health care providers further integrate vertically and horizontally, make increased use of electronic medical records, and build their performance measurement capabilities, the experiences of VA facilities may become increasingly relevant outside the VA as well.

Conclusion

This study makes three key contributions to the literature on geographic variation in quality and to the literature on quality of care in the VA. I examine variation in and explore the determinants of a new, ordinal measure of BP control for patients with diabetes that is tightly linked to evidence-based practice guidelines. I develop and apply two frameworks from the geographic variation literature in ways that have not previously been applied in the VA context. And I employ both cross-sectional and panel data models to validate and reinforce my findings.

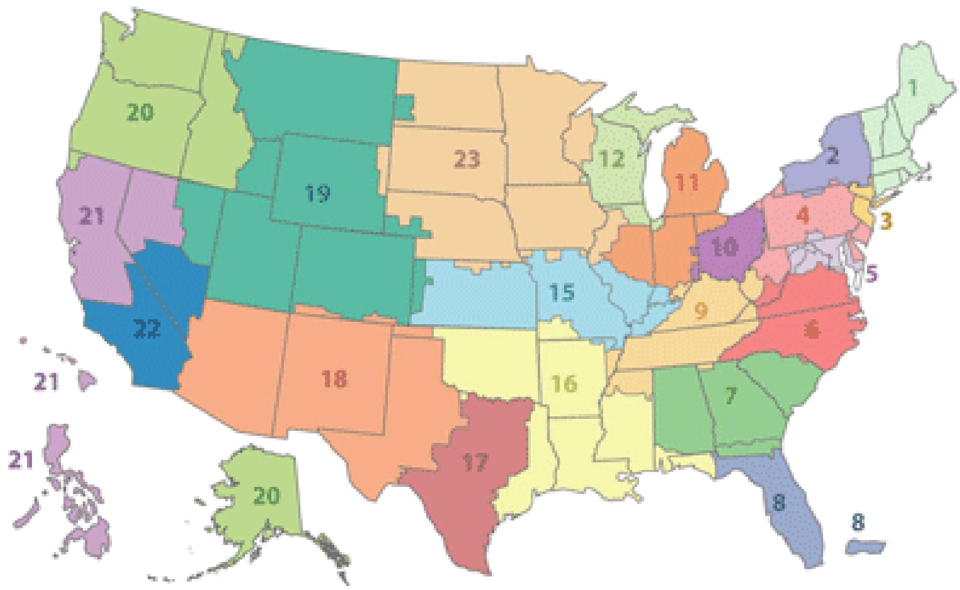
Ultimately, I find that there is meaningful variation in BP control quality across VA facilities, though there is less variation here than has been shown for other measures and outside the VA. I also find that the resource availability and coordination structures, broadly defined, at the VA facility level have little effect on diabetes care quality within the facility, while there is marked evidence supporting a framework of Physician Learning and Peer Effects. The peer effects I identify support the persistence of variation in care quality across facilities, and they suggest that physicians' performance on quality metrics can be influenced by their local care environments.

Further work is needed to describe variation in quality across VA facilities using other measures, particularly those with fewer well-established, related measures in the EPRP performance measurement system. And as non-VA facilities increase their use of robust electronic health record systems or other systems recording detailed clinical information about patients, it will also be important to explore variation in the quality of care delivered to non-VA patients using clinically enriched measures tightly linked to evidence-based guidelines. Advances in both of these literatures will be valuable for identifying the modifiable organizational and market characteristics that can improve evidence-based quality both within the VA and without.

Chapter Three Appendix

Figure 14 is a map of the VA's 21 VISNs. Although they are numbered to 23, there remain only 21 VISNs, as VISNs 13 and 14 were collapsed to become VISN 23.

Figure 14: VA Veteran's Integrated Service Networks (VISNs)



Source: VHA, December 2009.

Table 29, Table 30, Table 31, and Table 32 present complete lists and descriptive statistics for the individual variables used in measuring resource availability, coordination as management, coordination as facilitation, and coordination as both, respectively.

Table 29: Data Items Used to Measure Resource Availability

		Cross-sectional Sample (episode level)		*Longitudinal Sample (episode level)*	
Data Item	Source	Mean	Std. Dev.	Mean	Std. Dev.
Resource Availability Subscale 1: Clinical Staff Resources					
Generalist physician staff mostly or completely sufficient to meet PC program's current goals	VHA Primary Care Survey	56.3%		59.5%	
Insufficient numbers of PCPs not a barrier or only a small barrier to improving performance at the facility	CPOS, Chief of Staff Module	69.6%		74.5%	
Total primary care physicians with 20+ visits at site during January	VA CDW	81.9	(39.7)	75.1	(48.8)
No more than 20% of facility's physicians are part-time	CPOS, Chief of Staff Module	37.6%		30.5%	
Has trained endocrinology/diabetology specialists on site	CPOS, Chief of Staff Module	84.1%		83.5%	
PC program patients typically get same-day laboratory services on site in primary care	CPOS, PC Director Module	32.5%		41.3%	
PC program patients typically get disease management program support for a metabolic syndrome (e.g., diabetes) on site in primary care	CPOS, PC Director Module	44.4%		42.2%	
Nurse staff mostly or completely sufficient to meet PC program's current goals	VHA Primary Care Survey*	40.9%		41.1%	
Insufficient numbers of outpatient nurses not a barrier or only a small barrier to improving performance at the facility	CPOS, Chief of Staff Module	79.5%		84.5%	
Resource Availability Subscale 2: Non-Clinical Resources					
Total FTE clinic officers, administrators, and supervisors	CPOS, PC Director Module	1.1	(0.9)	1.2	(1.1)
Total FTE clerks and receptionists	CPOS, PC Director Module	3.1	(4.7)	3.3	(3.5)
Appropriately equipped exam rooms usually or always sufficient to meet PC program's needs	VHA Primary Care Survey*	58.5%		54.8%	
Total exam rooms available per PCP when seeing patients (per 1,000 cases)	CPOS, PC Director Module	1.0	(3.3)	1.9	(5.3)
Clinical space usually or always sufficient to meet PC program's needs	CPOS, PC Director Module*	33.0%		31.1%	
Personal computers or workstations usually or always sufficient to meet PC program's needs	VHA Primary Care Survey*	87.1%		88.2%	
Access to medical informatics support usually or always sufficient to meet PC program's needs	VHA Primary Care Survey*	37.8%		38.6%	

* Data item available in previous surveys as well as source listed.

Table 30: Data Item Used to Measure Coordination as Management

Data Item	Source	*Cross-sectional Sample (episode level)* Mean	*Longitudinal Sample (episode level)* Mean
PCPs are required to obtain pre-authorization for specified medications	CPOS, PC Director Module	87.3%	83.6%

Table 31: Data Items Used to Measure Coordination as Facilitation

Data Item	Source	*Cross-sectional Sample (episode level)* Mean	*Longitudinal Sample (episode level)* Mean
PCPs never or rarely have problems coordinating care with endocrinology specialists when caring for patients with multiple chronic illnesses	CPOS, PC Director Module	37.3%	35.7%
Service agreements fully or partially implemented between PCPs and endocrinologists/diabetes clinics for coordinating specialty services	CPOS, PC Director Module*	37.9%	36.3%

* Data item available in previous surveys as well as source listed.

Table 32: Data Items Used to Measure Coordination as Both

Data Item	Source	*Cross-sectional Sample (episode level)* Mean	*Longitudinal Sample (episode level)* Mean
Facility systematically identifies patients with diabetes using registries or panels	CPOS, Chief of Staff Module	62.3%	64.6%
Facility employs performance profiling and provider feedback to promote adherence to guidelines or initiatives	CPOS, Chief of Staff Module	78.6%	85.2%
Facility employs incentives to promote adherence to guidelines or initiatives	CPOS, Chief of Staff Module	24.2%	19.1%
Facility employs incentives to promote adherence to cholesterol screening guidelines or initiatives	CPOS, PC Director Module	23.1%	23.9%
Always or most of the time, PCPs are notified promptly following the delivery of their patients' subspecialty consultation results	CPOS, PC Director Module	85.0%	68.9%
Designated support staff (e.g., RN) can adjust medications between PCP visits for patients with diabetes	CPOS, PC Director Module	54.7%	56.0%
Nurses, clerks, or medical assistants routinely order or make referrals for HbA1c tests without a separate order	CPOS, Chief of Staff Module	32.7%	32.6%
To a great or very great extent, facility has provided visible support for clinical guideline implementation within the facility	CPOS, Chief of Staff Module	53.0%	40.7%
To a great or very great extent, facility has established teams to work on specific diseases/conditions covered by VA performance measures	CPOS, Chief of Staff Module	70.1%	77.8%
To a great or very great extent, facility has implemented a program to enhance cooperative culture	CPOS, Chief of Staff Module	52.1%	40.1%
To a great or very great extent, teamwork existed at the facility in implementing guidelines	CPOS, Chief of Staff Module	73.7%	77.2%

Conclusion

The expansive literature on decision-making by physicians, including both organizational and medical care decisions, has historically dedicated greater efforts to exploring the effects of financial incentives rather than organizational factors, interpersonal dynamics, policy changes, and other non-financial factors. In the three chapters of this dissertation, I examine these non-financial factors intently and identify the roles select non-financial factors play in affecting the decisions of primary care practice managers, specialist consultants, and Veterans Health Administration (VA) clinicians serving veterans with diabetes.

First, in my study of the laws and regulations governing the practices of non-physician clinicians and how they affect physician practice decisions about Medicaid participation, I find interesting heterogeneity in regulatory effects across non-physician clinician types and across practices. Relaxing regulations on physician assistants leads to small increases in Medicaid participation among many primary care practices. However, relaxing regulations on nurse practitioners leads to a reduction in Medicaid participation among practices that have seen relatively few Medicaid patients historically and an increase in Medicaid participation among practices that have seen relatively more Medicaid patients historically. These findings suggest that policymakers should not take it for granted that relaxed NPC regulations will have little effect on current Medicaid participants' willingness to see Medicaid patients and lead to improvements in access overall.

Second, in my study of medical consultations provided to complex surgical inpatients, I find that the decisions of previous consultants can significantly affect the next consultant's decisions about how many visits to pay a patient. These consistent findings reflect a dual-role of medical consultants not widely recognized previously: they provide active management care support to the attending physician while also answering questions specific to their specialties. I also find that the patterns of consultants' responses to other consultants' care decisions are consistent with a framework of Diminishing Marginal Productivity. This suggests that many consultants are aware of this role of active management and calibrate the intensity of their consult provision to meet what they perceive to be the patient's needs. In this case, the appropriateness of consultants' decisions about their roles as active managers of care may be increased by ensuring the case information available to them at the time of their initial involvement is as complete as possible.

Finally, in my study of variation in the quality of care delivered to veterans with diabetes, I find moderate variation in blood pressure control effectiveness across VA facilities. Moreover, I find no consistent evidence that the facility's available resources and coordination structures affect quality measure performance, and yet there is strong evidence that physicians' quality measure performance is significantly influenced by their peers and their local care environments. These findings help to fill important gaps in the geographic variation literature and offer valuable insights to VA administrators evaluating alternative strategies for improving diabetes care quality both within individual facilities and across the VA health care system.

These three studies contribute a more complete understanding of several non-financial factors that influence medical decision-making and care delivery by physicians. Through further analysis building on this work and by infusing key findings into policy and organizational structures at different levels of the health care system, meaningful steps can be taken to modify the environments in which physicians practice, facilitating the decisions that promote health and efficient use of medical care resources.

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