Three Essays in Physician Behavior

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Hannah Toby Neprash

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Dissertation Advisors:
Michael E. Chernew (Chair)
David M. Cutler
J. Michael McWilliams

Author:
Hannah Toby Neprash

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Abstract

Physicians are the foundation of health care in the United States. Their decisions drive both spending and quality of care and it is their actions that will largely determine the success of efforts to achieve a more value-based, sustainable health care system. For this reason, it is crucial to understand how physician behavior responds to the increasing pressures - both financial and workload-related - of modern medicine. These findings have the potential to inform policy regarding health care spending and quality.

Primary care physicians face increasing stress to see more patients in the same or less time. This leads to crowded appointment schedules and increased schedule disruptions. In Chapter One, I examine how physicians respond to schedule disruptions, instrumenting for appointment start time with the office arrival time of the physician's previous patient. I use novel data from athenahealth, Inc., a national provider of electronic health records, medical billing, and practice management services. I find that when primary care physicians fall behind schedule, they truncate appointment duration, perform fewer in-office procedures, and record fewer diagnoses. The likelihood of a patient revisiting the primary care practice within two weeks significantly increases as a function of delayed appointment start time. Physician ordering behavior also responds to a schedule disruption. In particular, physicians who run behind schedule increase antibiotic and opioid painkiller prescribing and increase referrals of a new patient to a specialist. For patients with preexisting prescription drug regimens, physicians running behind schedule are less likely to change the existing course of treatment. These findings suggest possible unintended consequences of the increasing time pressures placed on physicians by policymakers and

private payers. Implications may include higher health care spending and lower quality care.

Chapter Two (with Mike Chernew and Michael McWilliams) explores the association between recent changes in provider market structure and changes in spending and prices for commercially insured services. We use Medicare data to observe financial integration between physicians and hospitals and the Truven Health MarketScan database to measure individual-level, annual, commercially insured spending. We find that physician-hospital integration is associated with significantly higher commercial prices and spending for outpatient care, but not inpatient care, suggesting that this type of vertical integration may enhance bargaining power more for the physicians than for the hospitals involved. Despite the prevailing wisdom that payment reform may accelerate consolidation, we find minimal evidence that consolidation was associated with ACO participation, though there is evidence of potential defensive consolidation in response to new payment models.

Chapter Three tests whether primary care physicians' adjust their labor supply in response to an increase in Medicaid reimbursement. The Affordable Care Act (ACA) greatly increased access to insurance, partially through state Medicaid expansions. In conjunction with this insurance expansion, the ACA increased Medicaid reimbursement for primary care services to national Medicare levels for two years (2013-2014), with the goal of incentivizing physicians to treat more Medicaid patients. The policy change affected physicians differently, based on their state's generosity of Medicaid reimbursement, relative to Medicare rates, prior to the policy change. I use this natural experiment to test whether primary care physicians respond to Medicaid payment increases by changing their Medicaid participation decision and labor supply, as predicted by a mixed-economy model. To do so, I rely on a new database of claims and electronic health record data compiled by athenahealth, Inc., a national provider of electronic health records, medical billing, and practice management services. As predicted, I find evidence that physicians increased their total labor supply in response to the Medicaid payment increase. I do not, however, find any change in Medicaid program participation, except among physicians in states that continued the payment increase beyond 2014. This suggests that the temporary Medicaid primary care payment increase may not have had the intended effect of increasing access to physician services for Medicaid beneficiaries, though a more permanent increase may be more successful.

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Part I

Physician Productivity

Chapter 1

Better Late than Never? Physician Response to Schedule Disruptions

1.1 Introduction

Primary care physicians' time has become an increasingly scarce resource, as they are pushed to see more patients, comply with more complex documentation and quality reporting requirements, monitor a greater number of medications and chronic conditions, and follow more screening and preventive service recommendations. This pressure is increasingly felt in primary care. Primary care physicians are expected to attend to a range of acute and chronic medical and psychosocial issues, provide preventive care, coordinate care with specialists, and encourage informed decision-making that respects patients' preferences [47].

Primary care physicians generally organize their time by keeping appointment schedules that dictate whom they see, when, and for how long [17, 66]. Although survey estimates suggest that average visit duration has increased over the past two decades [113], increased visit complexity and added documentation burdens may have led to the perceived increased time pressures on physicians discussed in the popular press [18, 102]. In an era of more compressed visits, keeping to schedule becomes very important.

A tight timeframe for primary care visits raises issues of quality and cost. On the quality side, the concern is that shorter visit durations will lead to more missed problems, less recommended care, and less adherence to chronic care needs. On the cost dimension, the concern is that harried physicians will schedule expensive referrals or diagnostic tests to minimize appointment duration, leading to greater total spending.

In this paper, I study how appointment schedule disruptions affect the input choices and decision-making of primary care physicians. I ask whether physicians respond to a schedule disruption by spending less time with patients or changing the inputs they provide, and what implications these changes have for health care spending and quality. To answer these questions, I use claims and electronic health record data from athenahealth, Inc., a national provider of electronic health records, medical billing, and practice management services. With this novel dataset, I am able to observe intended and realized appointment timing, in addition to detailed insurance claims and orders placed by the physician for follow-up care.

In the first step of my analysis, I develop a model of physician disutility arising from appointment schedule disruptions. The primary insight of this model is that the shadow price of time is increasing in the difference between the observed and scheduled appointment start time. In response to a schedule disruption, the physician cuts back on total time spent with the patient, other time-costly inputs, and the number of complaints or conditions (e.g., a persistent cough or hypertension) addressed. Less time spent with the patient decreases the probability of accurately observing the patient's true health state, which in turn affects ordering behavior for follow-up care. The model predicts that a schedule disruption may increase orders for follow-up care regarding new or acute conditions, while potentially decreasing orders for follow-up care that modify an existing treatment course for an established condition.

The remainder of my analysis applies this conceptual model to more than one million primary care physician appointments in office-based settings. Consistent with concerns about being rushed, appointments start almost half an hour late on average, however much of this may be endogenous. My empirical strategy employs an instrumental variables framework to circumvent the endogeneity of appointment start time. Specifically, I use the physician's previous patient's office arrival time as an instrument for their current appointment start time. I find that the office arrival time of the previous patient is highly predictive of the start time of the current appointment. A previous patient who arrives 15 minutes late to her appointment delays the physician by roughly 7 additional minutes.

I find that physicians respond to schedule disruptions by significantly shortening appointment duration; the 7 minute delay in appointment start time caused by a 15 minute late previous patient results in a roughly 1.5 minute shorter appointment. During these shortened appointments, physicians bill significantly fewer procedures and record fewer diagnoses, saving appointment documentation for after-hours. A delayed appointment start increases the likelihood that the patient will revisit the same physician within two weeks - possibly due to worsening symptoms or at the urging of the physician, who did not have time to adequately address care needs during the initial appointment.

A schedule disruption also affects physician decision-making regarding follow-up care. For new patients, I find that a 7 minute delay in appointment start increases the likelihood that a physician will refer the patient to a specialist by 2 percentage points, or 15% relative to a base rate referral probability of 13%. I focus on two frequently scrutinized decisions: antibiotic and opioid painkiller prescribing. For both, I find that the likelihood of receiving a prescription increases with a delayed appointment start. A 7 minute delay in appointment start time results in a 3 percentage point increase in antibiotic prescribing, or 5% relative to the base rate of 58% among patients with upper respiratory infections. For patients with a new diagnosis of spinal disorder, arthropathy, or rheumatism, the same 7 minute delayed appointment start increases the likelihood of an opioid painkiller prescription by 0.3 percentage points, or 4% relative to the base rate of 7%. I also find some evidence that physicians are less likely to alter an existing course of treatment as they run increasingly behind schedule; a 7 minute delay in appointment start time resulting in a 0.5 percentage point decrease in the likelihood of a modification to an existing prescription, or 1% relative to the base rate of 9%. Overall, the results suggest that quality of care may suffer when physicians are unexpectedly behind schedule.

This paper contributes to several strands of literature. First, this paper relates to the literature on productivity within health care. In particular, it introduces visit duration to the study of primary care physician productivity. The literature concerning non-health worker productivity frequently uses throughput time, but this metric is rarely used to examine physician productivity

[37, 69, 115]. Recent studies have begun to measure physician productivity using throughput time, but exclusively in the emergency department setting [27, 116, 119]. Most existing research generally quantifies physician productivity using metrics calculated with claims or survey data. These include visit or patient count, payment, and service intensity [79, 131]. These metrics are unlikely to capture all aspects of physician productivity. I build on traditional productivity measurement in health care by using a rich dataset containing claims and time-stamped electronic health record information for primary care visits.

Second, this paper contributes to the literature on physician labor supply. In health care, appointment schedules structure physician labor supply. Instead of a real-time optimization between labor and leisure, physicians prespecify - frequently a month or more in advance - whom they see, when, and for how long. Limited existing research suggests that appointment schedules matter a great deal, with evidence pointing to a behavioral norm of equalizing time across patients and "slacking off" as a physician nears the end of a work day [26, 124]. I build on this research by examining intended and realized labor supply decisions in the context of primary care physicians' appointment schedules.

Third and finally, this paper joins the literature on variation in health care utilization. Considerable evidence demonstrates the influence of physicians on health care consumption, both theoretically and empirically [7, 40, 46, 85]. Policymakers and public health experts express concern about certain problematic utilization patterns, including the overuse of antibiotics and the ongoing opioid epidemic [25, 126, 128]. In this paper, I document another factor that may contribute to these concerning trends and to variation in health care expenditures in general: schedule disruptions and time pressure.

The paper proceeds as follows. Section 4.2 discusses the background and institutional setting. In Section 4.3, I present a conceptual framework linking physician disutility of appointment schedule disruptions to input use and ordering behavior. Section 4.4 discusses data and sample selection. Section 1.5 details my empirical strategy. Section 4.6 presents results and robustness checks. Section 4.7 concludes.

1.2 Background and Institutional Setting

In this section, I describe the institutional setting of office-based primary care, including the role of primary care physicians in the U.S. health care system, the nature of primary care appointments, and the supply of primary care physicians.

1.2.1 The Role of Primary Care Physicians

Every year, more than four out of five of adults in the United States visit a health care professional [89]. The vast majority of these visits occur in an office setting, with an estimated 929 million physician office visits in 2012. These physician visits and clinical services account for 19.9% of national health care expenditures, or $597 billion [91]. Of the nearly one billion physician office visits, more than half (54.6%) were to a primary care physician [90].

Primary care is considered a cognitive rather than a procedural specialty, and primary care physicians are expected to perform a wide range of functions. Historically, these functions included serving as a patient's point of first contact with the health care system, maintaining the continuity of care, providing comprehensive care, and coordinating with other health care providers [123]. These tasks have grown increasingly complicated, due to the growing burden of chronic conditions, a greater number of medications to monitor, and a higher volume of screening and preventive recommendations. The scope of primary care work has also widened as documentation and reporting requirements expand and quality reporting and EHR adoption increasingly affect reimbursement.

1.2.2 Primary Care Appointment Duration and Composition

The average primary care appointment includes 21-24 minutes of interaction with the patient [90]. Increasingly short appointments have received much attention in the popular press, as patients complain about feeling rushed with their physician [18, 29, 102, 103]. However, survey estimates suggest that primary care appointment duration has increased over the past two decades, from an average of 17.9 minutes in 1993 to 22.6 minutes in 2012 [90, 113].

Increased documentation time is one possible explanation for the discrepancy between the perceived and reported trend in appointment duration, if surveyed physicians include this in reported visit length. Estimates of the time spent on documentation (increasingly using an electronic health record) range from a quarter to two thirds of physicians' total in-office time and rising [33, 96, 117]. In addition to clinical documentation, physicians spend time complying with quality reporting requirements imposed by private and public payers. A study of two dozen health insurers found that more than 500 quality measures in use, few of which matched across insurers or with the more than three times the number of measures used by federal agencies [14, 56]. Estimates suggest that primary care practices devote more time and staff resources to quality reporting than any other specialty, spending an estimated 19.1 hours per week, at an annual cost of $50,468 in wages [21].

Increasing visit complexity is another possible explanation that would explain the differently perceived trend in visit length. The average primary care appointment covers six "topics" or conditions (e.g., chronic hypertension or a persistent cough) during the visit. Videotape analysis reveals that topics do not receive equal time. The longest topic receives roughly five minutes, while remaining topics receive an average of 1.1 minutes [125]. The number of topics covered during the average primary care visit grew more than 30% between 1997 and 2005, while visit duration grew less than 10% - resulting in a decrease of time per topic [4].

Depending on the topics that surface during a primary care visit, the physician may recommend follow-up care. More than two thirds of office visits result in instructions to return at a specified time, while 8% include a referral to another physician, and 0.5% include a referral to the emergency room or admission to the hospital [90]. Other types of recommended follow-up care include prescription medications, lab and imaging tests, non-medication treatment (e.g., physical therapy, wound care), and health education (e.g., nutrition, stress management, tobacco cessation), but statistics on the frequency of these orders are not reported.[1]

[1] The National Ambulatory Medicare Care Survey (NAMCS) tracks these categories, but does not separate services provided during the appointment from services ordered as follow-up.

1.2.3 Supply of Primary Care Physicians

There are roughly 305,000 primary care physicians practicing in the United States today, representing one third of all active physicians [62].[2] This number has been relatively steady in recent years, with fewer than one in ten domestic medical school graduates entering a primary care residency program [16, 92]. Policymakers and researchers express increasing concern about the supply of primary care physicians within the next decade, with estimates ranging from a shortage of 6,400 to 52,000 PCPs [15, 54, 57, 100].

Two main factors motivate concern about primary care physician supply. First, primary care is relatively unattractive relative to other specialties. Primary care physicians have relatively low payment rates and incomes, with an average primary care salary of $195,000, or 69% of the $284,000 that specialists receive [98]. Primary care physicians also have lower job satisfaction than their specialist peers, with more than half reporting dissatisfaction with their work-life balance [110]. This is reflected in a higher and increasing rate of burnout, which poses the risk that the annual number of retiring primary care physicians will soon exceed the number of new entrants [15, 111].

Second, researchers project demand for primary care services to rise as the U.S. population grows and ages. Most recently, the Affordable Care Act's expansion of health insurance coverage to more than 16 million individuals increased the pool of those seeking primary care. Nearly half of primary care physicians reported an influx of new patients due to the Affordable Care Act, compared to only 30% of specialists [99]. There is considerable uncertainty about how physicians may respond to an increase in demand for their services. It is possible that the time between appointment scheduling and appointment occurrence (currently an average of 19.5 days to see a family practice physician) may increase [82]. Appointment schedules may also change, with existing research finding that health care providers responded to public insurance expansions by increasing their program participation (i.e., seeing more Medicaid patients), increasing the number of weekly appointments, modifying the number of hours spent with patients, and shortening appointments [19, 49].

[2] This number includes internal medicine, family practice, and general practice specialties.

1.3 Conceptual Framework

Office-based primary care is ideal for studying the importance of work schedules and disruptions to those schedules. Physicians control their schedules in a broad sense - in terms of defining a daily appointment template, deciding whether to accept new patients, and allocating their time between patient interaction and other tasks. However, on any given day, a physician has committed to see a certain list of patients. Bumping someone from that list is costly, both to the physician and the patient. In this section, I propose a simple model to consider how appointment schedule disruptions may affect decision-making among primary care physicians.

I model appointments in two stages. First, the primary care physician allocates time to an appointment, where total time is composed of time spent on one or more conditions (e.g., persistent cough, hypertension). After time spent on each condition, the physician observes the patient's health state and decides on necessary follow-up care for that patient, including lab tests, imaging, medication, or referral to a specialist. Because an office-based physician faces a daily time constraint, the shadow price of time increases when a schedule disruption occurs, with implications for both appointment time and follow-up care.

1.3.1 Efficient Time Allocation

Consider first what efficient time allocation would look like for a rational physician. Over the course of a day, this physician maximizes the sum of the expected net benefits of appointment time to patients, subject only to a 24-hours-in-the-day constraint or alternatively, the value of leisure or another activity. An individual appointment ends when the marginal cost of an additional minute exceeds the marginal benefit to that patient. For this physician, a schedule disruption (i.e., a later-than-anticipated appointment start) would have no effect on the time spent with subsequent patients that day.

In practice, physicians do not allocate time to patients in this way, but rather seem to apply a behavioral rule about "target" visit duration [124]. In the extreme, this might (and does, in my data) look like a single appointment template of 15 minutes, regardless of what the physician knows *ex ante* about how much time specific patients might need, based on their health states.

That 15-minute target may be flexible, but subject to certain behavioral norms. If the physician spends much less time with the patient, she risks causing offense. Spending much more time risks irritating subsequent patients who must wait or angering staff who expect to go home at 5pm.

1.3.2 Model Setup

Physicians maintain appointment schedules, such that each appointment has an intended start (ω_s) and end (ω_e) time. Realized appointment start (τ_s) and end (τ_e) time define total appointment time (T). Total appointment time is allocated to one or more conditions $c = (c_1, ...c_K)$ where K is the total number of conditions discussed and time per condition must sum to total appointment time, such that $\sum_{k=1}^{K} c_k = T$. I specify an appointment-level physician utility function, including a term expressing the disutility of a schedule disruption:

$$U = f(T) - C(T) - D(T, a; \tau_s - \omega_s, N - n) \tag{1.1}$$

where $f(T)$ represents the monetary and non-monetary rewards to the physician for providing care. $C(T)$ is the physician's private cost of effort. $D(T, a; \tau_s - \omega_s, N - n)$ is a customer service component, which is a function of the time allocated to the appointment (T), physician characteristics (a), appointment start time relative to scheduled start ($\tau_s - \omega_s$), and how many patients remain to be seen that day (daily patient total [N] minus the number of patients seen so far [n]).

Intuitively, the disutility of a schedule disruption arises from the physician's desire to provide good "customer service", in addition to good medical care, which is built into $f(T)$. Since most primary care physicians practice in groups with other physicians, mid-level practitioners, and administrative staff - and because patient-physician relationships are frequently maintained over the course of years, physician utility suffers when office staff or patients are inconvenienced by a schedule disruption. Note that this does not imply that a rational physician with this utility function necessarily schedules only 15-minute appointments. Rather, conditional on a pre-existing appointment schedule, the physician does not simply maximize the sum of the expected net benefits of appointment time to patients during a day.

1.3.3 Schedule Disruptions and the Shadow Price of Time

A schedule disruption effectively increases the shadow price of a physician's time during the subsequent appointment(s). To illustrate this, consider an appointment with two conditions and a disutility of schedule disruption component that simply scales the private cost of spending more time on that appointment. The physician's utility function is now $U = f(T) - C(T) - (\tau_s - \omega_s)T$, subject to the constraint $c_1 + c_2 = T$. The physician first decides how much time to spend on an appointment and then allocates time to maximize $f(c_1, c_2)$. Solving this two-stage problem by backwards induction, the second-stage indirect utility function is:

$$V(T) = \max f(c_1, c_2) \text{ s.t. } c_1 + c_2 <= T$$

The first-order conditions of this problem are $f_1 = f_2 = \mu$, where μ is the Lagrange multiplier on the time constraint - or the shadow price of time. Applying the envelope theorem, $V'(T) = \mu \equiv$ shadow price of and the physician's first-stage problem is:

$$\max V(T) - C(T) - (\tau_s - \omega_s)T$$

Now the first-order condition is $V' = \mu = C' + (\tau_s - \omega_s)$ and this demonstrates that the difference between scheduled and observed appointment start time, $\tau_s - \omega_s$, directly influences the shadow price of time, μ. When the physician experiences a schedule disruption, she decreases her time spent per appointment ($\frac{\partial T^*}{\partial(\tau_s - \omega_s)} < 0$).

Proposition 1. *Denote decisions that maximize physician's expected utility in Equation 1.1 with a * superscript. As $\tau_s - \omega_s \to \infty$, T^* decreases, $c^* = (c_1, ..., c_K)$ decreases and K^* weakly decreases.*

1.3.4 Deciding on Follow-Up Care

In this simplified model, patients vary only in their health state, $\beta \in \{0, 1\}$, for any given condition. Consider an appointment where one condition is discussed. The physician observes a patient's true health state with probability $p \in (0, 1)$. Patient care increases the probability p

of observing β and making appropriate decisions regarding the patient's course of treatment. p is increasing and concave with respect to T. After time spent on the condition, the physician decides whether to order follow-up care ($\Gamma = 1$) or not ($\Gamma = 0$). Patients with $\beta = 0$ should receive no further care, while patients with $\beta = 1$ should receive follow-up care. Physicians are risk averse, such that failing to order follow up care for a sick patient is particularly harmful: $f(\beta = 1, \Gamma = 1) - f(1,0) > f(0,0) - f(0,1)$. If β remains unobserved, the physician will order follow-up care if and only if $p > p^* < \frac{1}{2}$:

$$E[f|\Delta = 0, p = p^*] = E[f|\Delta = 1, p = p^*]$$

$$p^* f(1,0) + (1 - p^*) f(0,0) = p^* f(1,1) + (1 - p^*) f(0,1)$$

$$\frac{1 - p^*}{p^*} = \frac{f(1,1) - f(1,0)}{f(0,0) - f(0,1)} > 1$$

If the physician spends less time on a condition, she is more likely to over-order follow-up care for the patient.

Proposition 2 *As* $\tau_s - \omega_s \to \infty$ *and* $T^* \to 0$, $E[\Gamma]$ *weakly increases.*

Consider now a chronic condition. This is a condition where the treating physician (or another physician in the practice) has already observed β during a previous encounter. Decisions regarding time allocation and appropriate follow-up care for a chronic condition may differ from a new or acute condition. If conditions are addressed in descending order of acuity (or marginal benefit to the patient), a chronic condition may be less likely to surface during a shorter appointment. Alternatively, economizing on time by simply continuing the patient's ongoing course of treatment for this condition may be more acceptable from a customer service viewpoint than failing to address a new or acute condition. For these reasons, I will explore empirically the difference in ordering behavior by type of condition.

1.4 Data and Sample Selection

Physicians may also alter decisions for follow-up care in response to a delayed appointment start. In the remainder of this paper, I will provide empirical evidence regarding the relative size and direction of physician response to schedule disruptions. This section describes the data used to answer these questions, presents descriptive statistics, and delves deeper into observed appointment duration.

1.4.1 Data

I rely primarily on data from athenahealth, Inc., ("athenahealth"), a company that sells cloud-based medical billing, practice management, and electronic health record (EHR) services to health care providers nationwide. Clients span provider types and specialties, with a high concentration of office-based primary care providers.

These novel data contain claims information for all athenahealth providers during 2013-2014, including date of service, patient age, sex, marital status, insurance type, diagnosis and procedure codes, provider place of service, provider type and specialty, allowable charges, and patient cost-sharing. A subset of athenahealth clients also purchase practice management and EHR services. For this group of providers, I use data derived from the athenahealth EHR, including appointment date, time stamps, date of scheduling, scheduled start time, intended duration, and orders placed by the physician for prescriptions, consults, imaging, and lab tests. This combination of claims and EHR data is unique in four important ways:

Physician and Group Identifiers: These allow for observation of practice organization, from the smallest department level (i.e., office location) to the highest health system affiliation. I can then observe daily staffing patterns, presence of non-physician providers, and availability of affiliated, non-office settings.

Time Stamps: My analysis relies heavily on the reporting of scheduled and observed appointment start and end times. I use these data elements to a) calculate appointment duration, b) construct physician schedules, and c) and observe deviations from these schedules.

All-Payer Prices: The data detail reimbursement for all payers, including those negotiated between the physician and commercial insurers. This allows me to construct a measure of spending per appointment which accurately reflects the physician's compensation.

Orders for Future Care: In addition to the procedures conducted during the appointment, I also observe physician orders for a patient's follow-up care. These include orders for lab and imaging tests, medication prescriptions, and referrals to specialists.

An important limitation of the data is the inability to track patients. If a patient visited a non-athenahealth provider, that utilization is not captured in the data. This generally means that I cannot observe whether a patient followed through on a referral to a specialist, filled a prescription, or received the physician-ordered imaging or lab test.

1.4.2 Sample Selection and Descriptive Statistics

The main sample comprises adult appointments with office-based primary care physicians (internal medicine, family practice, general practice) during 2013-2014. I restrict the sample to weekday appointments scheduled for 10,15, 20, or 30 minutes time blocks, occurring in the scheduled order, with no breaks immediately before, and non-anomalous[3] time stamps documenting the start and end of the exam, as I need to accurately measure a) when an appointment began, relative to the scheduled start time, and b) how much time the physician spent with the patient. Physicians with very few appointments or a high proportion of same-day appointments are dropped, as I rely on within physician variation and am interested in the behavior of the vast majority of physicians who organize their labor supply using appointment schedules. My final sample includes 4,253,010 primary care appointments for 1,309,815 patients, seeing 7,022 primary care physicians, working at 1,481 practices or health systems.

[3] Examples of anomalous time stamps include missing start or end times for the exam stage, non-sequential appointment stages, and a bunching of time stamps indicating that documentation was not conducted in realtime.

Descriptive Statistics

My data provider's clients comprise a convenience sample of all primary care appointments in the United States. Table 1.1 provides descriptive statistics of all appointments, as well as those I use as my analytic sample. Both datasets have a similar patient gender and age composition, with each subsequent age category representing a greater share of appointments. Insurance type distribution is also similar across datasets, with the bulk of appointments (58.3% in the full dataset and 60.7% in the analytic sample) covered by commercial insurance, followed by Medicare, Medicaid, self-pay, and workers' compensation. The analytic sample has a higher burden of chronic disease than the full dataset. Geographically, both datasets overrepresent the South and underrepresent the West. The analytic sample has a smaller share of appointments for new patients (13.7%) than the full dataset (19.4%), which likely reflects the exclusion of specialist physicians, with whom patients may not need an established relationship. Finally, the seasonal distribution of appointments is similar between datasets, with slightly more appointments occurring in the autumn than the other seasons, and 2014 shows an increase in appointment count - likely reflecting growth in the athenahealth client base. Despite being a convenience sample, patient characteristics of appointments largely mirror national survey-based estimates, as shown in Table A.1.

Table 4.2 compares characteristics of physicians and physician practices between my analytic sample, the full dataset, and all PCPs in the full dataset. Physicians in my sample have higher average volume (weekly appointment count and panel size) than all physicians or primary care physicians in the full dataset. They also work more days per week, with an average of 4.6 days in the analytic sample, compared to 3.3 days per week for all physicians and 3.5 days per week for all primary care physicians. Practices in my analytic sample look similar to PCP practices in the full sample, with an average of 21 physicians, 4.5 nurse practitioners, and 2.2 physician assistants billing at the practice.

Table 1.1: *Appointment Descriptives*

	Full Dataset	Analytic Sample
Age		
0-9	0.095	-
10-19	0.081	-
20-29	0.099	0.068
30-39	0.108	0.098
40-49	0.118	0.137
50-59	0.153	0.196
60-69	0.155	0.219
70+	0.192	0.258
Female	0.588	0.582
Insurance		
Commercial	0.583	0.607
Medicare	0.235	0.309
Medicaid	0.094	0.050
No Insurance	0.048	0.026
Workers' Compensation	0.014	0.004
Chronic Condition Count		
0	0.787	0.463
1	0.098	0.141
2	0.041	0.131
3+	0.073	0.265
Geography		
Northeast	0.222	0.263
Midwest	0.194	0.194
South	0.482	0.427
West	0.107	0.124
New Patient	0.194	0.137
Season		
Winter (Jan-March)	0.223	0.219
Spring (Apr-June)	0.242	0.240
Summer (July-Sept)	0.256	0.259
Fall (Oct-Dec)	0.279	0.281
2014	0.558	0.588
Total Charges	$147.97	$113.55

Note: This table presents descriptive statistics on all appointments within the full dataset, compared to the main analytic sample of appointments with office-based primary care physicians.

Table 1.2: *Physician and Practice Descriptives*

	Full Dataset	Full Dataset (PCPs only)	Analytic Sample
Physician Characteristics			
Volume			
Weekly appointment count: Average physician	41.8	45.0	68.0
Weekly appointment count: 10th percentile physician	2.2	2.8	31.3
Weekly appointment count: 90th percentile physician	93.0	97.2	108.8
Panel size: Average physician	1103.1	1089.9	1855.5
Panel size: 10th percentile physician	12.0	15.0	759.0
Panel size: 90th percentile physician	2764.0	2600.0	3146.0
Days active, per week	3.3	3.5	4.6
Appointment Time			
Scheduled Duration: Average physician	18.5	18.8	17.1
Scheduled Duration: 10th percentile physician	11.1	13.9	14.1
Scheduled Duration: 90th percentile physician	29.9	29.9	22.4
Practice Characteristics			
Physician Count: Average Practice	11.7	22.5	21.0
Nurse Practitioner Count: Average Practice	3.2	4.5	4.5
Physician Assistant Count: Average Practice	1.4	2.5	2.2

Note: This table presents descriptive statistics on physicians and practices within the full dataset, primary care physicians in the full dataset, and the analytic sample used in this paper. Panel size is defined as the number of distinct patients who see any given physician or practice during the study period. Days active is defined as the average weekly count of days during which a physician billed for patient care. While the analytic sample only includes primary care physicians, this table presents the average number of mid-level providers (nurse practitioners and physician assistants) billing within the same practice.

1.4.3 Appointment Duration

The data provider's EHR organizes each appointment into five stages, as depicted in Figure 1.1: checkin, intake, exam, checkout, and signoff - followed by any post-visit documentation that the provider may do. Checkin generally happens with front-office staff, depending on staffing arrangements, and includes insurance status confirmation and other administrative details. During intake, a non-physician provider (or in some instances, the physician) measures the patient's vitals. The exam stage encompasses all interaction between patient and physician. checkout and signoff involve all post-appointment administrative functions and are generally not conducted by the physician.

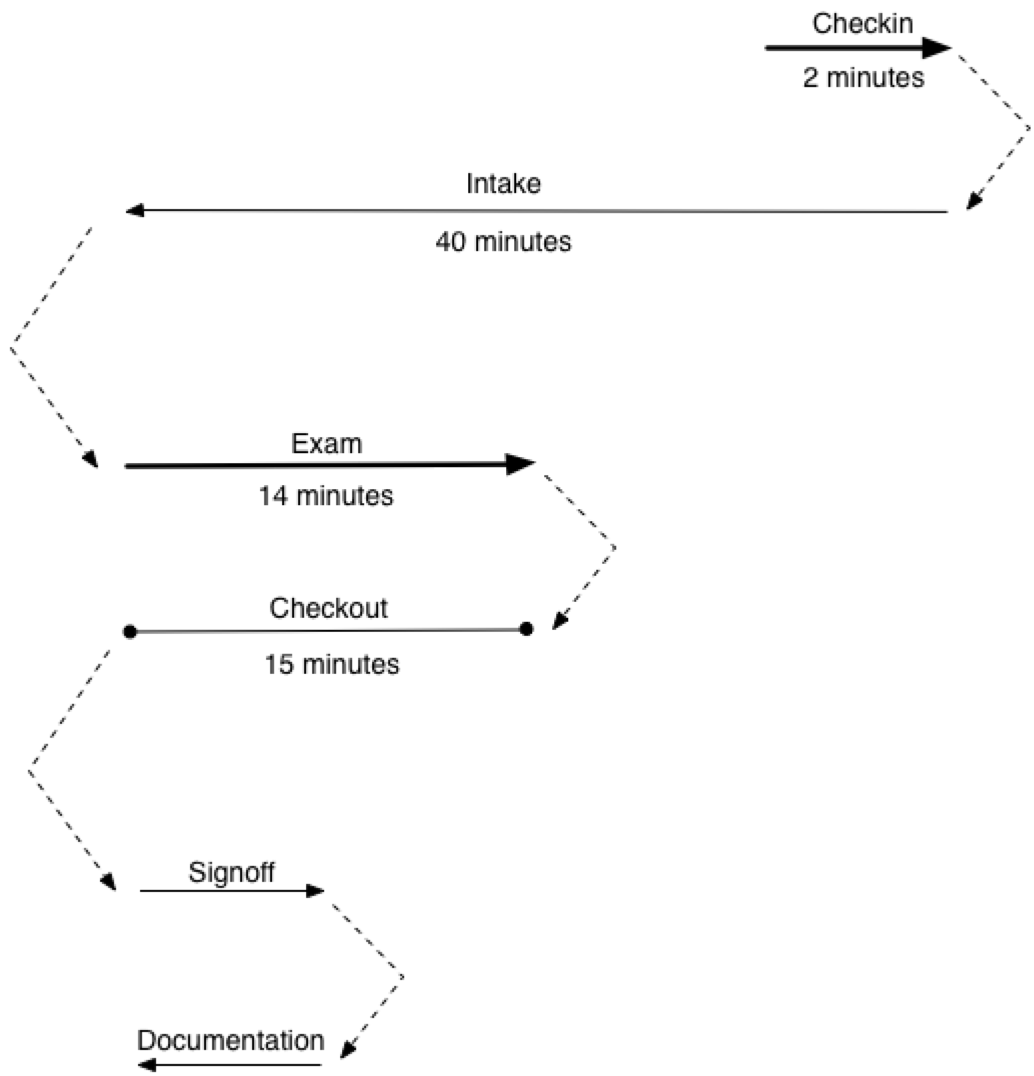
I measure observed appointment duration as an important input in patient care. This is defined by the EHR as the time elapsed between the minimum and maximum keystroke entry time during the exam stage. I define excess appointment duration as the difference between observed duration and scheduled duration[4] and trim the top and bottom 2.5% of appointments, to reduce the influence of outliers on my findings. I frequently observe overlapping appointments, suggesting that the physician had the EHR open in two different exam rooms. While double-booked appointments are a common occurrence in primary care practices, it is impossible to accurately observe how much time the physician spent with each patient when appointments overlap, so these are excluded from any analyses of appointment duration.

Appointments in my sample are scheduled for 10, 15, 20, or 30 minutes ($>$ 95% of appointments in the full dataset are scheduled for one of these times). Figure 1.2 plots the distribution of observed duration for each scheduled duration category, excluding overlapping appointments. Average observed appointment duration is monotonically increasing in scheduled duration, but consistently shorter than the scheduled appointment duration. Including all appointments (overlapping and non-overlapping) shows a similar pattern, with observed durations exceeding the scheduled duration, as one would expect.

Most appointments in my sample (95%) start at or after their scheduled start time. Figure 1.3

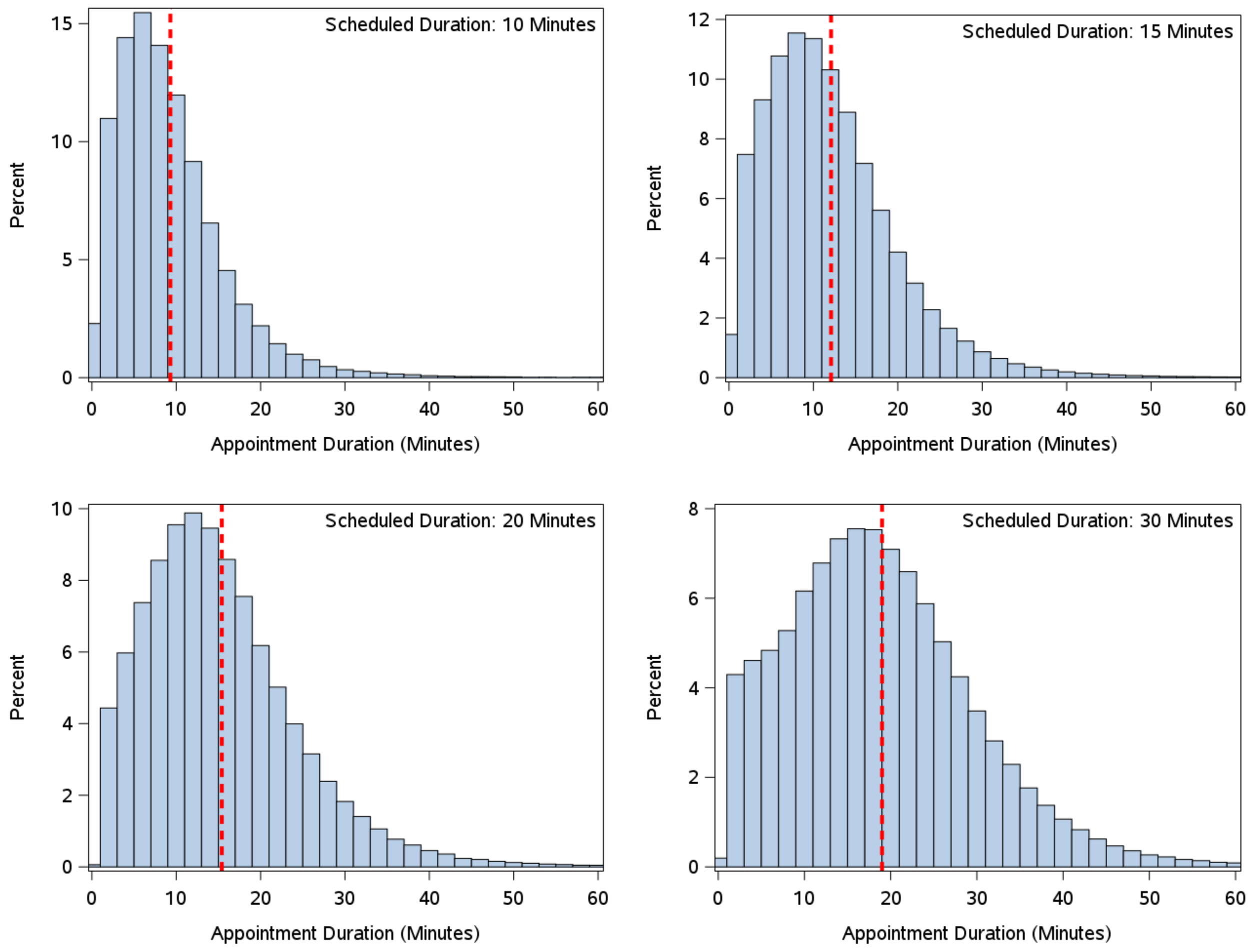
[4] An appointment scheduled for 15 minutes that actually lasts 17 minutes will have an excess duration of 2 minutes. Conversely, if that appointment had an observed duration of 10 minutes, its excess duration would be -5 minutes.

Figure 1.1: *Appointment Stages in the athenahealth, Inc., Electronic Health Record*



Note: This figure shows a graphical depiction of sequential appointment stages within the athenahealth electronic health record. Arrows indicate the flow through an appointment. Dotted lines indicate that there may be time between each stage. Each stage with recorded time stamps has a time estimate, calculated as the average observed duration within my analytic sample. Bold lines indicate the stages (checkin and exam) where I rely on time stamps for my analysis.

Figure 1.2: *Observed Exam Duration by Scheduled Duration*



Note: This figure plots the distribution of observed appointment duration for appointments of scheduled durations including 10, 15, 20, and 30 minutes. I trim the top and bottom 2.5% of appointments, to reduce the influence of outliers on my findings. Dotted red lines display the average observed appointment duration for each scheduled duration.

plots the distribution of observed appointment start time, relative to the scheduled start time. On average, appointments start 28 minutes after the scheduled start time. Lateness appears to compound over the course of a day. The first scheduled appointment starts less than 20 minutes late (Panel B of Figure 1.3), but this more than doubles, for an average last appointment start time almost 40 minutes later than the scheduled start time (Panel C of Figure 1.3).

1.5 Instrumental Variables Framework

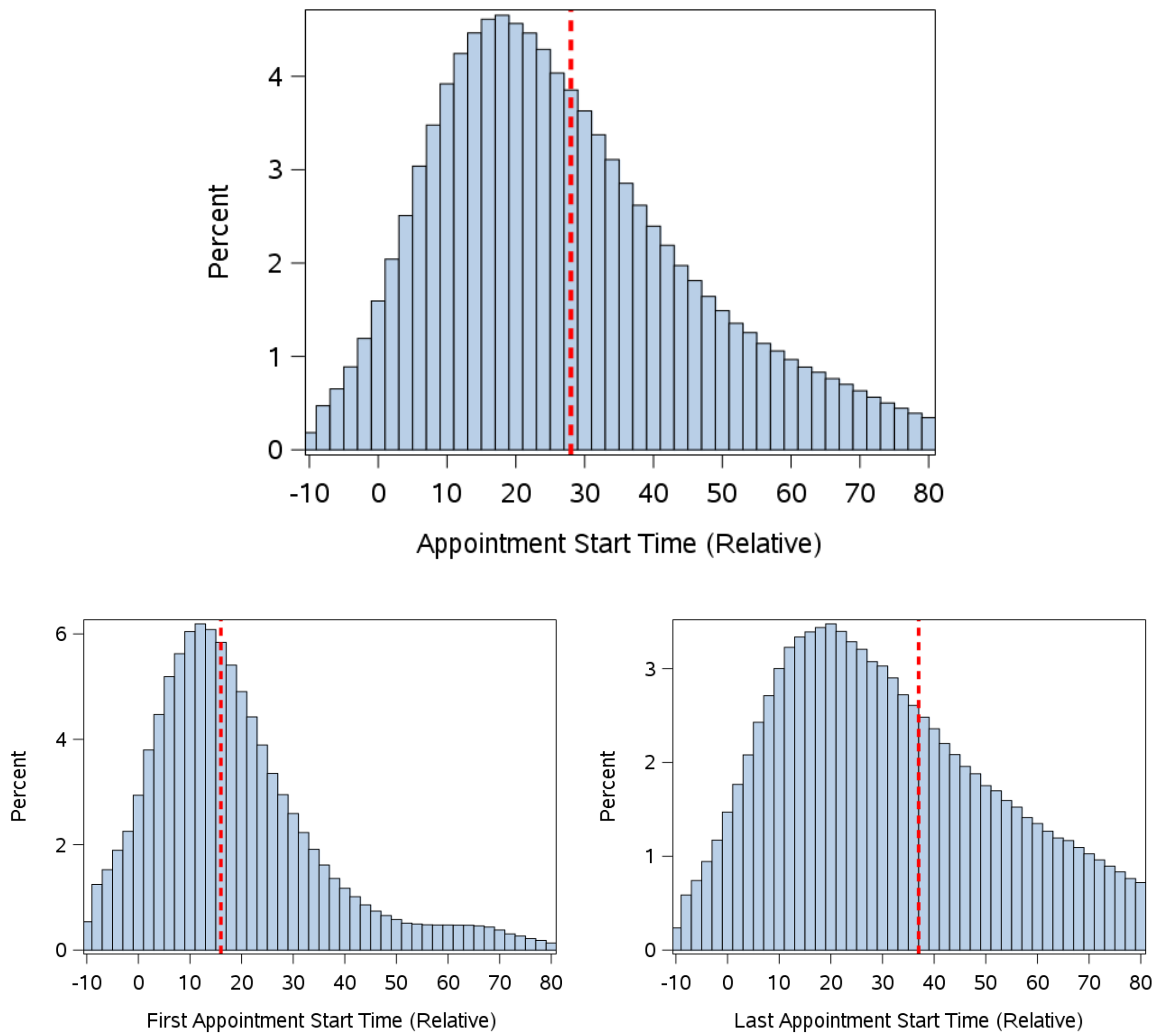
Having presented background and descriptive statistics, I now turn to a discussion of my empirical strategy for identifying the importance of schedule deviations on physician resource utilization and decision-making. In this section, I detail my instrumental variables approach, the underlying identifying assumptions, first stage results, and my outcomes of interest.

A naive approach to this research question might examine the association between appointment schedule disruptions and physician input use or clinical decision-making. There are two main concerns with this approach. First, physicians differ tremendously, both in their deviations from schedule and in their rates of the outcomes of interest. Second, physician schedule disruptions may themselves be endogenous to the treatment choices for a particular patient. Put another way, a physician may allow appointment A to run long, resulting in a late start for appointment B, if the physician knows something about how much time or effort appointment B will require. More generally, any unobserved appointment characteristics that simultaneously affect appointment start time and the outcome of interest render ordinary least squares (OLS) estimation unlikely to provide a causal estimate, even after adopting a within-physician design. To mitigate this concern, I employ an instrumental variables approach and use physician fixed effects.

1.5.1 Instrumental Variables Design

I instrument for *current* observed appointment start time relative to scheduled start time with the office arrival time relative to the scheduled appointment start of the *previous* patient. If a late previous patient affects physicians only by generating deviations from the intended appointment schedule, then the arrival time of a physician's previous patient serves as a valid instrument for

Figure 1.3: *Distribution of Observed Appointment Start Time*



Note: This figure plots the distribution of observed appointment start time, relative to the scheduled start time. The first panel plots the distribution for the entire analytic sample. The second and third panels plot the distribution for only first or last appointments, respectively. First appointments are not included in the 2SLS analysis, as their was no previous patient arrival time. Dotted red lines display an on-time appointment start (observed appointment start time minus scheduled start time is equal to zero).

estimating the effects of current physician lateness on resource use and decision-making.[5] My model for estimating the effect of schedule deviations on outcomes is:

$$Y_{ijt} = \beta StartTime_{ijt} + X'_{it}\gamma + A'_{it}\eta + T'_{it}\theta + \delta_j + \epsilon_{ijt} \tag{1.2}$$

where $StartTime_{ijt}$ is indexed for patient i, seeing physician j, at appointment time t. X_{it} is a vector of patient characteristics including patient age, gender, insurance status, new patient indicators, and chronic condition indicators. A_{it} is a vector of appointment characteristics, including scheduled duration, appointment rank, and an indicator for being a same-day visit. T_{it} are day-of-the-week-season-year fixed effects. δ_j is a physician-practice combination fixed-effect, controlling for time-invariant differences between physicians.

If, as discussed in the previous section, unobserved characteristics affect both the appointment start time and the outcome of interest, OLS estimation of this model is unlikely to provide a causal estimate of β. I therefore predict minutes behind schedule using the arrival time of the physician's previous patient:

$$StartTime_{ijt} = PatientArrivalTime_{ijt-1} + X'_{it}\beta + A'_{it}\eta + T'_{it}\eta + \delta_j + \epsilon_{ijt} \tag{1.3}$$

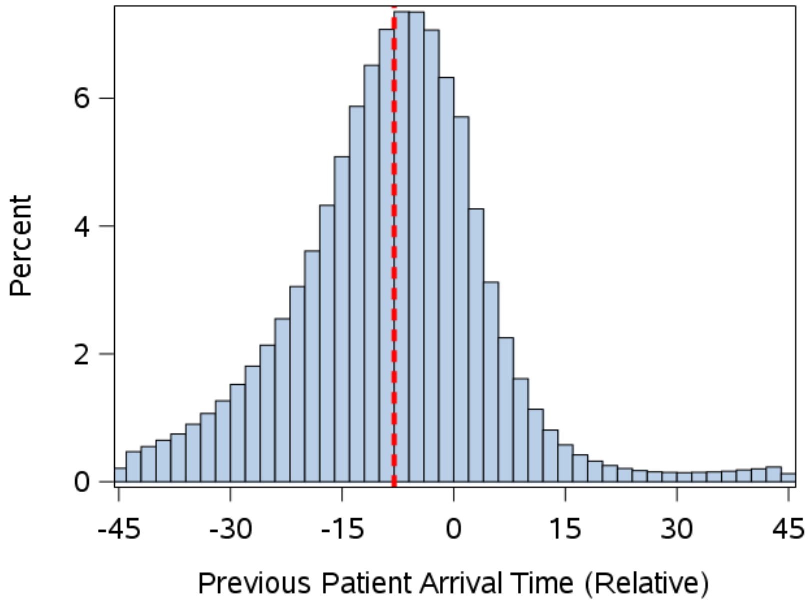
where $PatientArrivalTime_{ijt-1}$ is that physician's previous patient's office arrival time, relative to the scheduled start time. This measures the schedule deviation induced by the previous patient and is the excluded instrument in the system of equations specified by Equations 1.2 and 1.3. All standard errors are clustered at the physician level.

1.5.2 Identifying Assumptions

The instrumental variables framework for identifying the causal effect of appointment start time on input use and ordering behavior relies on three main assumptions: a relevance condition,

[5] A late-arriving patient may affect physician-making in a way that is more related to stress than to time, confounding this identification strategy. For this reason, I also include reduced form estimates in the presentation of results.

Figure 1.4: *Distribution of Previous Patient Arrival Time*



Note: This figure plots the distribution of previous patient office arrival time, relative to the scheduled appointment start time. Dotted red lines display an on-time office arrival time (previous patient office arrival time minus scheduled start time is equal to zero).

a monotonicity assumption, and an exclusion restriction. I now turn to a discussion of each assumption. The relevance condition requires that the office arrival time of a physician's previous patient affects the current appointment start time. Figure 1.4 plots the distribution of previous patient arrival times relative to the appointment start time. The average patient in my sample arrives roughly 8 minutes early to the office.[6] Previous patients arrive later than their scheduled appointment time for roughly a quarter of appointments.

Patient arrival time is likely one of many factors that determines how closely a physician adheres to the intended appointment schedule. In Figure 1.5a, I plot appointment start time (relative to scheduled start time) as a function of the previous patient's office arrival time (again, relative to the scheduled appointment start time), including physician fixed effects, such that all comparisons are within-physician. This shows very little relationship between previous patient arrival

[6]Patient arrival time is measured as the start of the checkin stage. My analysis uses patient arrival time relative to the scheduled appointment start time, such that a patient arriving at 2:05 PM for a 2:15 appointment would have an arrival time of -10 minutes.

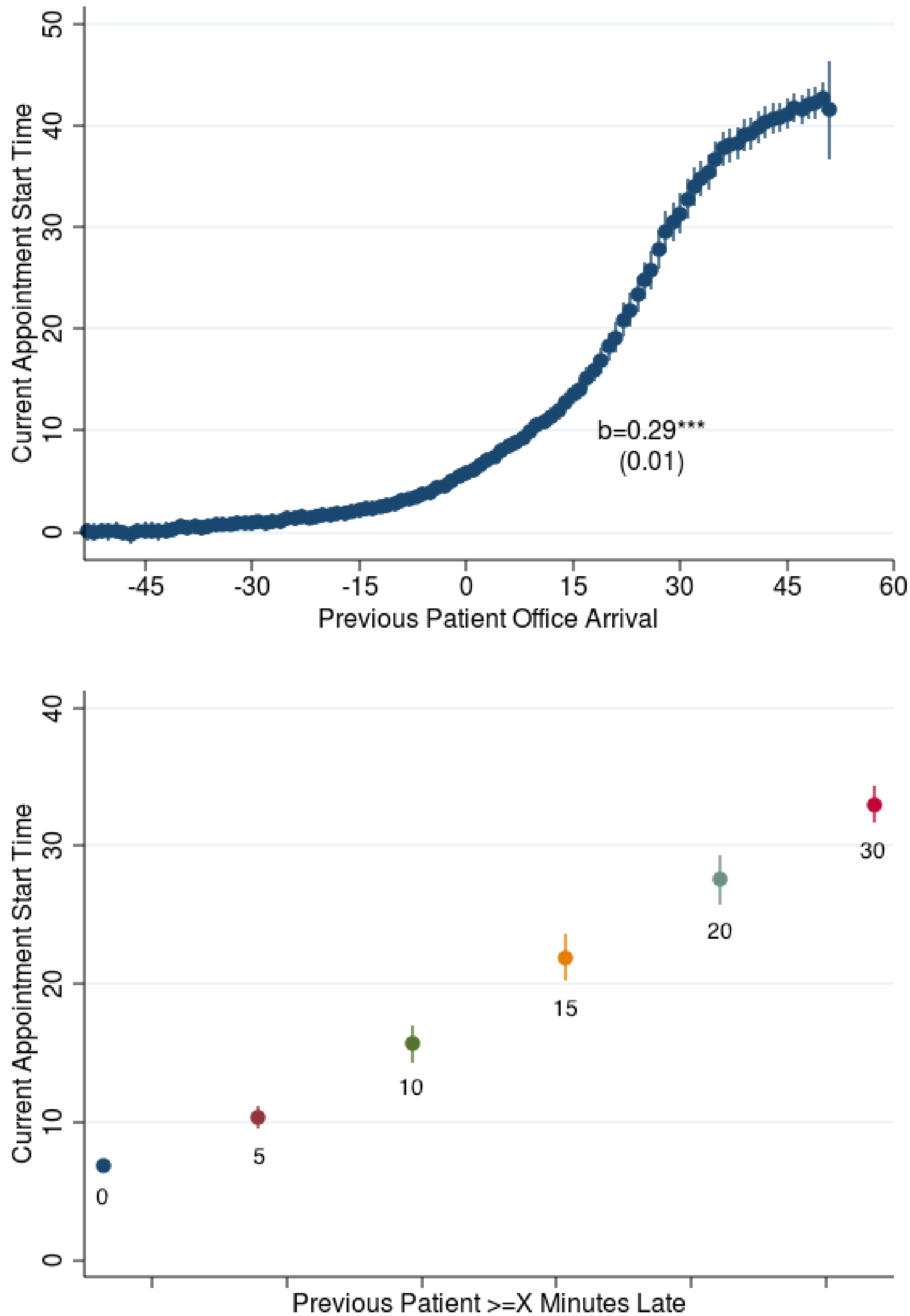
time and appointment start time when the previous patient arrived more than 30 minutes early. After that, I observe a positive relationship between appointment start time and the office arrival time of the previous patient. This figure suggests that even an "on-time" patient can still delay the appointment start time. Figure 1.5b categorizes previous patient arrival time into buckets, ranging from $\geq$ 0 minutes late to $\geq$ 30 minutes late. Again, current appointment start time is increasing in previous patient arrival time.

Figure 1.6 shows estimates of equation 1.3, including physician fixed effects and clustering standard errors at the physician level, and present results. This specification controls for patient characteristics (age, gender, insurance, new patient status, and chronic condition indicators), appointment characteristics (scheduled duration and indicators for whether the appointment is a same-day visit or double-booked), and time fixed effects (appointment rank within the day, day of the week, season, and year). The office arrival time of a physician's previous patient indeed affects the start time of the current appointment. I find that a 15 minute late previous patient (i.e., roughly 2 standard deviations from the mean arrival time of 8 minutes early) delays the start time of the current appointment by an additional 7 minutes ($6.71 s.e. = 0.0094$).

A late-arriving patient may disrupt the start time of multiple subsequent appointments during the physician's day. While my main instrument for appointment start time at time t is the office arrival time of the previous patient ($t-1$), I test multiple similar instruments and find that a late-arriving patient at time $t-2$, $t-3$, $t-4$, and $t-5$ continues to predict the appointment start time at time t. However, the effect of a late patient decreases with temporal distance, as Figure 1.6 shows. I return to these possible alternative instruments when I discuss robustness checks.

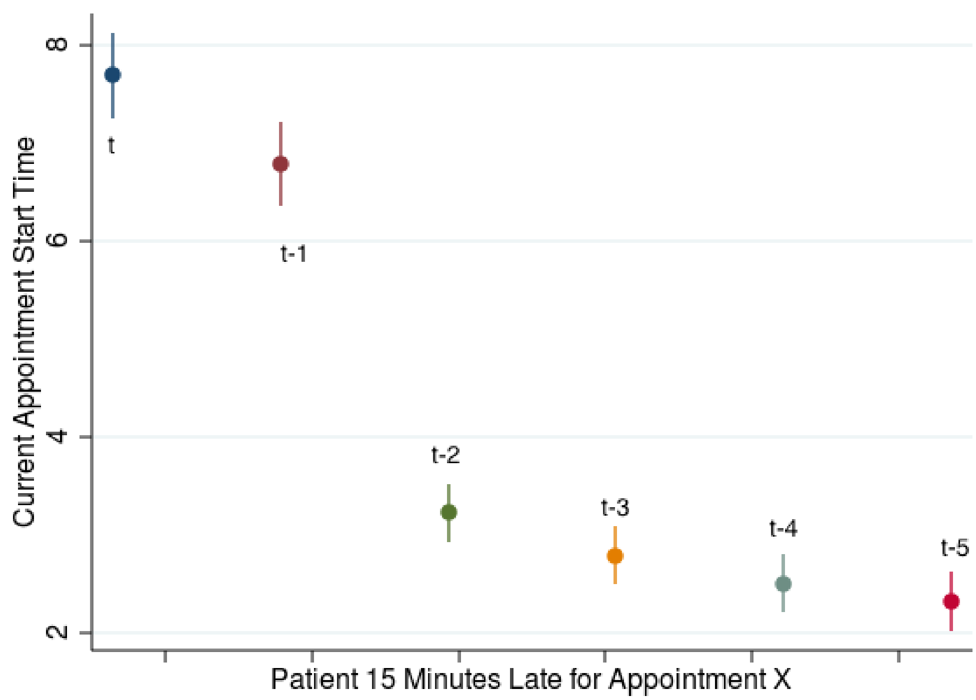
Finally, I estimate Equation 1.3 using the current patient's office arrival time to predict the current appointment start time. As expected, this yields the strongest first stage, with a 15 minutes late current patient delaying the start of the current appointment by an additional 8 minutes. That the late patient's appointment seems to be most severely truncated is compelling evidence that physician utility functions do indeed include a patient experience or patient fairness component.

Figure 1.5: *Appointment Start Time as a Function of Previous Patient Office Arrival Time*



Note: This figure plots average minutes behind schedule as a function of previous patient arrival time, with standard error bars. Estimates are adjusted for physician fixed effects, so all comparisons are within-physician.

Figure 1.6: *Effect of a 15-Minute Late Patient Arrival at Time t through $t-5$ on Appointment Start at Time t*



Note: This figure plots the appointment start time at time t as a function of a 15-minute late patient arrival at time t through $t-5$. Full controls are used, including patient characteristics (age, gender, insurance, new patient status, and chronic condition indicators), appointment characteristics (scheduled duration and indicators for whether the appointment is a same-day visit or double-booked), and time fixed effects (appointment rank within the day, day of the week, season, and year). Estimates are adjusted for physician fixed effects, so all comparisons are within-physician. Vertical bars display 95% confidence intervals.

Monotonicity

In addition to the relevance condition, identification of a local average treatment effect within an IV framework is only possible with a monotonicity assumption [6]. In this context, monotonicity assumes that if a 15-minute late previous patient delays a physician's subsequent appointment start time, a 15-minute late previous patient will always do so (rather than causing the physician to run earlier). While monotonicity is fundamentally untestable, I estimate my first stage on a series of distinct subgroups, dividing my sample by patient and appointment characteristics. Figure 1.7 presents the results of this exercise, splitting the sample by patient gender, insurance, physician relationship (i.e., new vs. established), and time of day. I find that splitting my sample in these ways yields results suggesting that late-arriving patients with different characteristics have a similar effect on physicians' subsequent appointment start time.

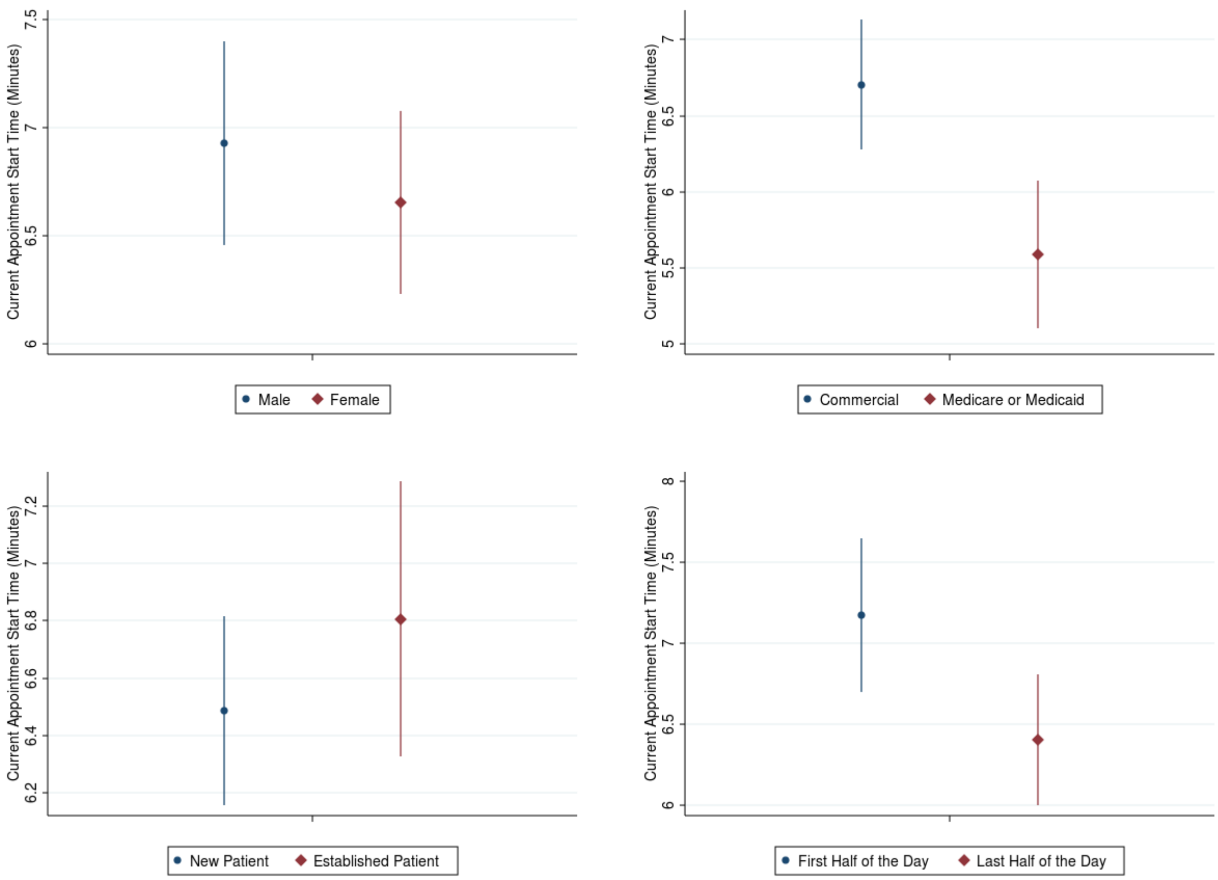
I am also concerned about a possible monotonicity violation for very late-arriving patients. If a patient is significantly delayed in arriving at the office, it is likely that the next scheduled patient will be in the waiting room. If the physician chooses to see the patient who is present in the waiting room, this suggests that a very late patient may actually hasten the start of the subsequent patient's appointment. For this reason, I trim the top and bottom 2.5% of appointments by previous patient arrival time and I restrict my sample to appointments that occurred in the scheduled order.

Exclusion Restriction

Given a strong first stage, my identification strategy depends on the similarly untestable exclusion restriction: the timing of the previous patient's arrival to the office cannot affect the physician's decision-making during the subsequent appointment outside of its effect on the subsequent appointment's start time.

I test for balance on covariates in Table 1.3, asking whether a given physician sees different patient types immediately following appointments that differed by patient arrival time. I present the difference in conditional means of appointment observables, stratified by quartile of previous patient office arrival time. These estimates are adjusted for physician fixed-effects and are there-

Figure 1.7: *First Stage Estimates, by Mutually Exclusive Patient and Appointment Characteristics*



Note: This figure presents first stage results of Equation 1.3, predicting current appointment start time as a function of the previous patient's office arrival time, using distinct samples that vary on patient and appointment characteristics. Each point depicts the change in appointment start time resulting from each additional minute of previous patient office arrival time, with bars showing 95% confidence intervals. Full controls are used. Standard errors are clustered at the physician level.

Table 1.3: *Balance on Patient Chronic Conditions Count*

	Difference	Std. Error	P-Value
Quartile of Previous Patient Lateness			
2	0.002	0.005	0.617
3	0.003	0.005	0.593
4	-0.006	0.005	0.191
Previous Patient Late: Yes or No			
Yes	-0.007	0.004	0.082
Quartile of Current Patient Lateness			
2	-0.0417	0.007	0.000
3	-0.122	0.008	0.000
4	-0.233	0.009	0.000

Note: This table presents the difference in conditional means of observables for appointments by quartile of previous patient arrival time to the office. Estimates are adjusted for physician fixed effects, so the comparisons are all within-physician.

fore all within-physician comparisons. The covariate of interest is count of chronic conditions, a variable generated using diagnoses from 1-2 years of past claims.[7] Overall, I do not see statistically significant differences in the count of chronic conditions across quartiles of previous patient arrival time. Relative to appointments in the bottom quartile of previous patient office arrival time (i.e., appointments where the previous patient arrived more than 15 minutes early), the difference in chronic condition count (0.002) for appointments in the second quartile (where the previous patient arrived between 15 and 7.5 minutes early) is small and statistically insignificant (p=0.617). This is also true for the difference between the first and third quartile (0.003, p=0.593) and the difference between the first and fourth quartile (-0.006, p=0.191). I find no significant difference between these coefficients (F-statistic = 1.54). I additionally divide appointments by whether they did or did not follow a patient who arrived late to the office. I find that these groups differ by 0.007 chronic conditions (p=0.082), or 0.3% of the mean chronic condition count.

I next rule out current patient arrival time as an instrument for current appointment start time, as it likely violates the exclusion restriction. The last panel of Table 1.3 shows balance on covariates by quartile of current - rather than previous - patient office arrival time. Here I see that every

[7] This calculation adheres as much as possible to the algorithm used by the Chronic Condition Warehouse.

subsequent quartile of current patient arrival has significantly fewer chronic conditions than the group of patients who arrive earliest to their appointment. Relative to the bottom quartile, the top quartile of appointments by current patient arrival time has 0.23 fewer chronic conditions, or roughly 10% percent of the mean chronic condition count. This suggests the presence of unobserved variables that affect both current patient arrival time and physician decision-making for that patient.

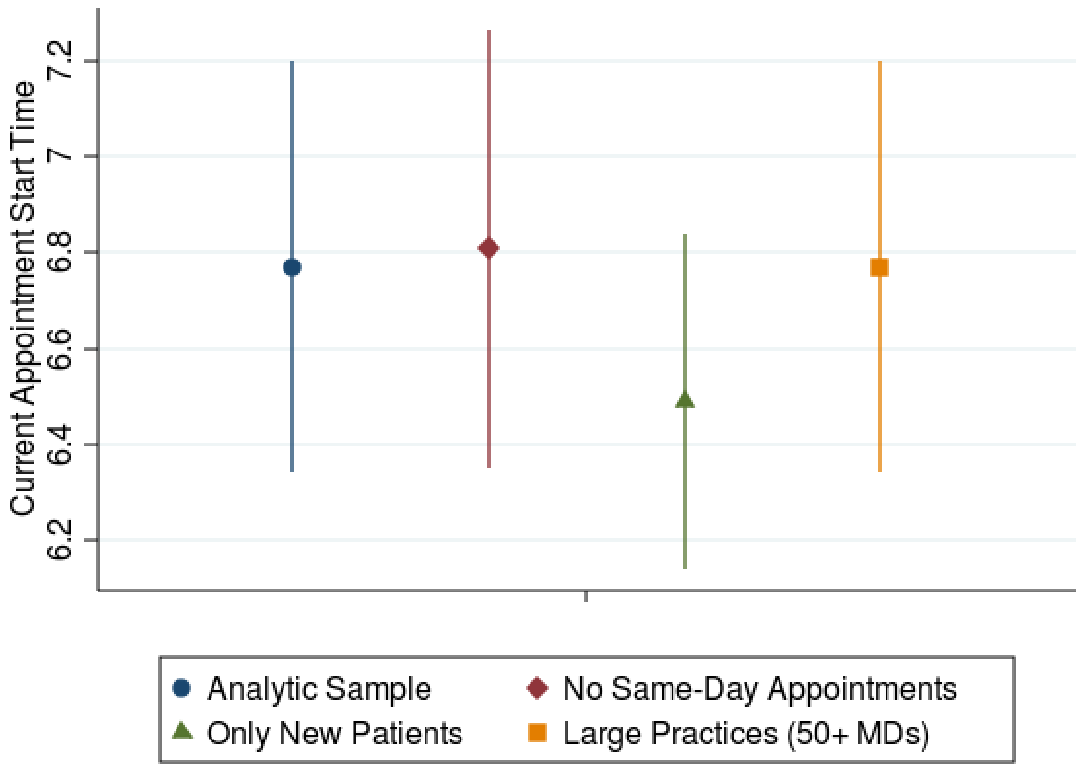
Patient sorting might lead to a violation of the exclusion restriction if physicians systematically schedule particular patients to follow others, based on anticipated arrival time. This is unlikely given the fact that most appointments are scheduled more than a week in advance. However, a physician might choose to reorder her schedule following a late patient or squeeze in a straightforward same-day appointment. I reestimate Equation 1.2 in Figure 1.8, subsetting my main sample to include only non-same-day appointments, which might be systematically and strategically accommodated within a day, based on the complexity or time requirements of other patients. I also eestimate using only those appointments following new patients, such that the physician cannot anticipate the previous patient arriving late, based on past experience. Finally, I limit my sample to appointments with physicians in large group practices ($\geq$ 50 physicians), where appointments are most likely to be scheduled by administrative staff, without input on schedule order from the physician. I find that these three coefficients estimated in different samples are statistically indistinguishable from each other. The fact that these sample restrictions result in minimal changes in my first stage result suggests minimal cause for worry about physician selection of patients based on the previous patient's office arrival time.

To summarize, I find considerable degrees of balance in patient characteristics across appointments that vary by office arrival time of the previous patient. Supporting this, I find that omitting certain appointments that might represent the best opportunities for patient sorting yields estimates very similar to my full sample.

1.5.3 Outcomes

I use the instrumental variables framework detailed in Section 1.5.1 to examine a range of outcomes along which physicians may respond to schedule disruptions, split broadly into two cat-

Figure 1.8: *First Stage Estimates for a 15-Minute Late Previous Patient, Excluding Appointments Likely to Exhibit Selection*



Note: This figure presents first stage results of Equation 1.3, predicting current appointment start time as a function of the previous patient's office arrival time, excluding appointments likely to exhibit selection due to certain patient or appointment characteristics. Each point depicts the change in appointment start time resulting from a 15-minute late previous patient, with bars showing 95% confidence intervals.

egories: time-costly physician inputs and follow-up care. Time-costly physician inputs include exam time, procedure count (Current Procedural Terminology [CPT] codes), allowed charges, coded visit intensity, and diagnosis count (International Classification of Diseases, 9th edition [ICD-9]). I use diagnosis count as a proxy for how many conditions were discussed, classifying each diagnosis as “new" or “established", based on whether it has previously appeared on any claim for that patient between January 1, 2010 and the appointment date.

I also examine a group of possible time-economizing strategies that physicians may employ, when running behind schedule, including deferred clinical documentation and blow-off behaviors. I create an indicator for deferred documentation (equal to one if time stamps indicate that the physician returned to the EHR after ending the appointment). While I cannot observe blow-off behaviors directly, I do observe subsequent visits made by a patient to either that physician or a hospital (when the PCP practices within a group with an inpatient setting). I create an indicator for whether the patient revisited their PCP or was hospitalized within two weeks.[8] These measure are challenging to interpret, as a revisit or hospitalization could happen for a variety of reasons. The physician may have instructed the patient to book another appointment in the near future or the patient may seek additional care for worsening symptoms. Regardless of the motivation for a follow-up visit or hospitalization, any increase in these measures represents a financial cost to the patient and broader health care system.

Finally, I examine ordering behavior for follow-up care. The conceptual framework predicts that physicians may modify ordering behavior for follow-up care when they are running behind schedule. I observe orders for lab tests, imaging tests, referrals to specialists, and prescription medications - and link these to an appointment using patient-physician-practice-date combinations. For prescriptions, I am able to classify them as “new" or “existing" based on whether they have received an order for that medication (from any provider) since January 1, 2010. I can also identify changes to existing prescriptions (e.g., strength or dosage changes) and changes within a therapeutic class (e.g., substitutions between antidepressants).

[8]For specifications with hospitalization as the dependent variable, I restrict my sample to appointments at physician offices that are affiliated with a hospital. By doing this, I can plausibly observe hospitalizations, assuming the patient goes to an affiliated hospital.

1.6 Results

The conceptual framework in Section 4.3 predicts that physicians respond to a schedule disruption by shortening total appointment duration, reducing other time-costly inputs, and potentially changing their ordering behavior regarding follow-up care for the patient. This section presents results testing these predictions, followed by robustness checks and placebo tests.

1.6.1 Do Physicians Speed Up When They Run Late?

I begin by examining the effect of appointment start time on exam duration. I instrument for appointment start time at time t with the office arrival time of the physician's previous patient at time $t-1$. The first panel of Table 1.4 reports results of 2SLS estimation of observed appointment duration as a function of predicted appointment start time, using the full analytic sample. In this and all subsequent specifications, I control for patient characteristics (age, gender, insurance, new patient status, and chronic condition indicators), appointment characteristics (scheduled duration and indicators for whether the appointment is a same-day visit or double-booked), and time fixed effects (appointment rank within the day, day of the week, season, and year). The coefficient on minutes behind is negative and significant, indicating that physicians speed up as they run increasingly behind schedule. For every additional 7 minutes of appointment start time (relative to the scheduled start time), physicians shorten the appointment by an average of 1.28 minutes (s.e. = 0.054). Given that the average appointment in my sample lasts 4.4 minutes less than its scheduled amount of time, this represents an almost 30% decrease in observed duration relative to scheduled duration.

In the remainder of Table 1.4, I examine heterogeneity in physician response to a late appointment start. First, I limit my sample to appointments occurring in the second half of physician days. With fewer appointments remaining to "catch up" during, one might expect physicians to speed up more in response to a schedule disruption during the second half of their day. As predicted, Panel 2 of Table 1.4 shows that physicians speed up more in response to a schedule disruption when they have fewer remaining appointments.

I also examine heterogeneity by physician scheduling patterns. The analytic sample includes 10,

Table 1.4: *Physicians Speed Up When Running Late*

	(1) 2SLS	(2) Reduced Form	(3) Mean
Analytic Sample			
Observed Duration	-0.1821***	-0.0153***	13.6
	(0.0079)	(0.0006)	
Observations	4,253,010	4,253,010	
2nd Half of Day			
Observed Duration	-0.2213***	-0.0145***	13.6
	(0.0149)	(0.0008)	
Observations	2,147,070	2,147,070	
Single Duration Physicians			
Observed Duration	-0.2002***	-0.0182***	13.6
	(0.0367)	(0.0029)	
Observations	766,598	766,598	
All Duration Physicians			
Observed Duration	-0.1572***	-0.012***	12.7
	(0.0216)	(0.0015)	
Observations	998,203	998,203	

Note: Full controls are used, including patient characteristics (age, gender, insurance, new patient status, and chronic condition indicators), appointment characteristics (scheduled duration and indicators for whether the appointment is a same-day visit or double-booked), and time fixed effects (appointment rank within the day, day of the week, season, and year). Standard errors are clustered at the physician level. * denotes significance at 10% level, ** denotes significance at 5% level, and *** denotes significance at 1% level.

15, 20, and 30-minute appointments, but physicians use very different mixes of these possible durations. Roughly 10% of physicians in my sample schedule appointments of a single duration (15 minutes is the most common single duration), while the majority of physicians schedule a mix of 15- and 30-minute appointments. Another $\approx$ 15% of physicians schedule appointments of all four durations (10, 15, 20, and 30 minutes). Physicians who schedule multiple appointment durations may do so to maximize expected net patient benefit over a day. These physicians may respond differently to a schedule disruption, knowing that a complicated patient later in the day has a 30-minute appointment, rather than the same 15-minute appointment as his uncomplicated peers. Panels 3 and 4 of Table 1.4 report the effect of running behind schedule on excess appointment duration, splitting the sample according to physician scheduling patterns. I find that physicians who only schedule one appointment duration reduce excess duration more that physicians with all four appointment duration templates, in response to the same 7 minute delayed appointment start time perturbation (1.40 minutes [s.e. = 0.252] vs 1.10 minutes [s.e. = 0.151].

1.6.2 How Do Physicians Speed Up?

Having established that physicians reduce total appointment duration in response to a schedule disruption, I now examine how physicians' use of time-costly inputs varies as a function of minutes behind schedule. I find that physicians reduce both time spent with a patient and use of time-costly inputs in response to a schedule disruption. Table 1.5 shows that physicians significantly reduce billed procedures when they run late. In response to a 7 minute delay in appointment start time (relative to scheduled start), physicians reduce their procedure billings by 0.06 CPT codes (s.e. = 0.011), which is a 3.2% decrease relative to the average of 1.89 CPT codes per appointment.

The count of recorded diagnoses (ICD-9 codes) also decreases as a function of appointment start time. A 7 minute delayed appointment start resulting in 0.04 fewer diagnoses (s.e. = 0.007) on a sample mean of 2.90 ICD-9 codes recorded. If each diagnosis is a condition, this finding indicates that physicians speed up by addressing fewer discrete conditions - a result consistent with previous research - in addition to shortening the time devoted to each condition [124].

Table 1.5: *Physicians Speed Up by Doing Less During the Appointment*

	(1) 2SLS	(2) Reduced Form	(3) Mean
Other Inputs			
Procedure Count	-0.0081***	-0.0007***	1.89
	(0.0015)	(0.0001)	
Diagnosis Count	-0.0059***	-0.0004***	2.90
	(0.0011)	(0.0001)	
Spending	-0.1489	-0.0128	$113.5
	(0.0985)	(0.0084)	
Visit Intensity	-0.0211	-0.0025	3.52
	(0.0434)	(0.0074)	
Overlapping Appointment	0.0183***	0.0015***	0.49
	(0.0006)	(0.0000)	
Post-Visit Documentation	0.0017***	0.0010***	0.51
	(0.0004)	(0.0001)	
Revisit within Two Weeks	0.0006**	0.0001***	0.13
	(0.0003)	(0.0000)	
First Stage			
Appt Start Time	0.2917****		
	(0.0094)		
Observations	4,253,010	4,253,010	
Practices with Inpatient Setting			
Ambulatory Care Sensitive Condition	-0.00006	-.000001	0.0002
Hospitalization within 2 weeks	(0.00004)	(0.00001)	
Observations	453,059	453,142	

Note: Full controls are used. Standard errors are clustered at the physician level. To examine multitasking as an outcome, I have reincorporated overlapping appointments into the sample. An appointment is considered to have an available inpatient setting when the physician works at a practice with inpatient hospital or emergency room claims. * denotes significance at 10% level, ** denotes significance at 5% level, and *** denotes significance at 1% level.

However, it may also indicate that physicians simply document fewer conditions, despite having discussed them.

Despite the evidence that physicians shorten appointments, perform fewer procedures, and record fewer diagnoses in response to a schedule disruption, I find no evidence that their reimbursement suffers. Table 1.5 reports negative coefficient on both spending and coding intensity,[9] but neither are statistically significant. This is not surprising, as evaluation & management (E&M) codes are the bulk of physician reimbursement; the average E&M CPT code reimbursement is $96, compared to an average of $31 for non-E&M codes. Any decrease in the intensity level of appointment billed, would be reflected in total appointment spending.

I find evidence that physicians are more likely to multitask - seeing multiple patients at once and going between rooms - when running late. Reincorporating overlapping appointments,[10] I find that a 7 minute delay in appointment start time increases the likelihood that the appointment will overlap with another by 12.8 percentage points (s.e.=0.004), or 26% on a base of 49%.

In addition to doing less during the appointment and multitasking, physicians seem to push some time-costly inputs to a later time or date. In response to a schedule disruption, PCPs defer documentation to a time outside of and after the appointment. For a 7 minute delay in appointment start time, the likelihood of post-appointment documentation increases by 1.1 percentage points (s.e. = 0.003), or 2.3% on a base rate of 51%. Appointment documentation may be a task with particular flexibility on timing, given that it only requires physician effort and does not rely on labor supplied by any other mid-level provider or administrative staff. However, this outcome raises particular concern regarding physician burnout, given research showing that documentation consumes nearly twice as much time as patient care and is a major source of job dissatisfaction [110, 111, 117].

I also find suggestive evidence that physicians postpone patient care when running late. Table 1.5 reports the likelihood that a patient revisits that physician within two weeks. A 7 minute delay in appointment start time results in a 0.4 percentage point increase (s.e. = 0.002), or 3% on a base

[9] This ranges from a level 1 to a level 5 visit

[10] My main sample excludes appointments with overlapping time stamps because I cannot accurately observe how much time the physician spent with either patient.

rate of 13%. This finding has multiple possible interpretations: the physician could be directly encouraging the patient to reschedule another appointment soon or the patient may return earlier because a condition that wasn't addressed during the initial appointment has worsened. To provide context for this figure, a back-of-the-envelope calculation suggests that a 1% increase in annual primary care office visits is roughly 5 million additional appointments, at a cost of almost $600 million.[11]

A weakness of my data is the inability to track patients when they see a provider in a non-office care setting. However, a subsample of the data provider's clients have an emergency room or inpatient hospital setting. If the patient receives care there, I will observe it in my data. The final panel of Table 1.5 reports results for physician appointments occurring within a practice affiliated with an inpatient setting. I construct a binary indicator for the existence of an inpatient hospital admission for a chronic "ambulatory care sensitive condition" within two weeks of a primary care appointment in my sample. Ambulatory care sensitive conditions are those for which outpatient care could potentially prevent the need for hospitalization (e.g., a patient with diabetes may be hospitalized for diabetic complications if inadequately monitored or educated in self-management). The rate of these potentially preventable hospitalizations is a frequently-used quality measure at the provider or market level [5]. I do not find any evidence that a patient is more likely to be hospitalized for an ambulatory care sensitive condition after seeing a physician running behind schedule.

Table 1.5 also presents reduced form results, which can be interpreted as incorporating all ways in which a late patient affects physician decision making during the subsequent visit. While the primary effect of a late patient is to delay the physician, it is possible that stress or other factors generated by patient lateness may affect physician decision-making. Reduced form estimates are smaller in magnitude, but similar in direction and statistical significance to the two-stage least squares estimates.

[11] To arrive at this spending estimate, I apply the average appointment-level spending in my sample ($111.25) to 1% of a rough estimate of the number of annual primary care physician office visits: $\$113.50 \times 507,015,000 \times 0.01 = \$575$ million.

1.6.3 Does Speeding Up Affect Follow-Up Care Decisions for a Patient?

Having examined how input use changes in response to an unexpected delay in appointment start time, I now turn to the effect a schedule disruption has on physician decision-making regarding appropriate follow-up care for the patient.

New Conditions

The conceptual framework in Section 4.3 yields different predictions regarding schedule disruption driven changes in follow-up care based on the type of condition addressed. For new or acute conditions, I predict the likelihood of orders for follow-up care to increase as a risk averse physician speeds up and is less likely to observe the patient's true health state. Appointments are likely to include discussion of multiple conditions (based on the average of 2.9 ICD-9 diagnoses per appointment) and, while I can match orders to an appointment, I cannot necessarily match orders to the specific condition they address. For this reason, it is necessary to subset my sample by patient type, to focus on certain types of follow-up care relevant to particular conditions.

I begin by focusing on the effect of running behind schedule when a physician sees a new patient.[12] For this subset of patients, all conditions discussed during the appointment are new (though some conditions may be chronic and this is simply the first discussion between this patient-physician pair) and any orders - labs, prescriptions, imaging, or specialist referrals - placed in this context are more likely to indicate a change in the patient's treatment course. The first panel of Table 1.6 reports results for new patient visits to office-based PCPs. I find no significant change in overall ordering behavior, nor in the likelihood of lab, imaging, or prescription medication orders.

Unlike other order types, the likelihood that a new patient receives a specialist referral increases considerably as their physician falls behind schedule. A 7 minute delay in appointment start results in a 2.0 percentage point increase (s.e. = 0.008) in referrals to a specialist. Relative to a base rate of 13% of appointments resulting in a specialist referral, this is a 16% increase in referral likelihood. To provide context for this figure, a back-of-the-envelope calculation suggests

[12] I define a new patient as any patient that the physician has not submitted a claim for since January 1, 2010.

Table 1.6: *Response of Ordering Behavior to a Schedule Disruption*

	(1) 2SLS	(2) Reduced Form	(3) Mean
New Patients			
Prescription Drug	-0.0006	-0.0000	0.49
	(0.0018)	(0.0001)	
Lab Test	-0.0011	-0.0001	0.37
	(0.0019)	(0.0000)	
Imaging Test	-0.0013	-0.0001	0.18
	(0.0024)	(0.0001)	
Specialist Referral	0.0029**	0.0002**	0.13
	(0.0011)	(0.0001)	
All Orders	0.0005	-0.0000	0.71
	(0.0014)	(0.0001)	
Observations	947,871	947,871	
New Pain Diagnoses			
Opioid Painkiller	0.0004**	0.0003**	0.07
	(0.0002)	(0.0001)	
Non-Opioid Painkiller	0.0008	0.0005	0.13
	(0.0005)	(0.0004)	
Observations	466,430	466,430	
URI Diagnoses			
Antibiotic Order	0.0044***	0.0075***	0.59
	(0.0019)	(0.0025)	
Observations	351,614	351,614	

Note: Full controls are used. URI is upper respiratory infection. New pain diagnoses include any new diagnosis of arthropathies, spinal disorders, or rheumatism. Standard errors are clustered at the physician level. * denotes significance at 10% level, ** denotes significance at 5% level, and *** denotes significance at 1% level.

that a 4% increase in annual specialist visits among new patients is roughly 8 million additional appointments, at a cost of more than $1.4 billion.[13]

Next, I examine patients with a first-time diagnosis of a painful condition, including arthropathies, spinal disorders, and rheumatism.[14] For this subset of patients, opioid painkillers are a relevant prescription drug order. By focusing on appointments where the patient receives a first-time diagnosis of a painful condition, I limit my sample to appointments where I likely observe the initiation of opioid treatment. The second panel of Table 1.6 shows that the likelihood of receiving an opioid prescription during an appointment where a new painful condition is recorded increases as a function of appointment start time. A 7 minute delay in appointment start results in a 0.3 percentage point (s.e. = 0.004) increase in the likelihood of a narcotic painkiller prescription. This is an increase of 4% relative to the base rate of 7% of appointments in this subset that result in an opioid prescription. I also find an increase in non-opioid painkiller prescribing as a function of minutes behind, but this is not statistically significant.

Acute Conditions

The predicted response of a physician to a schedule disruption when treating a patient with an acute condition is similar to that for a new condition. I now examine the subset of appointments for which the physician records an upper respiratory infection (URI) diagnosis, which is likely to be an acute condition. For this subset of patients, antibiotics are a possible prescription drug order - and not always an appropriate one. Public health experts have long been concerned about overprescription of antibiotics for URIs [24]. I examine the likelihood of an antibiotic prescription as a function of schedule disruptions in the final panel of Table 1.6. I find that a 7 minute delay in appointment start time increases the likelihood of a patient receiving an antibiotic prescription by 3.1 percentage points (s.e. = 0.013), or 5% relative to the sample mean of 59%.

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[13] To arrive at this spending estimate, I apply the average appointment-level spending in the full athenahealth dataset for physicians with a non-primary care specialty ($161.76) to 16% of a rough estimate of the number of annual specialist visits, scaled by the proportion of patients in my analytic sample who are new (12.9%): $\$161.76 \times 421,584,000 \times 0.16 \times 0.129 = \$1.41$ billion.

[14] I define a new diagnosis as anything that has not previously been recorded on any claim for that patient.

Table 1.7: *Likelihood of a Prescription Modification*

	(1) 2SLS	(2) Reduced Form	(3) Mean
Any Change to Prescription	-0.0008**	-0.0002**	0.9
	(0.0003)	(0.0000)	
Strength Change	-0.0004	-0.0000	0.05
	(0.0003)	(0.0000)	
Brand Name Switch	-0.0005**	-0.0001**	0.05
	(0.0002)	(0.0000)	
Observations	4,253,010	4,253,010	

Note: Full controls are used. Standard errors are clustered at the physician level. * denotes significance at 10% level, ** denotes significance at 5% level, and *** denotes significance at 1% level.

Established Conditions

The conceptual framework in Section 4.3 suggests that physicians may respond differently to a schedule disruption when deciding on follow-up care for a chronic condition. In Table 1.7, I look at the likelihood of modifying an existing prescription as a function of appointment start time.[15] I find that a 7 minute delay in appointment start time results in a 0.6 percentage point (s.e. = 0.002) reduction in the likelihood of any change to an existing prescription. In my sample, roughly half of the changes to existing predictions are changes in medication strength, while the other half are brand name changes within a therapeutic class. The decrease in overall prescription modifications as a function of minutes behind schedule is driven by a significant decrease in the likelihood of a brand name change within therapeutic class. The same 7 minute delay in appointment start results in a 0.3 percentage point (s.e. = 0.001) reduction in the likelihood of a brand name change, which is roughly an 2% decrease relative to the sample mean of 5%. If switching brand name medications is a more drastic change than adjusting the strength of the same medication, this result suggests that physicians are particularly likely to avoid making major treatment course changes when running late.

[15]I identify existing prescriptions as any prescription submitted by any physician on a date prior to the current appointment. This includes prescriptions ordered during or outside of an appointment.

1.6.4 Robustness Checks

As discussed in Section 1.5, the start time of appointment t may be a function of patient arrival time prior to $t-1$ (my primary instrument). In Figure 1.6, I show that a late-arriving patient at time $t-2$, $t-3$, $t-4$, and $t-5$ continues to significantly delay the appointment start time at time t. However, the effect of a late patient decreases with temporal distance. I repeat my main regressions using each of the four possible alternative instruments and present these results in Table A.2. I find that a delayed start caused by a late patient at time $t-2$ through $t-5$ results in a shortened appointment at time t. Changes in observed appointment duration and documentation deferral remain significant through multiple sequential instruments, while other coefficients are directionally similar, but insignificant.

I also construct an instrument for appointment start time that is a binary indicator of whether the physician's previous patient arrived at the office after their scheduled appointment start time - rather than a continuous measure of patient arrival time at $t-1$. Like the continuous instrument, this binary instrument has a strong first stage, with a late previous patient adding an additional 1.35 minutes (s.e.=0.06) to the current appointment's predicted start time. Again, physicians respond to a delayed appointment start time by truncating the appointment duration, billing fewer procedures, recording fewer diagnoses, and deferring appointment documentation (Table A.3).

Finally, I construct an instrument for appointment start time that is the log of the previous patient's arrival time. I find that a 10% increase in previous patient arrival time delays the start of the current appointment by 0.2% (s.e. = 0.02%). A 10% increase in appointment start time reduces the observed appointment duration by 4.9% (s.e.=0.5%), procedure use by 0.03 CPT codes (s.e. = 0.009), spending by 0.5% (0.003%), and diagnosis count by 0.02 ICD-9 codes (s.e. = 0.007). The likelihood of deferred appointment documentation increases by 0.07 percentage points (s.e. = 0.002) and a revisit within 2 weeks by 0.002 percentage points (s.e. = 0.0002) (Table A.3).

Placebo Tests

To confirm that my results are not spurious, I conduct the following placebo tests. I instrument for appointment start time using the office arrival time of a physician's *subsequent* patient. I present results of this placebo tests in Table A.4. As anticipated, I find that the subsequent patient's office arrival times (for appointments $t + 1$ and $t + 2$) are not predictive of the current patient's appointment start time.

To test my finding regarding increased likelihood of patient revisit to the PCP within two weeks, I create an indicator variable for whether the patient revisited the PCP within two weeks for an appointment that had already been scheduled prior to the current visit. Schedule disruptions should not affect the likelihood that a patient keeps an already-scheduled appointment in the future. I present results in Table A.5. As anticipated, I find that a 7 minute delay in appointment start time results in a statistically insignificant change in the likelihood of a *previously scheduled* patient revisit to the PCP within two weeks.

1.7 Implications and Conclusion

At the individual appointment level, the magnitudes of my findings are modest. A 15-minute late previous patient delays the current patient's appointment by an additional 7 minutes. In response to the unexpected schedule disruption, physicians reduce input use by 1 to 4%, depending on the input (i.e., procedure use, time). They also modify ordering behavior for certain relevant patient populations (e.g., new patients, patients with a new pain diagnosis or upper respiratory infection) by 3-5%.

To appreciate the broader impact of schedule disruptions, consider that nearly four out of five physician-days in my sample contain one or more late-arriving patients. More than 15% of the days in my sample include a patient who arrived at least 15 minutes late, resulting in changes in input use and ordering behavior for subsequent appointments. One in seven of all appointments followed a 15-minute late patient closely enough to delay the start time and affect the physician's decision-making.

My identification strategy relies on one source of plausibly exogenous variation in appointment start time, but many other factors likely contribute to a late appointment start. As physicians' time becomes an increasingly scarce resource, appointment schedules may adapt in a few possible ways: more appointments, denser appointment schedules, and/or shorter appointments. I examine the association between these three possible changes and schedule disruptions, specifically how accumulated daily "lateness" (i.e., how late the day's last appointment started - how late the day's first appointment started) responds. I find that all three of the possible schedule changes are associated with an increase in accumulated daily lateness.

First, physicians may add appointments to the day. In my analytic sample, I find that each additional appointment in a physician's day adds almost half a minute, on average, to accumulated daily lateness. Second, appointment schedule density may increase, with more double-booked appointments or fewer non-scheduled blocks of time. In my analytic sample, I find that a 10 percentage point increase in the number of double-booked appointments adds roughly 2 minutes to a physician's accumulated daily lateness. The same 10 percentage point increase in the share of in-office time devoted to patient care adds 3 minutes to a physician's accumulated daily lateness. Finally, appointment schedules may respond by shortening the time allotted to each patient. I examine the association between the daily share of short appointments (i.e., those scheduled for 10 or 15 minutes rather than 20 or 30 minutes) and the accumulated daily lateness. I find that a 10 percentage point increase in the share of short appointments adds 1 minute to a physician's accumulated daily lateness.

The association between possible appointment schedule changes (i.e., more appointments, denser appointment schedules, and/or shorter appointments) and schedule disruptions suggests two implications. First, more time-series data on primary care appointment scheduling are needed to understand how physicians respond to increased demands on their time. Ideally, these measures will *not* be derived from physician or patient surveys. Instead, these measures should be derived from utilization data with time-stamps, a type of data that is quite new to the health economics community and may require a reorientation towards proprietary data sources. Second, if physicians respond to increased time pressure in any of the ways described above, this will likely have implications for spending and quality of care.

1.7.1 Conclusion

In this paper, I show that schedule disruptions (specifically, running behind schedule) affect the input use and ordering behavior of office-based primary care physicians. In response to a delayed appointment start, PCPs spend less time with the patient, bill fewer procedures, record fewer diagnoses, and defer appointment documentation to after the appointment. A patient whose physician is running late is more likely to revisit that physician within the next two weeks, however likelihood of a potentially preventable hospitalization does not change. I find some evidence that a schedule disruption induces physicians to order more follow-up care for a new condition or complaint (i.e., specialist referrals for a new patient, antibiotics for a patient with an upper respiratory infection, opioid painkillers for a patient with a new diagnosis of back pain), but to decrease orders that change the existing course of treatment for an established condition.

My findings are relevant to multiple actors at various levels of the health care system. For policymakers and private payers, my findings suggest an unintended consequence of steadily squeezing primary care physician's appointment schedules. Whether the increasing scarcity of physician time is driven by increased documentation and quality reporting requirements or major insurance expansions, my results suggest that more schedule disruptions and shorter effective appointment times may have implications for health care spending and quality. Specifically, more frequent return visits to a PCP and specialist referrals place upward pressure on health care spending. Care quality may suffer if physicians increase use of contraindicated care (e.g., antibiotics for certain conditions) in response to a schedule disruption. Additionally, schedule deviations may be one factor that contributes to decisions of particular concern to policymakers, like opioid prescribing. To the extent that policymakers and payers are concerned about these outcomes, it may be appropriate to take legislative or regulatory action to modify the administrative requirements placed on physicians.

My results may also have bearing on discussions regarding expansion of the primary care workforce. I find that physicians respond to schedule disruptions by deferring appointment documentation. Current research estimates that physicians do nearly two hours of EHR and desk work for every one hour of direct clinical face time with patients. Given the clear relationship between administrative work and job dissatisfaction, increasing the time spent on such tasks poses the threat of exacerbating the already accelerating primary care physician burnout rates.

Finally, my results may have implications at the physician practice level. I find that certain scheduling patterns seem to weather the schedule disruption storm better than others. For example, physicians who schedule single-duration appointments (e.g., only 15-minute appointments) shorten appointment duration more than their multi-duration peers as they fall behind schedule. This finding may suggest a role for targeted clinical decision support, deployed in clinically questionable areas (e.g., antibiotic prescriptions for upper respiratory infections) as physicians run increasingly behind schedule. Additionally, there may be a welfare-improving role for appointment schedule innovations that incorporate existing data on patients into future scheduling decisions.

Part II

Provider Consolidation

Chapter 2

Association of Financial Integration Between Physicians and Hospitals with Commercial Health Care Prices

Hospital employment of physicians and ownership of physician practices has increased during the past decade [58, 63, 65, 95]. For hospitals and health care systems, financial integration with physicians may boost referrals for hospital inpatient and outpatient services and help to meet the challenges of new payment models that hold health care provider organizations accountable for spending across the full spectrum of care. For physicians, the resources and economies of scale offered by hospitals may be attractive as administrative and infrastructure costs of independent practice grow [22, 58, 86].

Conceptually, physician-hospital integration could increase or decrease spending on health care. Integration could yield efficiencies through better coordination and management of health care, but it could also strengthen the bargaining power of provider organizations over insurers, leading to higher commercial health care prices. Because evidence of efficiencies from physician-hospital integration is limited [20, 50, 68], even in the context of alternative payment models, such as accountable care organizations [76], concerns have been raised that any reductions in health care use achieved by new payment models [64, 76, 78, 122] could be offset by higher prices negotiated by provider organizations consolidating in response to them [8, 107].

Although the price-increasing effects of hospital mergers have been well documented [41, 50, 51, 106], less is known about the effects of consolidation among physicians and between physicians and hospitals. Greater concentration in physician markers has been associated with higher prices for physician services in California [109], and increases in physician market concentration have been associated with price increases for cardiology and orthopedic services [43] and for office visits [13] in national studies. Two regional studies examining the effect of financial integration between physicians and hospitals on hospital prices produced conflicting results [30, 39]. The only national, longitudinal analysis of physician-hospital integration examined prices for inpatient services only and found a positive association between physician-hospital integration and hospital prices for inpatient care [9].

The effect of physician-hospital integration on prices is likely to be greater for outpatient services than for inpatient services because commercial insurers may follow Medicare's outpatient payment system by paying more for services delivered in hospital outpatient settings than for the same services delivered in office settings [80, 127]. Moreover, because hospital markets are much more concentrated than physician markets on average, financial integration between hospitals and physicians may enhance bargaining power more for the physicians than for the hospitals involved. By exerting market power derived primarily from its preexisting share of the hospital market, the integrated entity may be able to command price increases for outpatient physician services by threatening to exclude its affiliated hospitals from an insurer's network [12, 51]. We examined the association between changes in physician-hospital integration from January 1, 2008, through December 31, 2012, and concurrent changes in commercial spending and prices, with a focus on outpatient services.

2.1 Methods

2.1.1 Data Sources

We analyzed deidentified data from the Truven Health MarketScan Commercial Database to assess spending, utilization, and prices in 2008 and 2012. The MarketScan data- base includes inpatient and outpatient claims for a convenience sample of private health care plans and self-insured employers. Because MarketScan data lack identifiers for provider organizations, we used Medicare claims to measure physician-hospital integration at the level of metropolitan statistical areas (MSAs) and linked this information to MarketScan data for each enrollee based on the MSA in which the enrollee resided. Our study was approved by the Harvard Medical School Committee on Human Studies. Because the data were deidentified, the committee deemed the study not to be human subjects research. Consequently, we did not have to apply for a waiver of informed consent.

2.1.2 Study Population

To focus our analyses on fee-for-service spending and prices, we limited our study population to enrollees in preferred- provider organization or point-of-service plans. Because MarketScan data vary geographically in representativeness and included an increasing number of employers and health insurance plans during the study period, we applied 2 restrictions to improve consistency across years and market representativeness in each year. First, we included only enrollees who were present in MarketScan data in 2008 and 2012. Second, we restricted our analyses to MSAs in which the non- elderly MarketScan preferred-provider organization and point-of-service populations constituted at least 15% of the total population of enrollees in these plans as quantified using HealthLeaders InterStudy data on commercial enrollment by plan type.

Because we used Medicare claims to assess physician- hospital integration, we further excluded MSAs with few physicians billing Medicare to focus analyses on MSAs with greater overlap between the physicians represented in each claims database (Appendix B). Our final study sample included 7,391,335 non-elderly enrollees in 2008 and 2012 in 240 MSAs (of 381 MSAs in the

United States).

2.1.3 Study Variables

Physician-Hospital Integration

To measure physician-hospital integration, we exploited a feature of the Medicare outpatient payment system. When a service is provided in a physician practice owned by a hospital, as in a hospital outpatient department (HOPD), Medicare pays a reduced professional fee (a reduced practice expense) and an additional facility fee, with the total payment exceeding what a physician would receive for rendering the same service in the office setting, often substantially so [80, 120]. Subject to a few additional conditions beyond ownership by a hospital, the physician and hospital can legally bill Medicare at the higher HOPD rate even if the physician's practice is not located on the hospital's campus [3]. The payment differential between HOPD and office settings provides financially integrated physicians and hospitals with a strong incentive to bill outpatient services at the HOPD rate, which requires a change in place-of- service code from office to HOPD on claims for physicians' professional services.

Using Medicare Carrier (physician/supplier) and Outpatient claims for a random 20% sample of beneficiaries in 2008 and 2012, for each physician in each MSA in each year we calculated the share of claims for outpatient care that was billed with an HOPD setting code. For each MSA in each year, we then calculated the proportion of physicians billing exclusively with an HOPD setting code. In a sensitivity analysis, we alternately specified this MSA-level measure of physician-hospital integration as the proportion of physicians with 25%, 75%, or 95% of their outpatient claims billed in this manner (Appendix B).

Increases in our claims-based measure of physician- hospital integration could result from the acquisition of physician practices by hospitals, physicians leaving or closing their practices to join hospital-owned practices, or market entry of integrated systems. In a validation analysis of the 10 MSAs with the greatest increases in physician-hospital integration accord- ing to our measure, we found (via web searches) public reports of major acquisitions or market entry causing greater financial integration between physicians and hospitals in all 10 MSAs .

Physician, Hospital, and Insurance Market Concentration

To control for other changes in provider organization or in- surer market structure that also may have affected prices during the study period, we constructed Herfindahl-Hirschman indices (HHIs) measuring hospital, physician, and insurance market concentration in each MSA in 2008 and 2012 (Appendix B). The HHI is a standard economic measure of concentration, calculated for each market as the sum of the squared market shares multiplied by 10 000, where higher numbers indicate a more concentrated market (in the extreme, a market served by a single provider organization or insurer would have an HHI of $1^2 \times 10,000 = 10,000$).

We constructed the hospital market HHI with 2008 and 2012 data from the American Hospital Association Annual Survey Database, using each hospital's share of admissions in an MSA as its market share and accounting for common hospital ownership in hospital systems. For the physician mar- ket HHI, we used Medicare Carrier claims from 2008 and 2012 to calculate the market share of each group of physicians bill- ing under a common taxpayer identification number (TIN) - specifically, the proportion of allowed charges for outpatient care in an MSA billed by each TIN (Appendix B). Prices in Medicare (allowed charges) are set administratively and are thus unrelated to provider organization mar- ket power. By relying on TINs to identify physician groups, we likely underestimated physician market concentration be- cause large provider organizations often bill under multiple TINs [74], but previous work suggests that physician concentration measures using TINs are highly correlated with measures derived from other data identifying physician groups [11]. Finally, we used the HealthLeaders InterStudy data from 2008 and 2012 to create an HHI for insurers by using the proportion of commercially insured lives in each MSA covered by each insurer as the insurer's market share.

We conducted 2 analyses to examine whether changes in prices associated with physician-hospital integration may have been explained by concurrent changes in physician or hospital market concentration. First, we estimated correlations be- tween MSA-level changes in physician-hospital integration and changes in physician or hospital market concentration. Second, we estimated the association between physician- hospital integration and spending with and without adjustment for physician and hospital market concentration.

Additional Covariates

To adjust for other time-varying predictors of health care spending in the MSAs, we assessed the unemployment rate, the proportion of the population in poverty, the proportion of the population older than 65 years, and the number of physicians per 1000 residents from the Area Health Resources File and the number of hospital beds per 1000 residents from the American Hospital Association Annual Survey Database and Census Bureau data for each MSA in 2008 and 2012. We also created a health risk score using Verisk Health DxCG Stand Alone Software (v4.1.1, Comprising the Budgeting and Under- writing Bundle for the Commercial, Medicaid, and Medicare Populations), which incorporates age, sex, and diagnosis codes from the prior year to predict spending for each enrollee in the year of interest. Finally, we measured inpatient and outpatient insurance benefit generosity at the plan level, calculated as the annual mean cost-sharing for a set of frequently used services (Appendix B).

Spending and Utilization

For each enrollee in each year, we calculated spending by sum- ming allowed charges for outpatient services (services with office or HOPD place-of-service codes), including facility payments. We also created an outpatient utilization measure equal to the sum of annual service counts for each service, with each service count multiplied by the national mean of allowed charges for the service, and services defined by Current Procedural Terminology codes (Appendix B). By holding the price constant at the national mean for each service, any variation between enrollees in this dollar-denominated mea- sure of utilization (price-standardized spending) indicates a different quantity or mix of services. We similarly calculated annual inpatient utilization by multiplying admission counts for each diagnosis related group by the national mean of allowed charges for that code.

Because spending is the product of price and quantity (i.e., utilization), comparisons of changes in spending vs utilization allowed us to deduce the extent to which changes in spending were driven by changes in prices. For example, a change in spending without a change in utilization must have been caused by a change in prices. We used this method to decompose spend- ing changes into changes in utilization and implied changes in prices rather than to assess prices directly because the data did not reliably support direct assessment of prices in hospital- owned practices but did reliably capture all spending and utilization in these settings (Appendix B).

Differences Between Settings in Prices for Office Visits

Prior research suggests that payment differences in Medicare for services in office vs HOPD settings are likely to be reflected to some extent in prices negotiated between provider organizations and commercial insurers [31]. Therefore, we would expect physician-hospital integration to be associated with higher prices, even if integration did not strengthen provider organizations' bargaining position.

We conducted supplementary analyses of between- setting differences in prices for office visits to determine whether market power likely contributed to price changes associated with physician-hospital integration. Specifically, for each MSA, we computed the difference between the mean payment in Medicare for established patient office visits (Current Procedural Terminology codes 99211-99215) with HOPD setting codes (payment = facility fee + professional fee, including reduced practice expense) and the mean payment for office visits in the office setting (payment = professional fee only, including full practice expense) (Appendix B).

We computed analogous price differentials using MarketScan data and expected these differentials to reflect set- ting-related differences transmitted from the Medicare payment system and price negotiations between commercial payers and provider organizations. If provider organizations' market position did not influence prices in the commercial sec- tor, between-setting price differentials would reflect only differences transmitted from Medicare and therefore would be similar across markets in both the Medicare and MarketScan populations despite variation in physician-hospital integration across markets; some variation in price differentials is expected from geographic adjustments for practice costs in Medicare. Under the scenario in which physician-hospital integration enhances provider organizations' bargaining power over commercial insurers, we would expect the between- setting price differentials to vary more widely across MSAs in the commercial sector than in Medicare. Our analytic approach does not distinguish between the development of new market power owing to physician-hospital integration and the transference of preexisting market power from hospitals to physicians, which could allow markups for physician services to rise to levels negotiated by hospitals.

2.1.4 Statistical Analysis

Data analysis was performed from December 1, 2013, through July 13, 2015. We used linear regression to estimate the association between changes in physician-hospital integration and changes in spending or utilization. Specifically, with the enrollee-year as the unit of analysis, we fit a model of annual spending or utilization per enrollee as a function of year (indicator of 2012, with 2008 as the reference year), MSA indicators, MSA-level physician-hospital integration, other MSA- level measures of provider and insurer market structure, and covariates. We included the year indicator to control for national trends and the MSA indicators to control for time- invariant differences between markets. Thus, the coefficient for each market structure term (including physician-hospital integration) equaled the mean change in spending or in utilization associated with a 1-unit greater change in that mea- sure of market structure, adjusting for changes in other measures of market structure and covariates.

The regression coefficients for the physician-hospital integration term yielded estimates of changes in spending or utilization that might occur if a market changed from no integration to full integration or, equivalently, estimates of changes in spending or utilization that might occur for an individual patient if the patient's physicians joined or were acquired by a hospital. To facilitate a realistic market-level interpretation from regression coefficients, we derived estimates of changes in spending or utilization associated with a change in physician- hospital integration equivalent to the 75th percentile of changes experienced by MSAs from 2008 through 2012 (an increase of 5.2 percentage points) while holding all other variables fixed. We report analogous estimates of changes in physician mar- ket concentration. We chose the 75th percentile to scale our estimates because we found little physician-hospital integration occurring in the bottom quartile of the MSAs (and apparent divestitures), and our analysis intended to support inferences about markets where integration occurred.

We weighted observations by the total preferred-provider organization population in the MSA (from the HealthLeaders InterStudy data) divided by the MarketScan population in our study sample in the MSA, giving greater weight to enrollees in MSAs where MarketScan data included smaller proportions of enrollees in preferred-provider organizations. We used Huber- White robust variance estimators to account for correlated data within the MSAs [108, 129]. Sensitivity analyses using generalized linear models with a log link and a proportional-to-mean variance function produced similar estimates. All statistical analyses were conducted using SAS (version 9.4; SAS Institute Inc) and STATA (version 13; StataCorp) software.

2.2 Results

Among the 240 MSAs, the proportion of physicians with billing patterns consistent with financial integration with hospitals increased from 2008 to 2012 by 3.3 percentage points (from 18.0% to 21.3%). This change varied considerably across MSAs (interquartile range, 0.8-5.2 percentage points). Metropolitan statistical areas with above- vs below-median growth in physician-hospital integration exhibited similar changes in other characteristics, including the concentration of physician and hospital markets (see Table 2.1). Across MSAs in 2008, physician-hospital integration was not significantly correlated with hospital market concentration ($r = -0.05; P = 0.47$) or with physician market concentration ($r = -0.03; P = 0.64$). Changes in physician-hospital integration from 2008 through 2012 were weakly and negatively correlated with changes in physician concentration ($r = -0.12; P = 0.05$) and were not correlated with changes in hospital market concentration ($r = -0.03; P = 0.60$). Changes in physician-hospital integration by specialty are presented in Table B.1.

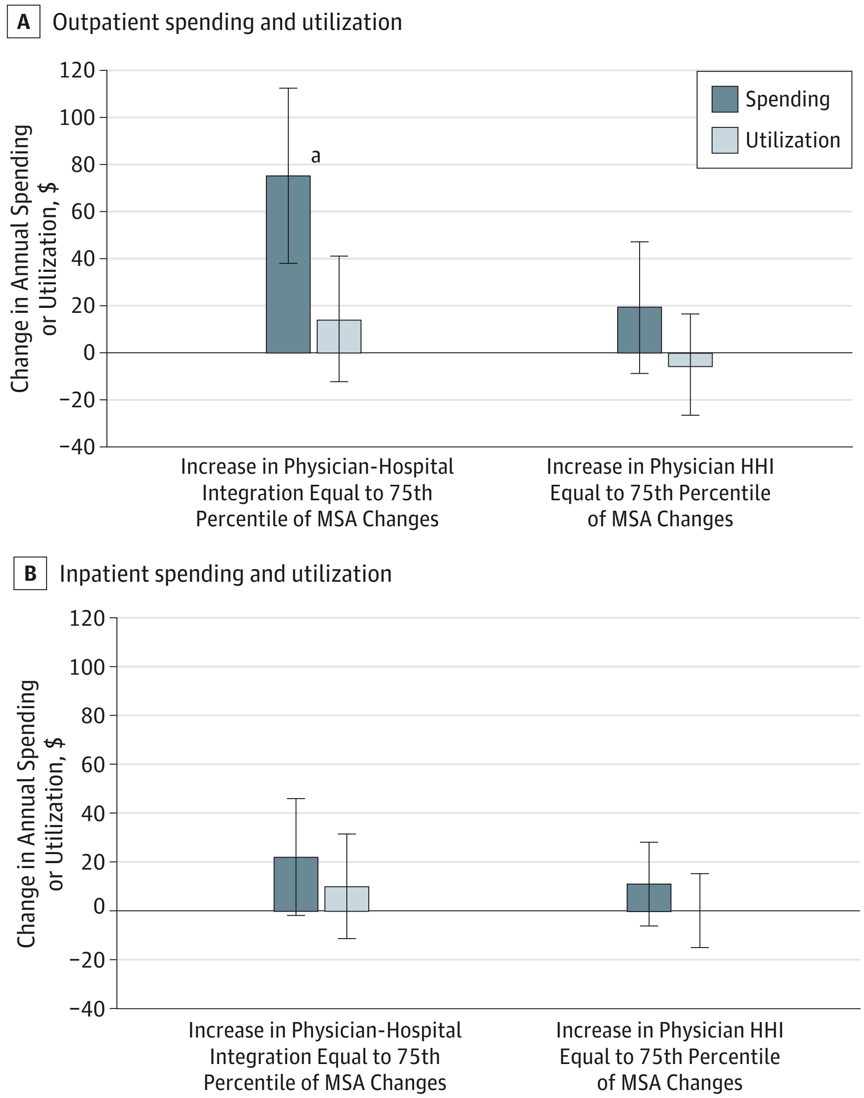
Table 2.1: *Comparison of Changes in Characteristics of MSAs with Above- vs Below-Median Changes in Physician-Hospital Integration from 2008 to 2012*

	Study Year Mean (IQR)		MSA Change in Physician-Hospital Integration Mean (IQR)		
MSA-Level Characteristic	2008	2012	Below Median	Above Median	*P* Value
Physician-hospital integration, %	18.0 (11.9 to 21.5)	21.3 (14.5 to 25.2)	-0.1 (-1.2 to 1.6)	6.8 (3.8 to 7.1)	$<$ .001
Physician HHI	675 (223 to 682)	726 (254 to 724)	54 (-7 to 114)	49 (-12 to 152)	.86
Hospital HHI	3962 (2346 to 5075)	4143 (2566 to 5134)	127 (-41 to 172)	234 (-15 to 314)	.14
Insurance HHI	2441 (1715 to 2716)	2386 (1701 to 2822)	-52 (-414 to 298)	-58 (-341 to 348)	.95
Population aged $\geq$ 16y and unemployed, %	5.7 (4.7 to 6.4)	7.8 (6.5 to 8.9)	2.3 (1.7 to 2.9)	2.1 (1.5 to 2.8)	.20
Population in poverty, %	13.1 (10.5 to 15.3)	15.7 (12.9 to 18.0)	2.6 (1.8 to 3.4)	2.6 (1.8 to 3.4)	.81
Population aged $\geq$ 65y, %	12.9 (10.9 to 14.2)	14.0 (11.9 to 15.0)	1.1 (0.7 to 1.3)	1.0 (0.7 to 1.3)	.82
No. of physicians per 1000 persons	2.79 (1.89 to 3.09)	2.87 (1.94 to 3.17)	0.08 (-0.02 to 0.12)	0.07 (-0.01 to 0.14)	.59
No. of hospital beds per 1000 persons	2.88 (2.02 to 3.46)	2.75 (1.92 to 3.29)	-0.12 (-0.21 to 0.04)	-0.15 (-0.24 to 0.06)	.51
DxCG risk score	0.69 (0.13 to 0.84)	1.18 (0.30 to 1.38)	0.46 (0.36 to 0.51)	0.44 (0.36 to 0.52)	.30
Mean outpatient OOP payment, $	29.23 (20.60 to 31.64)	34.44 (23.99 to 37.83)	4.99 (3.17 to 6.85)	4.35 (3.30 to 6.80)	.44
Mean inpatient OOP payment, $	605.55 (332.66 to 897.92)	796.92 (509.72 to 1196.73)	203.24 (135.29 to 265.26)	200.55 (129.42 to 291.92)	.88

Note: HHI is Herfindahl-Hirschman index. IQR is interquartile range. MSA is metropolitan statistical area. OOP is out-of-pocket. The last column reports *P* values for 2-tailed *t* tests of differences between changes.

For our study sample of 7,391,335 nonelderly enrollees in preferred-provider-organization or point-of-service plans, mean (95% CI) annual spending per enrollee in 2012 was $2407 ($2400-$2414) for outpatient care and $872 ($865-$880) for inpatient care. In adjusted analyses, an increase in physician- hospital integration equivalent to the 75th percentile of changes experienced by MSAs was associated with a minimal change in utilization as measured by price-adjusted spending ($14 [95% CI, -$13 to $41] per enrollee; P=0.32) but a significant increase in annual outpatient spending ($75 [95% CI, $38-$113] per enrollee; $P < 0.001$) or a 3.1% increase relative to mean outpatient spending in 2012. Because spending is the product of price and utilization, this increase in outpatient spending without an increase in utilization suggests that the spending increase was driven almost entirely by price increases (Figure 2.1 and Table B.2).

Figure 2.1: *Adjusted Estimates of Change per Enrollee in Spending and Utilization*



Note: Adjusted estimates of change are associated with increases in physician-hospital integration and physician market concentration from 2008 to 2012. Bars represent the change in spending or utilization (calculated as price-standardized spending) associated with a change in physician-hospital integration or physician market concentration (expressed as Herfindahl-Hirschman index [HHI]) equal to the 75th percentile of changes experienced by metropolitan statistical areas from 2008 to 2012. Error bars denote 95% CIs. Full regression results are given in Tables B.3 and B.4. [a]$P < .001$, Wald test.

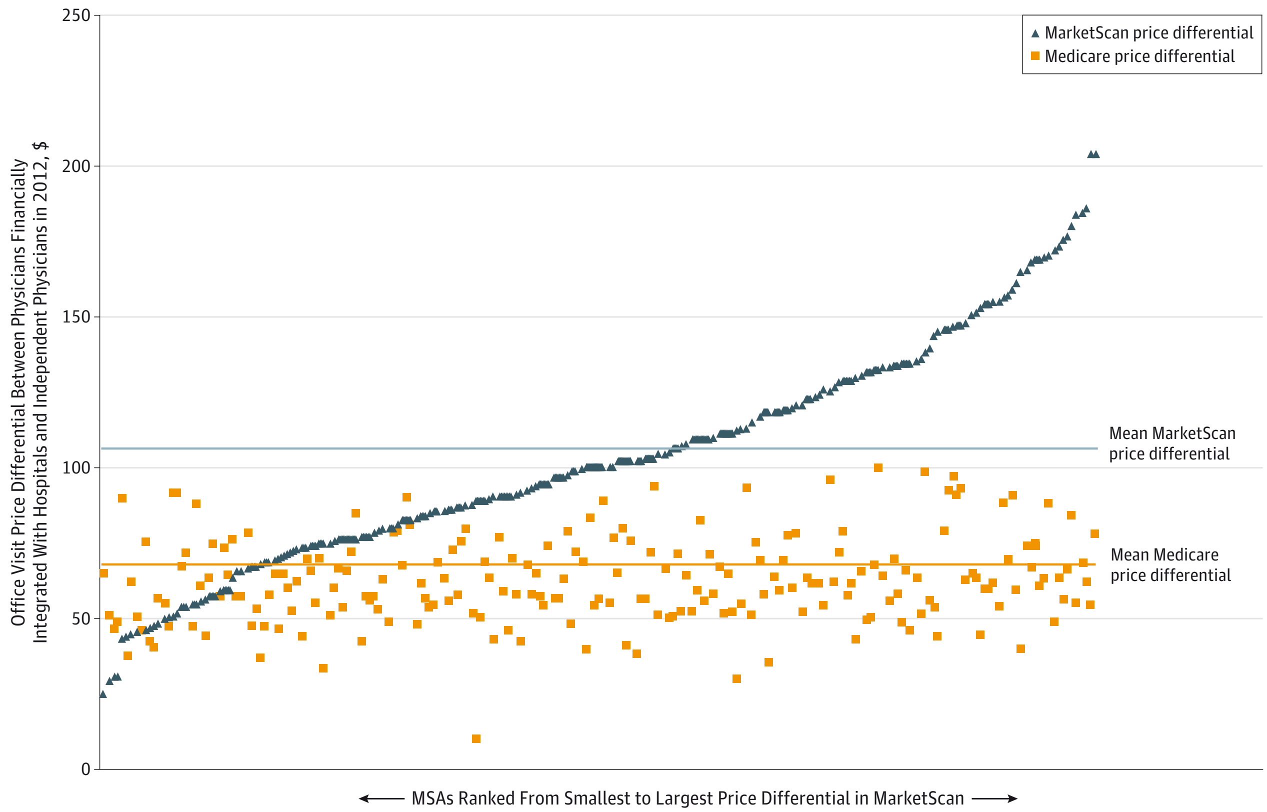
In contrast, greater increases in physician-hospital integration were not associated with significantly greater increases in inpatient utilization (change in price-adjusted spending associated with an increase in physician-hospital integration equal to the 75th percentile of MSA changes,

$10 [95% CI, -$12 to $31] per enrollee; P = .37) or inpatient spending ($22 [95% CI, -$1 to $46] per enrollee; P = .06) (Figure 2.1 and Table B.4). Alternative definitions of physician- hospital integration reduced the increase in inpatient spend- ing by 28% to 62% but did not appreciably affect estimates for outpatient spending (Tables B.4 and B.5). In- creases in physician market concentration were associated with lower utilization and higher outpatient spending, but these associations were not statistically significant (Figure 2.1).

Estimates from analyses adjusted only for enrollee and plan-level characteristics were similar (Tables B.2 and B.3). In addition, the results were not changed substantively by restriction to MSAs with large MarketScan populations (Table B.7), by weighting each enrollee equally (Table B.7), or by use of generalized linear models (Table B.8).

The mean price for an office visit billed with an HOPD setting code was $68 greater than the mean price for an office visit billed with an office setting code in the Medicare population and $108 greater in the MarketScan population. Price differentials varied substantially more across MSAs in the MarketScan population (interquartile range, $77-$134) than in the Medicare population (interquartile range, $54-$73) (Figure 2.2 and Figure B.1).

Figure 2.2: *Differences in Mean Prices for Office Visits Between Independent and Hospital-Integrated Physicians, by MSA for Medicare and MarketScan Populations*



Note: The mean difference between prices for office visits with a hospital outpatient department (HOPD) setting code and those with an office setting code (mean HOPD setting price - mean office setting price) is plotted for each MSA in the Medicare and MarketScan populations (after trimming outliers above the 95th percentile of Medicare and MarketScan price differences in 2012). The MSAs are ordered based on the price differential in the MarketScan Population.

2.3 Discussion

From 2008 to 2012, markets with greater increases in physician-hospital integration exhibited greater increases in spending for outpatient care for a large commercially insured population, almost entirely owing to price increases rather than changes in utilization. In contrast, physician-hospital integration was not associated with higher inpatient prices. These findings are consistent, on average, with hospitals conferring their existing market power to newly employed physicians or acquired practices as the integrated organization negotiates prices for outpatient physician services but not with physician-hospital integration strengthen- ing the organization's bargaining power in negotiating prices for inpatient hospital services.

Differences in prices for office visits between independent physicians and physicians integrated with hospitals were larger and varied across MSAs substantially more in the commercially insured population than in the Medicare population. These pricing patterns provide suggestive evidence that price increases associated with physician-hospital integration did not result solely from transmission of setting-related price differentials in the Medicare payment system but likely also resulted from the enhanced market power of the provider organizations.

Consistent with prior research [20, 50, 73], physician-hospital integration was not associated with lower utilization, suggesting that this form of provider consolidation has not led to gains in health care efficiency in recent years through improved care coordination or management. Efficiencies from physician-hospital integration may only manifest under alternative payment models with incentives to limit utilization, although early evidence from accountable care organizations in Medicare suggests spending reductions were not related to financial integration between physicians and hospitals [76, 87]. Similarly, price increases associated with physician-hospital integration may not generalize beyond the fee-for-service context, although provider organizations with greater bargaining power could negotiate higher global budgets under alternative payment models. Whether new payment models accelerate physician-hospital integration beyond ongoing trends remains to be seen. Although consolidation in the physician market was not associated with significant increases in spending in our study, it was associated with spending increases and reductions in utilization, which together implied sizable price increases consistent with the findings of prior studies [12, 109].

Our study has several limitations. First, changes in unobserved predictors of prices could have contributed to our findings. Changes in observed time-varying characteristics of patients, plans, and providers, however, were generally similar in MSAs exhibiting smaller vs larger increases in physician- hospital integration. Moreover, adjustment for changes in hospital and physician market concentration did not attenuate estimates, suggesting that our results were not likely driven by other unobserved changes in provider market structure correlated with physician-hospital integration.

Second, several sources of measurement error probably led us to underestimate the strength of the relationship between physician-hospital integration and price increases, assuming the error was unrelated to the extent of physician-hospital integration in a market according to our claims-based measure. Some physician practices owned by hospitals may not bill with HOPD setting codes despite the strong financial incentive for the integrated entity to do so. In addition, contractual relationships between hospitals and physicians that do not involve ownership of physician practices by hospitals (eg, physician-hospital organizations) may also enhance bargaining power and would not be detected by our claims-based mea- sure. Within-market differences in the providers represented in the Medicare and MarketScan database claims and sampling error from each data source also likely biased our findings toward the null.

Third, integration between physicians and hospitals mechanically causes greater concentration in the physician market because physician practices become financially integrated through relationships with common hospitals. We could not discern the extent to which this concentration in the physician market contributed to price increases related to physician-hospital integration. Finally, we did not assess quality of care. Improved quality would enhance value in the absence of changes in utilization.

2.4 Conclusions

Increases in physician-hospital integration from 2008 through 2012 were associated with increased spending and prices for outpatient services, with no accompanying changes in utilization that would suggest more efficient care from better care coordination and economies of scale. Changes in the structure of health care provider markets and in spending should be monitored, particularly as payment systems shift away from fee-for-service, and may require additional regulatory measures to control.

Chapter 3

Little Evidence Exists To Support The Expectation That Providers Would Consolidate To Enter New Payment Models

The past few years have seen the rapid expansion of new payment models that hold health care providers accountable for total spending and quality of care for their patients. The Department of Health and Human Services recently announced that it achieved its goal of tying 30 percent of Medicare payments to such alternative payment models by 2016 [112]. The Medicare accountable care organization (ACO) programs are the broadest alternative payment models, with over 460 participating provider organizations in 2016 that collectively covered 23.5 percent of fee-for-service Medicare beneficiaries [55]. These programs set a global budget for total spending for an ACOâĂŹs patient population, with incentives for the ACO to spend less than the budgeted amount and provide high-quality care. Commercial insurers have instituted similar payment systems, and many Medicare ACOs also participate in commercial ACO contracts [77, 88].

Although designed to remedy the incentives of fee-for-service payment systems, payment models that delegate financial risk to providers for the full continuum of patients' care have triggered concerns that providers will consolidate in response [8, 65]. Consolidation may lead to higher prices (or budgets) negotiated with commercial insurers. Thus, while ACOs may reduce spending in the Medicare population, provider consolidation associated with them may increase spending for the commercially insured.

Provider consolidation generally takes one of two forms: horizontal integration (two hospitals merge) or vertical integration (a hospital system purchases a physician group). However, both may be involved in a merger or acquisition (a merger of two health systems). The association between horizontal consolidation and higher prices has been well documented in hospital markets [50], and to a lesser extent in physician markets [11, 44]. Mounting evidence suggests that financial integration between physicians and hospitals also leads to higher prices and spending [9, 93].

3.1 Reasons for Consolidation

There are many possible reasons for the horizontal and vertical consolidations that began before the establishment of the Affordable Care Act (ACA) Medicare ACO programs in 2010. Consolidation may allow providers to negotiate higher rates from commercial insurers, boost the number of referrals or admissions, amass sufficient capital to invest in lucrative services, pool their malpractice risk, compete for physician labor, reconfigure their capacity in response to technological changes that shift care settings, or lower costs (for example, of information technology) through economies of scale. Hospitals and physicians may also consolidate to take advantage of Medicare payment rules that favor providing services in hospital outpatient departments instead of physician offices [120].

3.2 Empirical Evidence and a Widespread Concern

There has been widespread concern that a wave of consolidation would follow the launch of the Medicare ACO programs because providers might seek greater scale and scope to enter and succeed under new payment models [70, 97]. However, little empirical evidence exists to support this fear. While there are conceptual reasons why larger provider organizations might be better suited to succeed in ACO contracts, research suggests that consolidation beyond a modest level may be neither necessary nor advantageous for providers operating under new payment models.

Specifically, while large physician groups exhibit greater structural capacity for care management and perform better than smaller groups on some process measures of quality [38, 104, 105], these gains may be achieved at organizational sizes far smaller than large integrated health systems and have not translated into better patient outcomes or more efficient care [23, 73]. Moreover, previous studies do not support the assumption that establishing direct managerial control through ownership over the full spectrum of patient care is necessary to control spending and improve quality. Studies that compared medical groups and independent practice associations have produced mixed results [81, 105], and hospitals' ownership of physician practices has been associated with higher spending without clear gains in quality [10].

The lack of evidence extends to payment systems that reward more efficient care. Under capitation incentives, large physician groups have exhibited lower spending levels than small practices, but no lower than the levels of medium-size practices [73]. Thus far in the Medicare Shared Savings Program, independent physician groups have generated greater savings than larger vertically integrated organizations have [75, 77]. Organizations that own hospitals and specialty practices have weaker incentives than those that do not to limit use of inpatient and specialty care under ACO contracts, and evidence from Medicare and commercial ACO initiatives suggests that providers can influence the use of care in multiple settings without formal ownership arrangements that unite providers [36, 77, 121].

Finally, if gaining bargaining power in price negotiations with commercial insurers has been the primary motive for consolidation, one would not expect acceleration in provider consolidation to be associated with ACO contracting, because the desire to command higher prices (or budgets) and negotiate better terms exists in both fee-for-service and alternative payment models. Payment reform could even reverse some previous reasons to consolidate, such as pooling resources to invest in service lines that were profitable under fee-for-service but became cost centers under new payment models. Thus, it is not clear that providers participating or preparing to participate in new payment models will consolidate faster than other providers.

However, contrary to the standard narrative, payment reform might prompt some providers to consolidate to preserve their market position, as opposed to consolidating to enter and succeed under risk contracts. Hospitals and specialists in particular might consolidate to rebuff payer pressure to enter risk contracts or to attain sufficient market share to ensure continued referrals from ACOs that might otherwise steer patients to more efficient providers.

3.3 Study Overview

In this study we examined the relationship between Medicare ACO program participation and multiple measures of horizontal and vertical consolidation over time, from before to after the passage of the ACA in 2010. In two complementary analyses, we compared consolidation over time between markets with more versus less ACO contracting in 2014 and within markets between physicians who had entered an ACO contract by 2014 and those who had not.

Our analyses are descriptive but nevertheless useful in gauging the extent of consolidation associated with payment reform under various scenarios. For example, under the prevailing narrative of providers consolidating to enter and succeed under ACO contracts, we would expect increases from the pre- to the post-ACA period to be greater in markets with higher levels of ACO program entry. Because patient populations covered by ACO contracts are defined by where patients receive outpatient care, primarily primary care, under the prevailing narrative we would expect the uptake of ACO contracts in markets to be particularly associated with acceleration in horizontal consolidation among physician practices and vertical consolidation between hospitals and physicians, especially consolidation involving primary care physicians. According to this rationale, we would also expect physician groups that entered an ACO program to exhibit greater consolidation shortly before or after that entry, compared to other physician groups in their markets. In contrast, if providers have consolidated primarily as a defensive response to payment reform, we would expect greater increases among nonparticipating physicians, with ambiguous effects on the market-level relationship between ACO program entry and consolidation over time.

3.4 Study Data and Methods

3.4.1 Data and Population

To assess provider consolidation, we used Medicare claims data for the period 2008-13, data from the American Hospital Association (AHA) Annual Survey for the same period, and data for the period 2008-15 from Irving Levin Associates' Health Care Mergers and Acquisitions Database. We used definitions of ACOs from the Centers for Medicare and Medicaid Services (CMS) to identify physicians and practices participating in ACOs and to assess ACO contracting at the level of the Metropolitan Statistical Area. Finally, we used data from the Truven Health MarketScan Commercial Database to measure commercial health care prices at the same level, as an indirect measure of consolidation that our direct measures might not have reflected.

To calculate annual market-level measures of provider market structure, we relied predominantly on Medicare claims data for a 20 percent random sample of beneficiaries. We excluded small markets with few physicians billing Medicare (Appendix C). Our assessments of provider market structure based on Medicare claims data included 301,855 physician national provider identifiers used to bill under 103,745 tax identification numbers in 289 Metropolitan Statistical Areas. A tax identification number may represent a solo practitioner, a practice, or a larger provider organization. Large organizations typically bill under multiple tax identification numbers.

For within-market analyses, we included only those national provider identifiers or tax identification numbers that were present in Medicare claims data throughout the study period, so that we could assess the organizational characteristics of each provider in every study year, after determining whether or not the provider participated in an ACO contract that started in 2012, 2013, or 2014.

3.4.2 Study Variables

Medicare ACO Participation and Penetration

We used the ACO Provider-Level Research Identifiable File to identify tax identification numbers for provider groups participating in a Medicare Shared Savings Program ACO contract that started in 2012, 2013, or 2014, and we used CMS definitions of Pioneer ACOs to identify national provider identifiers for physicians participating in a Pioneer contract [2]. In 2012, 32 organizations entered the Pioneer program, and 114 entered the Medicare Shared Savings Program. In 2013 and 2014, an additional 106 and 115 organizations entered the Medicare Shared Savings Program, respectively. Based on that program's rules, we attributed each beneficiary to the ACO or non-ACO tax identification number that accounted for the most allowed charges for qualifying outpatient evaluation and management services delivered to the beneficiary by a primary care physician during each year.3 To calculate a measure of ACO penetration at the Metropolitan Statistical Area level, we divided the number of ACO-assigned Medicare beneficiaries in each area by the number of assignment-eligible Medicare beneficiaries in the area (Appendix C).

For within-market comparisons, we classified each physician as participating or not participating in an ACO by 2014. Physicians were identified as participating in an ACO if their national provider identifier was included in a Pioneer contract or if they billed primarily under a tax identification number included in a Medicare Shared Savings Program contract that started in 2012, 2013, or 2014.

Physician-Hospital Integration

To measure physician-hospital integration, we used place-of-service codes in Medicare claims, which distinguished between a service provided in a physician practice owned by a hospital (such as in an outpatient department) and a service provided in an office setting [80]. Specifically, for each year in the study period, we determined each physician' share of Medicare claims for outpatient care that was billed with a hospital outpatient department setting code. We considered physicians to be practicing in a hospital-owned practice if they billed at least 90 percent of their outpatient care with a hospital out-patient department setting code (Appendix C). From this physician-level variable, we calculated the share of physicians in a Metropolitan Statistical Area who displayed billing patterns consistent with physician-hospital integration.

Hospital and Physician Market Concentration

For market-level analyses, we calculated a Herfindahl-Hirschman Index - a standard measure of market concentration - for hospital and physician markets for each year in the study period. Higher values corresponded to greater concentration. Using data from the AHA Annual Survey Database, we defined each hospital's market share as its share of total hospital admissions in a Metropolitan Statistical Area, accounting for common hospital ownership in the case of hospital systems. Using Medicare claims data for professional services and tax identification numbers to define physician groups, we defined each group's market share as its share of total allowed charges for outpatient care in the area. We also explored alternative measures of market concentration, including the four-firm concentration ratio (the total market share of the four largest firms) (Appendix C).

Physician Group Size

For between-market and within-market comparisons, we assessed physician group (tax identification number) size, defined as the number of distinct physician national provider identifiers used to bill under each tax identification number in Medicare professional claims, excluding physicians with inpatient-based specialties. For between-market comparisons, we calculated an average group size at the Metropolitan Statistical Area level, weighting each group by its share of national provider identifiers in the market. This measure can be interpreted as a physician's average practice size in the market. For a supplementary analysis, we also assessed physician group specialty mix, defined as the percentage of national pro- vider identifiers with a primary care specialty used to bill under each tax identification number (Appendix C).

Mergers and Acquisitions

To identify instances of provider consolidation directly, we used data collected by Irving Levin Associates on publicly announced mergers and acquisitions that involved physician groups or hospitals in the period 2008-15 [1]. We used publicly available databases that linked practice names to tax identification numbers to identify the tax identification number or numbers for each acquired physician group. This allowed us to identify physicians who practiced in an acquired group (Appendix C). We linked the acquired tax identification numbers and their constituent national provider identifiers to identifiers for providers that participated in a Medicare Shared Savings Program or Pioneer ACO contract. In within-market analyses, this linkage allowed us to compare changes in rates of acquisition from before to after implementation of the ACA for physicians entering ACO contracts in 2012, 2013, or 2014 versus nonparticipating physicians.

Commercial Prices

With commercial claims data from the MarketScan database, we calculated a price index for inpatient and outpatient care at the Metropolitan Statistical Area level, using a group of services that covered a large share of spending. An index above 1 indicated an area in which mean services prices exceeded the national mean; an index below 1 indicated an area in which those prices were below the national mean (Appendix C).

Insurance Market Structure

We used data on commercial enrollment by plan type for the period 2008-13 from HealthLeaders InterStudy to create a commercial insurance market Herfindahl-Hirschman Index, using the share of covered lives as the measure of an insurerâĂŹs market share, and to assess commercial health maintenance organization (HMO) penetration in each year (calculated as the percentage of commercially insured people enrolled in an HMO). Finally, we used the Medicare Beneficiary Summary File to assess HMO penetration in Medicare (calculated as the percentage of Medicare beneficiaries in a Medicare Advantage HMO).

Between-Market Comparisons

Using linear regression, we compared changes in provider consolidation from 2008-10 to 2011-13 between markets with higher versus lower ACO penetration as of 2014. We used 2008-10 as the pre period because we would not expect significant consolidation in response to the ACO programs before their enactment by the ACA in 2010. Using 2011-13 as the post period gave us

1-3 years of anticipatory consolidation and up to 2 years of consolidation following ACO entry for providers that entered ACO programs in 2012, 2013, or 2014.

We modeled each market-level measure of provider market structure (physician-hospital integration, physician group size, physician market concentration, hospital market concentration, and prices) as a function of an indicator for the post period, an interaction between ACO penetration and the post period, and Metropolitan Statistical Area indicators. The interaction estimated the differential change in provider market structure from the pre period to the post period that was associated with greater entry into Medicare ACO programs, as measured by 2014 ACO penetration. In the models, to adjust for effects of insurance market changes on provider consolidation and prices, we also included commercial insurance market concentration, commercial HMO penetration, and Medicare HMO penetration.

For each measure of provider market structure and prices, to facilitate interpretation of results, we present annual means by quartile of 2014 ACO market penetration.We also estimated overall national trends in the pre period and tested whether these trends changed in the post period. Finally, to explore potential ceiling effects (that is, to see whether ACO contracting occurred predominantly in already concentrated provider markets with less opportunity for further consolidation), we restricted our analyses to Metropolitan Statistical Areas in the lower three quartiles of the distribution for a given measure.

Within-Market Comparisons

To hold market factors constant, we conducted within-market comparisons of changes in organizational characteristics from 2008-10 to 2011-13 between physicians or physician groups that entered an ACO contract by 2014 versus those that did not. The characteristics (linked to physicians via national provider identifiers or to groups via tax identification numbers) included a physician-level indicator of practicing in a hospital-owned facility, physician group size, and a physician-level indicator of practicing in a group acquired by a hospital or other group - all of which we assessed in each study year.

We modeled each characteristic as a function of Metropolitan Statistical Area indicators, a time-invariant indicator for Medicare ACO participation in 2014, an indicator for the post period, and an interaction between ACO participation and the post period. The interaction estimated the differential change from the pre to the post period in organizational structure for physicians who entered the ACO programs in 2012, 2013, or 2014, holding market factors constant. In the analysis of provider group size, we weighted each group (tax identification number) by the number of physicians at baseline in 2008-10 to facilitate our interpretation of results in terms of a physician's average group size, consistent with our between-market analyses.

In a supplementary analysis, we similarly modeled physician group size and primary care orientation after stratifying groups based on their baseline primary care orientation to determine whether any growth in group size was primarily due to the incorporation of more primary care physicians or specialists.

3.4.3 Limitations

Our study had several limitations. First, our analyses were descriptive and do not support causal conclusions about the effects of the ACO programs on provider consolidation. For example, ACO contracting could be associated with provider consolidation not because of the change in payment incentives but because providers that consolidated for other reasons were also more likely to participate in the ACO programs. Nevertheless, by assessing the relationship between ACO contracting and provider consolidation, we were able to observe whether trends were consistent with widely held expectations that new challenges from payment reform would accelerate consolidation as providers integrated to meet those challenges.

Second, changes in market-level drivers of both ACO participation and provider consolidation could have obscured or exaggerated a relationship between the two. In addition, Metropolitan Statistical Areas may not perfectly reflect the market for physician and hospital services. However, our supplemental between-physician comparisons within markets held factors at the area level constant, did not rely on market definitions to assess consolidation, and supported similar conclusions.

Third, we could assess provider consolidation only to the extent that it could be measured with claims data and publicly reported mergers and acquisitions. However, our analysis of prices should have reflected any unobservable provider consolidation, net of any independent effects of ACO contracting on price competition.

Finally, for most measures we could assess consolidation only through 2013 as related to ACO contracting through 2014, and therefore we may have missed more recent consolidation. Our post-ACA period allowed for three years of consolidation among providers planning to enter the ACO programs, however, and approximately one in five fee-for-service Medicare beneficiaries were in ACO contracts by 2014 [55].

3.5 Study Results

3.5.1 Overall Trends

In the period 2008-13 all measures of provider market concentration and prices increased significantly ($p < 0:001$ for annual changes; Table C.1). In the study period, the average Metropolitan Statistical Area experienced a cumulative increase in physician-hospital integration of 6.3 percentage points (from 16.8 percent of physicians in a hospital-owned practice to 23.1 percent); an increase in physician concentration (Herfindahl-Hirschman Index) of 76 points; an increase in average physician group size of 22 physicians; an increase in hospital concentration (Herfindahl-Hirschman Index) of 279 points; and increases in inpatient and outpatient price indices of 28 percent and 14 percent, respectively.

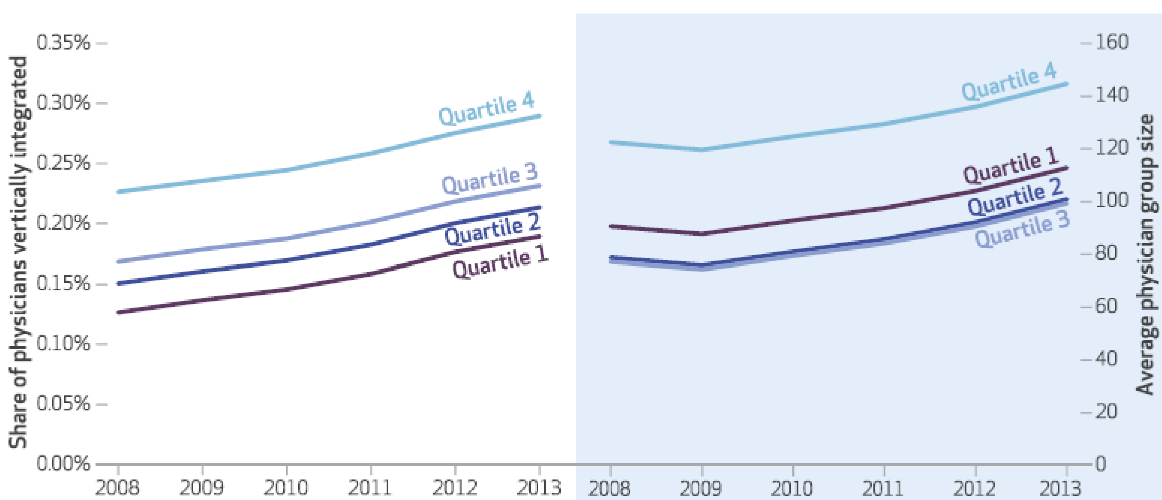
For most measures of concentration and prices, trends changed minimally from the pre period (2008-10) to the post period (2011-13) (Table C.2). However, group size grew much faster during the post period (adding an additional 1.6 physicians per group per year; p=.09). There was also a clear surge in the number of hospital mergers in the post period, but no clear increase in mergers and acquisitions involving physician groups, apart from a spike in 2011 (Table C.2).

3.5.2 Between-Market Analysis

By 2014, ACO penetration had reached an average of 21.3 percent but varied considerably across Metropolitan Statistical Areas (interquartile range: 2.7-32.6 percent) (Figure C.2). Notably, in 2008-10, markets with higher 2014 ACO penetration had significantly higher levels of physician-hospital integration but more competitive hospital and insurance markets and higher commercial HMO penetration (Table 3.1).

In comparisons of provider market consolidation by 2014 ACO penetration, we found that provider market structure differed at baseline by 2014 ACO penetration and changed over time. However, we also found that, compared to markets with lower 2014 ACO participation, those with high participation did not experience greater growth from the pre to the post period in vertical physician-hospital integration or physician group size (Exhibit 3.1) or in physician market concentration, hospital market concentration, or commercial health care prices (Table C.3 and Figure C.3). Our results were similar in sensitivity analyses that focused specifically on hospital integration of primary care physicians, used only Metropolitan Statistical Areas in the lower three quartiles of the distribution for each dependent variable, used an alternative measure of market concentration, or excluded insurance market structure variables.

Figure 3.1: *Provider Market Structure, by Quartile of 2014 Accountable Care Organization Penetration, 2008-2013*



Source: Authors' analysis of data from the Centers for Medicare and Medicaid Services, the

Table 3.1: *Baseline Characteristics in 2008-10 of Metropolitan Statistical Areas (MSAs), Physicians, and Physician Groups, by Accountable Care Organization (ACO) Market Penetration*

	2014 ACO Market Penetration Quartile			
MSA-level characteristic	1(lowest)	2	3	4(highest)
Physician-hospital integration	13.5%	15.7%	18.1%	23.8%**
Mean physician group size	96.2	77.8	75.5	118.6
Mean physician HHI	953	987	547	1,036
Mean hospital HHI	4,950	4,619	3,181	4,703**
Mean insurer HHI	2,958	2,550	2,275	2,480***
Medicare HMO penetration	8.0%	9.4%	11.8%	5.9%
Commercial HMO penetration	16.1%	18.6%	20.9%	21.0%***
Inpatient services price index	0.80	0.80	0.78	0.77*
Outpatient services price index	0.96	0.89	0.92	0.96

Physician- or practice-level characteristics	ACO nonparticipant in 2012,2013, or 2014	ACO participant in 2012,2013, or 2014
Physicians practice in a hospital-owned facility	16.9%	20.2%***
Physician practicing in a group acquired by a hospital or other group	0.1%	0.4%***
Mean physician group size	69.3	130.6***

Source: AuthorsâĂŹ analysis of data from the Centers for Medicare and Medicaid Services, American Hospital Association, HealthLeaders InterStudy, and Irving Levin Associates.
Note: There were seventy-two physician groups in each quartile except for quartile 1, where there were seventy-three. Mean physician group (practice) size was calculated as the average number of physicians billing for outpatient care within a tax identification number, weighting each group by its share of total physicians in the MSA. A practice refers to all providers using the same tax identification number. A price index above 1 indicates an MSA in which mean services prices exceed the national mean; a price index below 1 indicates an MSA in which mean services prices are below the national mean. Significance refers to a chi-square test for trend across quartiles. HHI is Herfindahl-Hirschman Index. HMO is health maintenance organization. $*p < 0.1 **p < 0.05 ***p < 0.001$

American Hospital Association, and Irving Levin Associates.
Note: Average practice (group) size was calculated as the average number of physicians billing for outpatient care within a tax identification number, weighting each group by its share of total physicians in the Metropolitan Statistical Area. Quartile 1 was the lowest level of 2014 ACO penetration and quartile 4 the highest. âĂIJVertical integrationâĂİ refers to the purchase or employment of a physician group by a hospital system.

3.5.3 Within-Market Analysis

In the pre period, compared to physicians who would not be participating in an ACO by 2014, physicians in the same Metropolitan Statistical Area who would later be participating were more likely to be integrated with a hospital, to practice in a large group, and to have their practice acquired by a hospital or physician group (Exhibit 3.2, Tables C.4 and C.5). Of our measures of physician organizational structure, only group size increased differentially by ACO participation. From the pre to the post period, the average group size for physicians who participated in an ACO grew by 11.4 more physicians than for physicians in the same Metropolitan Statistical Area who did not. An analysis of group size and primary care orientation after stratification by baseline specialty mix revealed that this growth in group size was driven largely by the addition of more specialists or specialty practices to organizations that were already large and composed primarily of specialists in the pre period (Figure C.4).

Table 3.2: *Changes in Organization Structure of Physicians and Physician Groups from Before to After Passage of the Affordable Care Act (ACA), by 2014 Participation in Accountable Care Organization (ACO) Programs*

	Not participating in ACO programs by 2014		Participating in ACO programs by 2014		Difference-in-differences over
Physician- or practice-level characteristics	Before ACA (2008-2010)	After ACA (2011-2013)	Before ACA (2008-2010)	After ACA (2011-2013)	time, participants vs. nonparticipants
Physicians practicing in a hospital-owned facility	16.9%	19.3%	20.2%	23.7%	1.1%
Physicians whose practice was acquired by a hospital, hospital system, or medical group	0.1%	0.2%	0.4%	0.3% -0.2%	
Mean physician group size	69.3	77.2	130.6	149.9	11.4**

Source: AuthorsâĂŹ analysis of data from the Centers for Medicare and Medicaid Services and Irving Levin Associates.
Note: Each line results from separate within-market analyses, presenting the average pre- and post-period value of the dependent variable, by 2012, 2013, or 2014 ACO participation. Mean physician group size was calculated as the average number of physicians billing for outpatient care within a tax identification number, weighting each group by its share of total physicians in the Metropolitan Statistical Area. Percentages of practices acquired were calculated as the shares of physicians billing under a tax identification number that was identified as the target of a merger or acquisition in any given year. $**p < 0:05$

3.6 Discussion

Many policy analysts have predicted that providers would respond to the rapid growth of new payment models by forming larger organizations to assume financial risk and succeed under these models. However, we found little evidence to support this prediction.

Markets with greater 2014 ACO participation did not experience differential changes in physician-hospital integration, physician group size, physician market concentration, hospital market concentration or, importantly, commercial health care prices from 2008 to 2013. We found that physicians who entered a Medicare ACO program between 2012 and 2014 showed no differential increase in integration with hospitals or rates of acquisition from the pre to the post period, compared with other physicians in the same market. Physician groups that entered an ACO program did exhibit significantly greater growth in size than other practices in their market. This differential increase in group size among ACO participants was driven largely by the addition of specialists - not primary care physicians - to practices that were already specialty oriented, which suggests that they did not grow in order to become ACOs. For a specialty-oriented group to position itself to enter an ACO contract, one would expect it to reorient itself toward primary care. Similarly, we found no evidence that greater integration of primary care physicians with hospitals from the pre to the post period was related to ACO participation.

We also found an overall increase in hospital mergers after the ACA without changes in hospital market concentration related to ACO penetration, and a significant inverse relationship between hospital market concentration in the pre period and the extent of subsequent ACO contracting. These findings suggest that new payment models may have triggered some consolidation as a defensive reaction to the threat these models could pose, rather than as a way to achieve efficiencies in response to the new incentives. Hospitals and specialists in particular might consolidate both horizontally and vertically to achieve sufficient market share to resist payer pressure to enter risk contracts18 or weaken ACOs' ability to exploit competition in hospital and specialty markets, and compel reductions in prices and service volume. Similarly, rhetoric about the benefits of integration under new payment models may have lent credence to arguments by hospitals and specialists about the clinical efficiencies derived from mergers and acquisitions that would have faced stiffer challenges before the ACA.

3.7 Policy Implications

In general, the overall weak relationship we found between ACO contracting and consolidation from the pre to the post period should ease the concerns that provider consolidation is an inevitable consequence of payment reform [8, 65] - concerns that might support arguments to slow the transition away from fee-for-service payment. Similarly, our findings would not support abandoning ACO-like global budget models in favor of smaller payment bundles to avoid price increases from the types of consolidation that many researchers and policy makers have assumed are required to manage a global budget.

However, our findings do nothing to diminish the importance of the trend toward less competitive provider markets and associated price increases. In fact, we also found suggestive evidence of acceleration in specialist and hospital consolidation potentially related to payment reform but not expected to support new payment models. Our methods could not determine whether this consolidation has been defensive in nature or attributable to other factors, such as those driving consolidation before the ACA. Nonetheless, our findings question the prevailing wisdom that payment reform is driving consolidation of providers as they seek to enter and succeed under new payment models. Thus, even if there has been some defensive consolidation, the weak relationship between ACO contracting and forms of consolidation that would support ACO contracts has important implications for antitrust law enforcement. Specifically, our study supports skepticism of claims by providers that they are consolidating primarily to engage in risk contracts and achieve efficiencies.

Part III

Physician Labor Supply

Chapter 4

Medicaid Payment Increases and Physician Labor Supply

4.1 Introduction

Policymakers have long been concerned about inadequate access to physician services for Medicaid beneficiaries because Medicaid reimbursement rates are below Medicare and commercial insurance rates for most services. The Affordable Care Act's expansion of Medicaid eligibility exacerbated concerns about access to care for newly-insured patients. Policymakers sought to allay these concerns with a temporary increase in Medicaid payments to physicians, specifically for primary care services. This policy change was designed to increase physician participation in the Medicaid program by temporarily bringing payment for primary care services up to national Medicare levels.

In this paper, I study the relationship between relative service prices and physician physician acceptance of Medicaid patients. I adapt the Sloan, Mitchell, and Cromwell (1978) model of a mixed economy with private and public insurers to generate predictions regarding physician response to increased reimbursement. I then test these predictions using claims and electronic health record data from athenahealth, Inc., a nationwide provider of electronic health records, medical billing, and practice management services. With this novel dataset, I am able to observe physicians' full panel of treated patients across payers and construct a variety of measures to quantify physician labor supply and participation in Medicaid.

I rely on a national policy change within the Affordable Care Act for exogenous variation in positive price shocks. Specifically, I exploit the two-year (2013-2014), nationwide Medicaid reimbursement increase for a collection of primary care services to Medicare payment levels. Since state Medicaid-to-Medicare fee ratios varied considerably prior to 2013, this policy change led to physician price shocks of varying magnitudes, but it is unlikely that the size of the physician price shock was systematically correlated with changes in supply or demand for health care services at the local level.

I find that most primary care physicians (PCPs) made no change to their Medicaid participation decisions in response to the Medicaid primary care payment increase. In the 31 states where the payment increase was temporary, PCPs did not change their Medicaid participation. In contrast, physicians in states that maintained the payment increase beyond the statutorily-required two years increased their Medicaid participation, in response to the positive price shock. In response to the average Medicaid payment increase, PCPs in these states were 6.5 percentage points more likely ($p = 0.010$) to treat any Medicaid patients and 5.5 percentage points more likely ($p = 0.005$) to treat any *new* Medicaid patients.[1] I also find that Medicaid-participating PCPs in all states responded to the price increase by increasing their labor supply. In response to the average price shock, PCPs saw an additional 136 patients and 91 appointments each quarter. There is some evidence that the Medicaid payment increase led to a decrease in both appointment wait time and duration, but no evidence that physician group practices responded to the policy change by hiring more physicians or mid-level providers.

This paper contributes to two strands of literature. The first analyzes how physicians respond to financial incentives. This is a literature with conflicting theoretical predictions and empirical findings. The theoretical literature on physician agency in the presence of asymmetric information does not yield a clear prediction about how supply of physicians services will respond to a change in administered price [28, 71, 72]. If the income effect dominates, a price increase results

[1] New Medicaid appointments are defined as a visit by a patient with Medicaid, for whm the physician billed an evaluation and management procedure code reserved for new-patient appointments.

in a volume decrease. If instead, the substitution effect dominates, physicians will increase their supply of services in response to a price increase.

Empirical findings provide evidence of the income effect dominating in certain instances [52, 53, 94, 130] and the substitution effect dominating in others [34, 45]. For example, recent work using a change in Medicare payment that decreased physician profit margins for providing chemotherapy treatment found that physicians increased their provision of chemotherapy in response to the fee cut [60]. On the other hand, research examining a change in the way Medicare adjusted physician payments across geographies found that an increase in payment rates yielded an increase in the supply of care, with a greater positive supply response among discretionary services [32]. While this paper cannot definitively settle the question, it provides evidence from a Medicaid price change, rather than more frequently studied price changes in Medicare.

This paper also contributes to the literature on physicians' decisions to participate in public insurance programs, specifically Medicaid. Survey estimates suggest that more than a quarter of physicians refuse to accept any Medicaid patients, with additional physicians refusing to accept any *new* patients [42, 59, 83]. Research suggests that non-participation decisions are correlated with reimbursement levels [35, 42, 114, 118], in addition to other factors including administrative burden [48], size of the Medicaid-eligible population in a physician's area [84], and physicians' political beliefs [118].

There are several reasons for the lack of research on physician response to financial incentives in the Medicaid population. One challenge in studying this relationship is that unobserved confounding variables may generate omitted variable bias. For example, paltry reimbursement levels and low rates of Medicaid acceptance among physicians could both result from hostile attitudes towards government assistance which may be difficult to observe or quantify. As Medicaid fees have historically been determined at the state level, existing studies have struggled to make causal, rather than correlational, statements about the relationship between financial incentives and Medicaid participation. This paper overcomes this challenge by identifying a federal policy change that affected state Medicaid reimbursement rates and was unrelated to specific changes in health care demand or supply at the state level.

Research has also been limited by the lack of available data reflecting a physicians' billing activity across payers and the particular challenge that Medicaid is a state-level program for which claims have historically been available on a state-by-state basis. This paper makes use of a novel dataset that captures utilization for the full patient panel or at least those who utilize care of a national group of primary care physicians. Additionally, this paper derives measures from both claims and scheduling data to allow for multiple measures of physician access for Medicaid patients.

The paper proceeds as follows. Section 4.2 discusses the background and institutional setting. In Section 4.3, I present a modified mixed-economy model and empirical predictions. Section 4.4 discusses data, sample selection, and descriptive statistics. Section 4.5 details my empirical strategy. Section 4.6 presents results. Section 4.7 concludes.

4.2 Background & Institutional Setting

Medicaid has existed since 1965 as a health care program for families and individuals with limited financial resources. It is jointly funded by state and federal governments, but managed by the states, with each state having considerable discretion to determine eligibility and implementation details, including the prices paid to providers. The Patient Protection and Affordable Care Act (ACA) of 2010 expanded Medicaid eligibility to include all U.S. citizens and legal residents with income up to 133% of the federal poverty line, including adults without dependent children. This expansion was subsequently ruled coercive by the Supreme Court and rendered optional for states, with 32 choosing to enact it, as of the writing of this paper.

Expanding Medicaid eligibility generated concern about access to care, particularly as physicians have expressed less willingness to accept Medicaid patients, citing low reimbursement rates. Historically, Medicaid fee-for-service (FFS) physician payment rates have been set at the state level. These rates were below Medicare rates in 44 states, averaging at two thirds of Medicare payment for primary care services, prior to the ACA [132]. Designed to incentivize physicians to treat more Medicaid patients, the ACA also included a provision that increased Medicaid primary care fees to Medicare levels. This fee bump was financed entirely by the federal government, but only in effect during 2013 and 2014 and only applied to 146 common primary care service codes. On average, the policy change increased Medicaid rates by an estimated 73% on average, but the size of this positive price shock varied considerably by state. Primary care payment rates doubled in six states (Rhode Island, New York, California, Michigan, New Jersey, Florida) and increased less than 10% in four states (Delaware, Oklahoma, Wyoming, Montana) [133].

The size of the physician price shock depended not only on the 2012 state-level Medicaid-to-Medicare fee ratio, but also on physician specialty. Family physicians, internists, and pediatricians automatically qualified for the payment increase. Board-certified subspecialists could also qualify for the higher Medicaid fees if they attested that at least 60 percent of the Medicaid codes they billed were for primary care [61]. In practice, this meant that many specialists did not experience a shock in the price they received for supplying medical care to Medicaid patients either because they did not supply much primary care or because they chose not to submit a formal attestation. Likewise, a similar ambiguity existed regarding non-physician providers (e.g., nurse practitioners, physician assistants, certified nurse midwives). These providers were eligible for the payment increase if under the personal supervision of a physician, but ineligible if practicing independently [**?**].

In addition to variation in payment levels, implementation of the Medicaid payment increase varied across states. For providers qualified to receive it, the federally-funded reimbursement increase applied to fee-for-service and managed care Medicaid programs alike, though states had considerable discretion over how to disburse the additional funds. Most states chose to modify their physician fee schedule (i.e., to increase the payment for each primary care service), though some chose instead to make an equivalent monthly or quarterly lump sum payment. Whatever the method, states had to receive approval from the Centers for Medicare and Medicaid Services. Table 4.1 shows that few states had received this approval by January 1, 2013, resulting in a delayed implementation of the payment increase.[2] All told, this policy change represented a large, positive price shock, but it was temporary, delayed, and inconsistently implemented for most states.

On top of the inconsistent implementation of the policy, there was variation across states as to whether they extended the payment increase beyond 2014, when federal funds expired. As of

[2] If a state's plan amendment was not approved by January 1, 2013, the state was permitted to either increase its fees and receive federal compensation later or continue paying 2012 fees and make retrospective payments following plan approval [61].

July 2016, 19 states had chosen to self-finance an extension of the Medicaid primary care payment increase beyond 2014 (see Table 4.1). Seven of these states opted to fully continue the payment increase for primary care providers.[3] Another six states partially continued the payment increase for primary care providers.[4] The remaining six states maintained higher primary care fees for all physicians, rather than only those with primary care specialties [**?**].[5] Thirty one states allowed the fee increase to expire entirely at the end of 2014, as legislated.

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[3]These states include Alabama, Iowa, Maine, Mississippi, Nebraska, New Mexico, and South Carolina.

[4]These states include Florida, Georgia, Michigan, New Jersey, Oregon, and Vermont.

[5]These states include Colorado, Idaho, Indiana, Maryland, Nevada, and Utah.

Table 4.1: *Primary Care Payment Bump Implementation Strategy*

State	Date Approved	Fee Schedule Update	Kept Fee Bump Beyond 2014	State	Date Approved	Fee Schedule Update	Kept Fee Bump Beyond 2014
Alabama	5/29/13	Y	Y	Montana	3/26/13	Y	-
Alaska			-	Nebraska	6/5/13	Y	Y
Arizona	6/11/13	Y	-	Nevada	6/10/13	-	Y
Arkansas	5/11/13	-	-	New Hampshire	5/15/13	-	-
California	10/24/13	Y	-	New Jersey	6/11/13	Y	Y
Colorado	6/4/13	-	Y	New Mexico	6/24/13	-	Y
Connecticut			-	New York	5/30/13	Y	-
Delaware	6/24/13	Y	-	North Carolina	6/12/13	Y	-
Florida	4/1/13	Y	Y	North Dakota	6/25/13	-	-
Georgia	6/4/13	Y	Y	Ohio	6/24/13	Y	-
Hawaii				Oklahoma	6/20/13	-	-
Idaho	5/30/13	-	Y	Oregon	5/30/13	Y	Y
Illinois	6/26/13	-	-	Pennsylvania	4/30/13	Y	-
Indiana	6/24/13	-	Y	Rhode Island	6/19/13	Y	-
Iowa	6/30/13	Y	Y	South Carolina	6/10/13	Y	Y
Kansas	4/19/13	Y	-	South Dakota	6/11/13	Y	-
Kentucky	6/7/13	-	-	Texas	6/21/13	-	-
Louisiana	6/6/13	Y	-	Utah	6/17/13	-	Y
Maine	6/5/13	Y	Y	Vermont	6/5/13	Y	Y
Maryland	5/24/13	Y	Y	Virginia	5/23/13	-	-
Massachusetts	6/12/13	Y	-	Washington	5/20/13	Y	-
Michigan	6/10/13	Y	Y	West Virginia	6/20/13	Y	-
Minnesota	6/10/13	Y	-	Wisconsin	6/13/13	Y	-
Mississippi	5/29/13	Y	Y	Wyoming	5/15/13	-	-
Missouri	4/17/13	Y	-				

Source: CMS State Plan Amendments, [**?**]

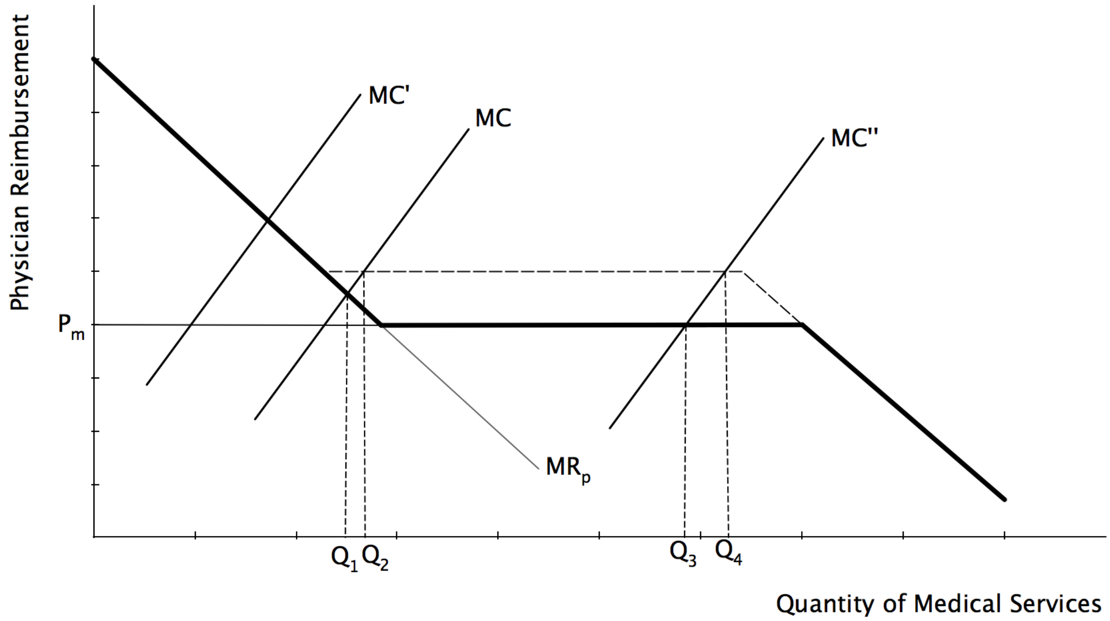
Existing evidence on the effect of the Medicaid primary care payment increase is mixed. Researchers used 'secret shopper' techniques to assess appointment availability by posing as either Medicaid enrollees or individuals with private insurance seeking new-patient primary care appointments. They estimated a 1.25 percentage point increase in appointment availability per 10% increase in Medicaid reimbursement, providing early evidence that the primary care payment bump was associated with improved appointment availability for Medicaid enrollees [101]. They did not find any concurrent change in appointment wait time. A recent follow-up piece by the same group of researchers found that this increased appointment availability for Medicaid enrollees persisted, past the expiration of the primary care payment increase [**?**]. On the other hand, semistructured interviews with Medicaid officials, plan administrators, and provider organizations in eight states found that the payment increase had little to no effect on physicians' Medicaid participation [67].

4.3 Conceptual Framework

I adapt the model of physician pricing in a mixed economy, originally introduced by Sloan, Mitchell, and Cromwell (1978) and subsequently modified by Garthwaite (2012) [49, 118]. In this model, physicians provide a homogenous good (e.g., office visits) and face two distinct markets of patients: one with private health insurance coverage and a downward-sloping marginal revenue curve and a second with publicly-insured (Medicaid) patients whose insurance pays an administratively determined and fixed price. Physicians treat patients from the privately insured market until the marginal revenue equals the Medicaid reimbursement rate. After that, they treat Medicaid patients until their marginal costs equal the Medicaid reimbursement rate.

Figure 4.1 represents this model graphically. Before the Medicaid payment increase, the physician's marginal revenue curve is the bold line comprising part of the private-insured marginal revenue (MR_p) and the fixed payment from Medicaid (P_m). Physicians with different marginal cost curves see a different mix of patients. In Figure 4.1, a physician with marginal cost curve MC or MC' treats only privately insured patients, whereas a physician with a marginal cost curve MC'' treats a mix of privately-insured and Medicaid patients.

Figure 4.1: *Physician Labor Supply and Program Participation in a Mixed Economy*



In this model, any factor affecting the marginal revenue or the marginal cost curve can affect Medicaid participation and labor supply decisions. For example, an increase in Medicaid reimbursement would shift up the horizontal portion of the marginal revenue curve that physicians face (Figure 4.1). A physician with MC would begin to treat Medicaid patients and would increase their labor supply (i.e., total quantity of medical services) from Q_1 to Q_2.. A physician with MC' would maintain the same Medicaid non-participation and labor supply. A physician with MC'' would continue participating in Medicaid, but would increase their labor supply from Q_3 to Q_4. This conceptual framework generates the following empirical predictions regarding an increase in Medicaid payment:

Prediction 1: The Medicaid primary care payment increase should increase physician participation in Medicaid among physicians with few or zero Medicaid patients in 2012.

Prediction 1A: Similar physicians for whom Medicaid patients were a large share of their patient panel in 2012 should not see any change in their Medicaid participation decisions.

Prediction 2: The Medicaid primary care payment increase should increase labor supply among physicians who accept Medicaid patients.

Prediction 2A: Physicians treating zero Medicaid patients should not change their labor supply decisions.

4.4 Data, Sample Selection, and Descriptive Statistics

In the remainder of this paper, I will provide empirical evidence regarding the relative size and direction of physician response to state-level Medicaid price shocks. This section describes the data used to answer these questions and presents descriptive statistics.

4.4.1 Data

I rely primarily on data from athenahealth, Inc., ("athenahealth"), a company that sells cloud-based medical billing, practice management, and electronic health record (EHR) services to health care providers nationwide. Clients span provider types and specialties, with a high concentration of office-based primary care providers.

These novel data contain claims information for all athenahealth providers during 2010-2014, including date of service, patient age, sex, marital status, insurance type, diagnosis and procedure codes, provider place of service, provider type and specialty, allowable charges, and patient cost-sharing. A subset of athenahealth clients also purchase practice management and EHR services. For this group of providers, I use data derived from the athenahealth EHR, including appointment date, time stamps, date of scheduling, scheduled start time, and intended duration. This combination of claims and EHR data is unique in three important ways:

Physician and Group Identifiers: These allow for observation of practice organization, from the smallest department level (i.e., office location) to the highest health system affiliation. I can then observe staffing patterns and the presence of non-physician providers over time.

All-Payer Claims: The data detail claims submitted by the physician to all payers. This allows me to observe a physician's payer mix and changes in utilization for patients of all payer types.

Scheduling Information: As part of the practice management functionality, the EHR records information on daily appointment schedules, including intended appointment duration and date of scheduling. This allows me to construct outcome measures that capture time allocation and wait time from date of appointment scheduling.

An important limitation of the data is the inability to track patients. If a patient visited a non-athenahealth provider, that utilization is not captured in the data. Additionally, the athenahealth data encompasses a convenience sample of physicians who may differ on certain dimensions from national averages and therefore is limited in its external validity. Finally, the athenahealth data only allows for observation of a physician's full patient panel insofar as those patients utilized care during the relevant time period.

Other Data Sources

I also rely on data from a variety of sources, to control for time-varying characteristics within local physician markets. These characteristics include county-level data on rates of uninsurance from the Small Area Health Insurance Estimates generated by the Census Bureau and median household income and unemployment rate from the Bureau of Labor Statistics.

Sample Selection

The main sample comprises appointments with physicians during 2010-2013. The pre-period includes 2010-2012 and the post-period includes 2013. While the primary care payment increase spanned 2013-2014, many other policy changes were implemented in 2014 (e.g., the Medicaid eligibility expansion and the individual mandate), so I restrict the post-period to include only 2013 in my main specification. I include any primary care physician who billed at least 20 claims in the athenahealth data for at least four quarters in both the pre- and post-periods.

My final sample includes 65,783 quarters, for 4,539 primary care physicians, working within 683 practices or health systems. A subset of athenahealth clients purchase the EHR and practice management functionalities, in addition to the medical billing services. Appointments for these physicians contain timing variables, in addition to data on claims volume and payer mix. This sample of all PCPs includes 44,895 quarters, for 2,219 physicians, working within 492 practices or health systems.

4.4.2 Descriptive Statistics

The athenahealth database comprises a convenience sample of providers within the United States, with good coverage of New England, the South, and the Midwest, though not the West. Table 4.2 compares characteristics (at the quarter level) of physicians between the full dataset, my analytic sample of all PCPs with claims data, and the subset of PCPs with additional EHR data.

Primary care physicians in my sample had higher average volume than physicians in the full dataset.[6] PCPs saw an average of 439 patients per quarter (640 appointments), compared to 285 patients (409 appointments) for physicians of all specialties in the full dataset. Volume was very slightly higher among primary care physicians with claims and EHR data (461 patients/quarter or 690 appointments), compared to those PCPs with only claims data. The average PCP with available EHR data had 8,498 minutes scheduled for appointment time with patients, per quarter, compared with 7,437 minutes among physicians of all specialties.[7]

Table 4.2 also shows that primary care physicians in the analytic sample were more likely to accept Medicaid patients. Few physicians (less than 1 in 5) did not accept Medicaid, but Medicaid patients were a fairly small share of the average physician's panel ($< 10\%$).[8] These patterns were broadly consistent between the claims-only and claims+EHR analytic samples.

Medicaid Acceptance in the Pre-Period

The athenahealth dataset provides a rare national, claims-based window into payer mix for primary care physicians. Estimates of payer mix - particularly what share of physicians accept

[6] To some extent this is by design, given that I exclude very low-volume physicians from the analytic sample.

[7] Assuming 13 weeks per quarter and a 5-day work week, PCPs scheduled an average of 2.2 hours per day for patient time, which is slightly smaller than national survey estimates, likely reflecting the presence of part-time physicians.

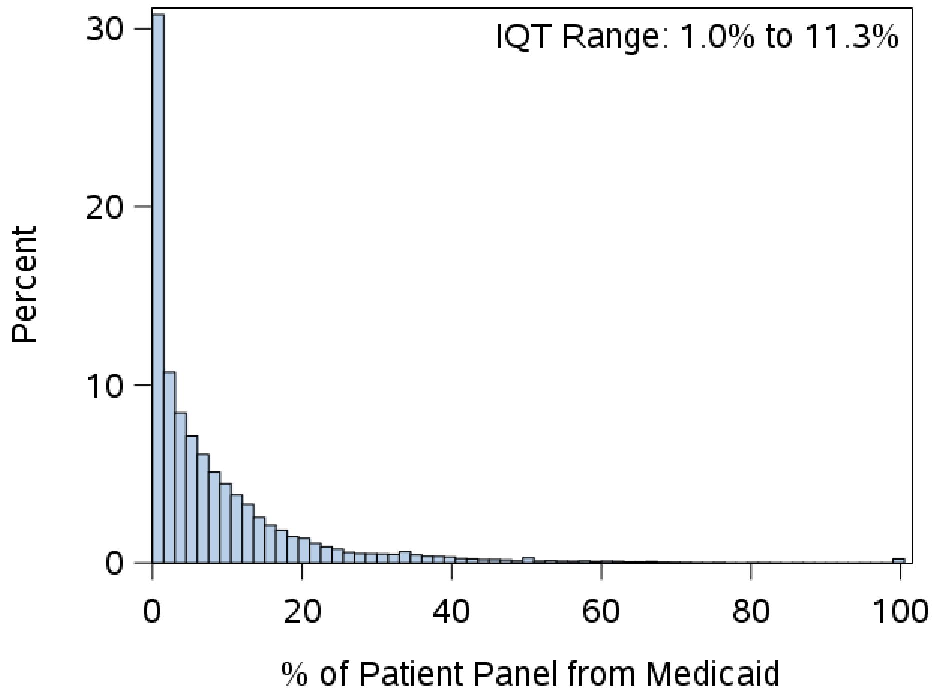
[8] No Medicaid acceptance is defined billing zero claims where Medicaid is listed as the primary insurer.

Table 4.2: *Provider Descriptives*

	Full Dataset w/Claims	Analytic Sample (PCPs only) w/Claims	Analytic Sample (PCPs only) w/Claims + EHR
Physician Characteristics, at the Quarter Level			
Volume			
Average quarterly panel size (patients)	285.4	439.4	461.3
Average quarterly appointment count	409.5	639.6	690.2
Medicaid Participation			
Not accepting any Medicaid patients	26.4%	18.3%	19.0%
Not accepting and *new* Medicaid patients	69.8%	63.6%	60.1%
Average share of panel with Medicaid	12.7%	8.7%	7.7%
Timing			
Average quarterly minutes scheduled	-	-	8,498
Average scheduled appt duration (minutes)	-	-	23.2
Average scheduled Medicaid appt duration (minutes)	-	-	21.8
Average appt wait time (days)	-	-	24.2
Average Medicaid appt wait time (days)	-	-	20.2
Geography			
Northeast	30.5%	35.5%	26.1%
Midwest	25.6%	27.0%	28.5%
South	35.1%	28.7%	31.3%
West	9.6%	10.0%	14.7%
Number of quarters	361,681	65,783	44,895
Number of physicians	45,437	4,539	2,219
Number of practices	2,858	683	492

Note: This table presents descriptive statistics on physician-quarters within the full dataset, the analytic sample of PCPs with claims, and the analytic sample of PCPs with claims and EHR data.

Figure 4.2: *Distribution of Physician-Quarters by Share of Patients from Medicaid*



Medicaid patients - have historically come from surveys. While there is considerable variation in findings, these estimates suggest that up to a quarter of physicians don't accept Medicaid patients, while still more don't accept any *new* Medicaid patients [42, 59, 83]. With all-payer claims data, I am able to quantify Medicaid participation without relying on self-reported estimates and biases inherent in survey research. Figure 4.2 shows the distribution of physician-quarters in the pre-period by share of patients from Medicaid. The median physician-quarter included 4.5% of patients from Medicaid, with an interquartile range of 1.0% to 11.3%.

Medicaid-to-Medicare Payment Ratio

The primary care payment increase was scheduled to bring Medicaid payments to the level of Medicare rates in 2013 and 2014. This represented a price increase for physicians in most states, though it varied considerably by generosity of the state Medicaid program prior to the policy change. Table 4.3 shows pre-policy generosity of state Medicaid payments for primary care services, relative to Medicare. In 2012, the average state paid 72% of what Medicare paid for the same set of services. Table 4.3 also reports the Medicaid-to-Medicare ratio as published by the Kaiser Family Foundation, using survey data. The correlation between these two measures is 0.82 ($p < 0.0001$).[9]

States varied in many dimensions of Medicaid policy, but these were not correlated with Medicaid primary care payment generosity in 2012. Most importantly, states were not systematically more or less generous based on whether they would eventually decide to retain the primary care payment increase beyond 2014 ($r = -0.040, p = 0.781$). Similarly, states were not more or less generous with their 2012 Medicaid rates for primary care, based on whether they would expand Medicaid eligibility in 2014 ($r = -0.165, p = 0.252$).

[9] Variations between the calculated athena MMR and the Kaiser Family Foundation MMR likely reflect the fact that states with large managed Medicaid populations may not pay purely fee-for-service.

Table 4.3: *Medicaid-to-Medicare Ratio, Primary Care Services, 2012*

State	athenahealth	KFF/Urban Institute	State	athenahealth	KFF/Urban Institute
Alabama	0.68	0.70	Missouri	0.65	0.57
Alaska	1.90	1.27	Montana	0.89	0.94
Arizona	0.73	0.75	Nebraska	0.75	0.76
Arkansas	0.66	0.70	Nevada	0.64	0.68
California	0.50	0.43	New Hampshire	0.62	0.60
Colorado	0.74	0.74	New Jersey	0.65	0.50
Connecticut	0.63	0.71	New Mexico	0.81	0.85
Deleware	0.81	0.98	New York	0.70	0.42
District of Columbia	0.77	0.80	North Carolina	0.85	0.85
Florida	0.50	0.49	North Dakota	-	1.35
Georgia	0.62	0.70	Ohio	0.62	0.59
Hawaii	0.60	0.57	Oklahoma	0.96	0.97
Idaho	0.87	0.89	Oregon	0.79	0.72
Illinois	0.58	0.54	Pennsylvania	0.50	0.56
Indiana	0.58	0.55	Rhode Island	0.40	0.33
Iowa	0.64	0.77	South Carolina	0.79	0.74
Kansas	0.61	0.82	South Dakota	0.65	0.69
Kentucky	0.64	0.72	Texas	0.54	0.61
Louisiana	0.65	0.75	Utah	0.70	0.74
Maine	0.68	0.63	Vermont	0.97	0.81
Maryland	0.76	0.70	Virginia	0.82	0.74
Massachusetts	0.79	0.68	Washington	0.78	0.66
Michigan	0.43	0.46	West Virginia	0.76	0.74
Minnesota	0.75	0.73	Wisconsin	0.51	0.60
Mississippi	0.89	0.90	Wyoming	0.94	0.96

Source: Author's analysis of athenahealth data and KCMU/Urban Institute Medicaid Physician Fee Survey

4.5 Empirical Strategy

Having presented background and descriptive statistics, I now turn to a discussion of my empirical strategy for quantifying the effects of changes in physician reimbursement on supply of medical care. In this section, I detail my difference-in-differences and difference-in-difference-in-differences approaches, the outcome variables of interest, and evidence supporting the parallel pre-trends assumption.

4.5.1 Difference-in-Differences Strategy

I first implement a difference-in-differences (DD) design, where treatment is the 2012 (pre-policy change) gap between Medicaid and Medicare rates. This determined the size of the exogenous price shock that physicians experienced following implementation of the Medicaid primary care payment increase. The estimating equation is as follows:

$$Y_{ijkt} = \beta_0 + \beta_1 PriceShock_j + \beta_2 (Post_t \times PriceShock_j) + \beta_3 X_{kt} + \gamma_i + \tau_t + \epsilon_{ijkt} \tag{4.1}$$

indexing physician i in state j and county k and time t. $Post_t$ is an indicator variable equal to one after the Medicaid primary payment increase went into effect in 2013. $PriceShock_j$ is defined as one minus the 2012 state Medicaid-to-Medicare ratio, scaled by 100. Relatively ungenerous states with a low Medicaid-to-Medicare ratio prior to the policy change received a larger price shock when Medicaid and Medicare prices equalized, and would thus have a larger value of $PriceShock_j$ than a state with generous Medicaid payment. The coefficient of interest is β_2, which represents the effect of an increase from a one percentage point larger positive price shock on a physician's supply of medical care to Medicaid patients, after the payment increase policy took effect. A positive sign on β_2 indicates that physicians responded to the reimbursement increase by increasing the dependent variable (Medicaid participation or labor supply).

X_{kt} is a vector of time-varying county characteristics (uninsurance rate, median household income, and unemployment rate). γ_i is a practice-level fixed effect that controls for baseline outcome differences between physician group practices. τ_t is a time (quarter and year) fixed effect that captures common changes in the outcome variable across physicians in all states in a time period. ϵ_{ijkt} is an idiosyncratic error term. Standard errors are clustered at the practice level, as Medicaid participation decisions appear to be correlated between physicians practicing in the group.

Triple Difference

A threat to the proposed difference-in-differences (DD) strategy described above is the existence of unmeasured and time-varying factors differentially affecting physicians experiencing larger versus smaller price shocks. To overcome this threat, I identify a group of physicians who should experience and react similarly to these unmeasured factors, but aren't affected by the Medicaid primary care payment increase and use them as a placebo test group in a difference-in-difference-in-differences (DDD) specification.[10]

Proposition 1A of the mixed-economy model in Section 4.3 predicts that the reimbursement increase will not alter the Medicaid participation decision of physicians participating heavily in Medicaid prior to the policy change (MC'' in Figure 4.1). I implemented a DDD estimating equation using these primary care physicians as an additional control, where Medicaid participation is the dependent variable:

$$\begin{aligned} Y_{ijkt} = \eta_0 + \eta_1 PriceShock_j + \eta_2 (Post_t \times PriceShock_j) \\ + \eta_3 (Post_t \times PriceShock_j \times LowMcaidPre_i) + \eta_5 X_{kt} + \gamma_i + \tau_t + \epsilon_{ijkt} \end{aligned} \tag{4.2}$$

where $LowMcaidPre_i$ is an indicator for whether $\leq 1\%$ of the physicians patient panel in 2012 came from Medicaid (this is roughly the bottom quartile of physicians, by Medicaid participation). I omit a main effect of $LowMcaidPre_i$ and the interaction between $Post_t$ and $LowMcaidPre_i$, as the physician fixed effect will absorb these terms. All other variables are defined as in Equation 4.1 and the parameter of interest is η_3.

[10] This research design is similar to Garthwaite, 2012.

Similarly, Proposition 2A of the mixed-economy model in Section 4.3 predicts that the reimbursement increase is unrelated to the labor supply of physicians who do not treat Medicaid patients (MC' in Figure 4.1). Therefore, these primary care physicians can be used as an additional control in a difference-in-difference-in-differences estimating equation where quantity of medical services is the dependent variable and $YesMcaidPre_i$ is an indicator variable for whether physician i accepted any Medicaid patients before the policy change and η_3 is again the coefficient of interest:

$$
\begin{aligned}
Y_{ijkt} = \eta_0 + \eta_1 PriceShock_j + \eta_2 (Post_t \times PriceShock_j) \\
+ \eta_3 (Post_t \times PriceShock_j \times YesMcaidPre_i) + \eta_5 X_{kt} + \gamma_i + \tau_t + \epsilon_{ijkt} \quad (4.3)
\end{aligned}
$$

4.5.2 Outcomes

I use the empirical framework detailed in Section 4.5.1 to examine a range of outcomes along which physicians may respond to payment increases, split broadly into three categories: labor supply, Medicaid participation, and other measures of access.

There are multiple ways to observe and quantify physician participation in Medicaid. To begin, I construct a binary measure, indicating the presences of at least one Medicaid patient within the claims submitted by that physician in that quarter. I also use procedure codes indicating a new-patient visit to calculate a binary measure indicating whether the physician saw at least one *new* patient with Medicaid during that quarter.[11]

Similarly, there are multiple ways to quantify the quantity a physician's labor supply within the athenahealth dataset. To begin, I calculate the panel size (number of unique patients) and appointment count, by physician-quarter. I also sum the number of total minutes scheduled for patient care, among the subset of PCPs with these data available.[12]

[11] I use CPT codes 99201-99205, which indicate evaluation and management visits for new patients. These likely underestimate true visits by new patients, if other non-evaluation-and-management codes are billed.

[12] The minutes variable derives from the EHR, this analysis is limited to the subgroup of physicians who purchase the full suite of athenahealth services. It does not account for double-booking of appointments, which is a common occurrence within primary care practices.

While physician participation in Medicaid and labor supply are the outcomes relevant to the mixed-economy model in Section 4.3, I also examine access as an outcome, given recent empirical interest in the literature [101]. While I cannot observe the extensive margin of appointment availability (i.e., I cannot observe occurrences where a patient requested an appointment and was denied), I can quantify any changes in the intensive margin. Specifically, I define the intensive margin of access as the average number of days elapsed from date of appointment scheduling to date of appointment occurrence, by physician-quarter. Finally, I also include scheduled appointment duration as another measure of appointment timing.

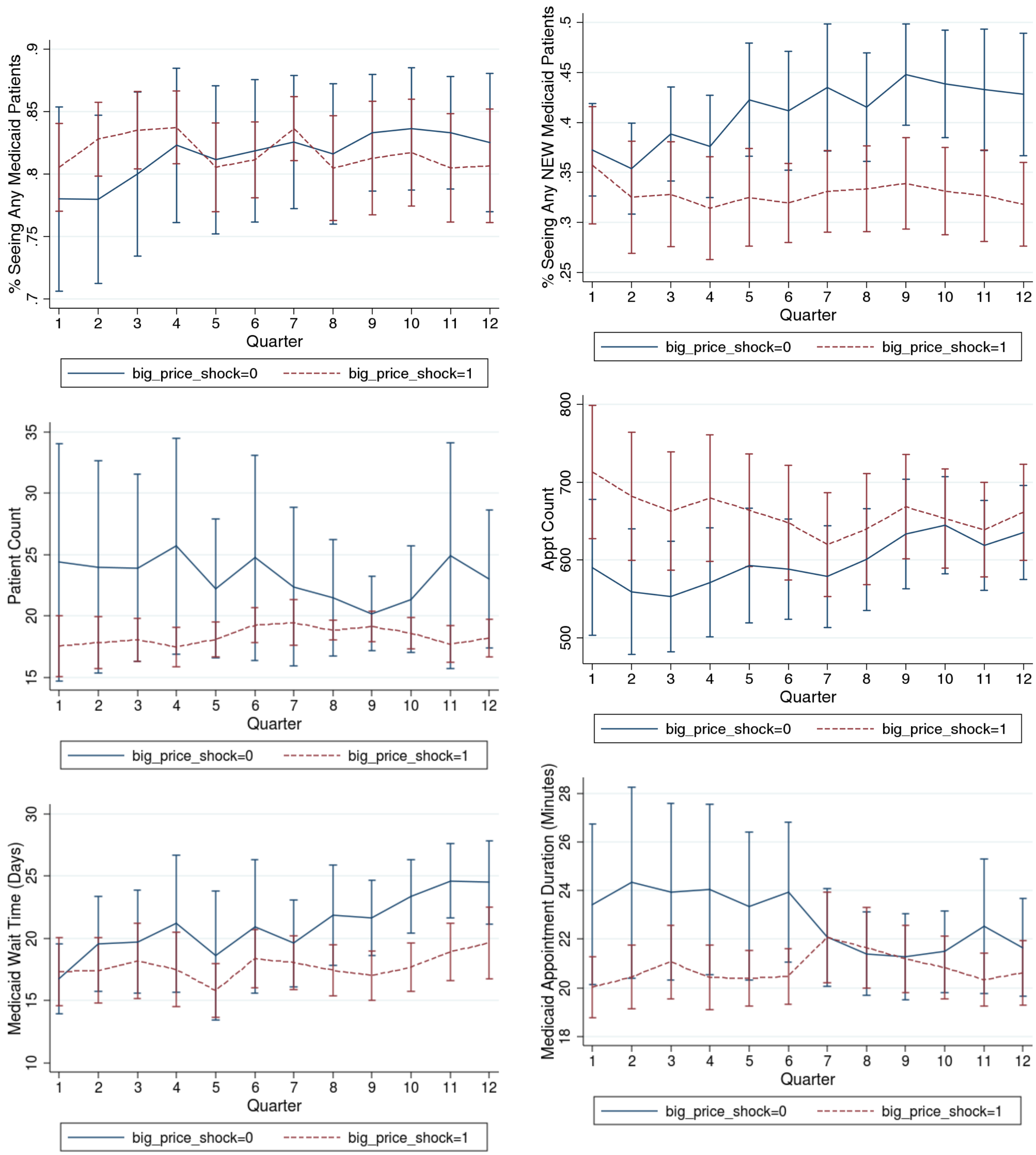
4.5.3 Parallel Trends

The proposed difference-in-differences identification strategy hinges on the assumption that existing trends would have continued, if not for the policy change. While this assumption is not directly testable, it is possible to provide suggestive evidence of parallel pre-period trends existing between physicians in states with varying price shocks resulting from the policy change (i.e. varying levels of Medicaid payment generosity in 2012). The athenahealth data begin twelve quarters prior to the enactment of the payment increase, allowing for a direct examination pre-period trends in outcomes, using data from January 2010 through December 2012.

Figure 4.3 presents results testing the equivalency of pre-period trends in dependent variables. Here I regress the dependent variables on the size of the price shock (above or below median), dummy variables for every year-quarter combination, and an interaction between price shock size and year-quarter, during the pre-period. If pre-period trends differ by size of the price shock, this will be reflected in the coefficients on the interaction terms. For nearly all dependent variables, I cannot reject the null hypothesis that the parameter estimates on the interaction terms for the years prior to 2013 equals zero with 95% probability, supporting the parallel trends assumption. Figure 4.4 presents the same results, limiting the sample to physicians in states that retained the Medicaid primary care payment increase beyond the 2014 expiration stipulated in the Affordable Care Act. Again, I cannot reject the null hypothesis for pre-period trends in the dependent variables of interest.

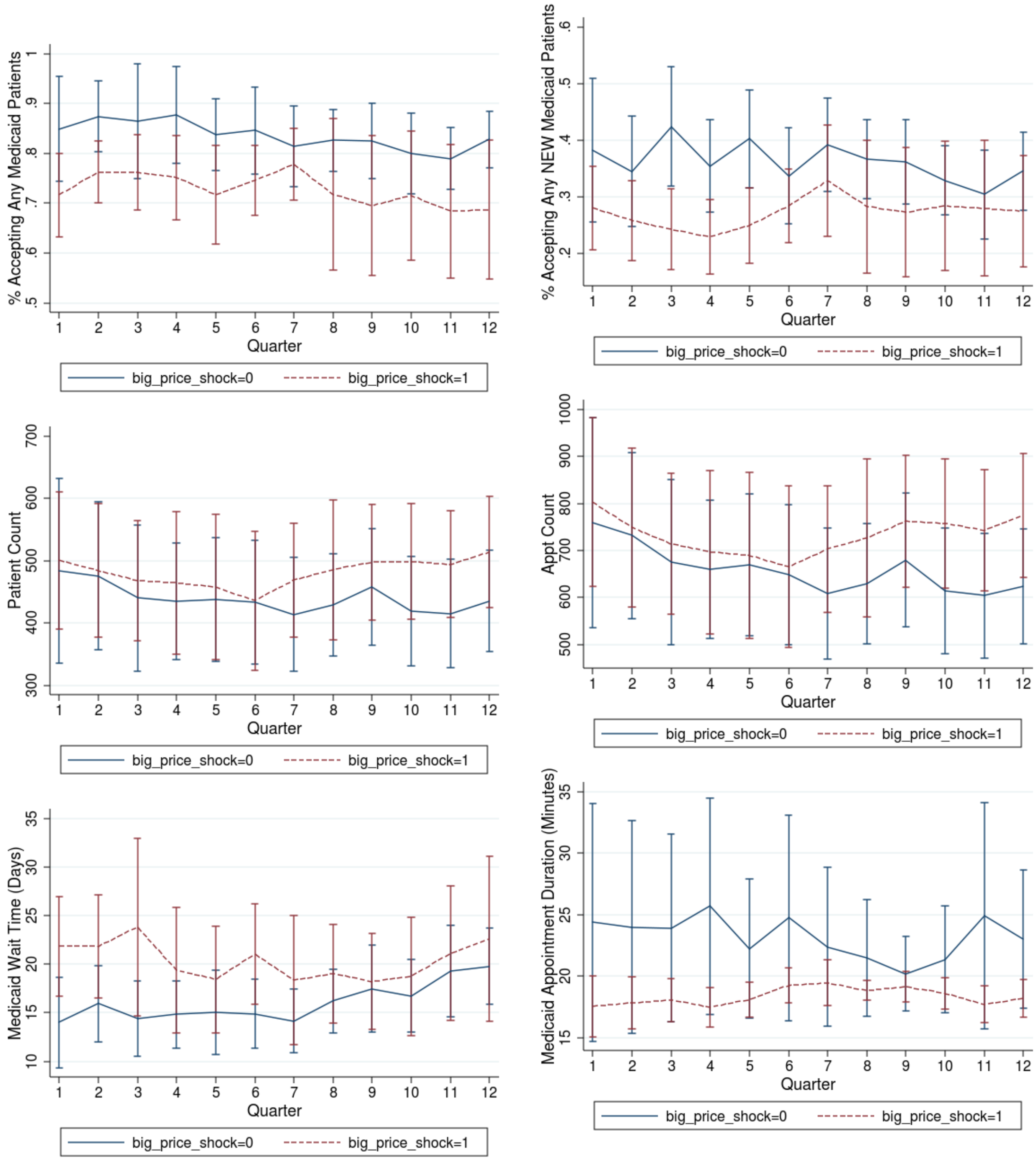
Figure 4.5 presents results testing the equivalency of pre-period trends in dependent variables,

Figure 4.3: *Pre-Period Trends in Dependent Variables, DD*



Note: These figures presents the results of individual equations, regressing each dependent variable on year-quarter (dummy variable), an indicator for being in a state with an above median price shock, and an interaction between the two.

Figure 4.4: *Pre-Period Trends in Dependent Variables, Only in States that Kept the Payment Increase After 2014*



Note: These figures presents the results of individual equations, regressing each dependent variable on year-quarter (dummy variable), an indicator for being in a state with an above median price shock, and an interaction between the two.

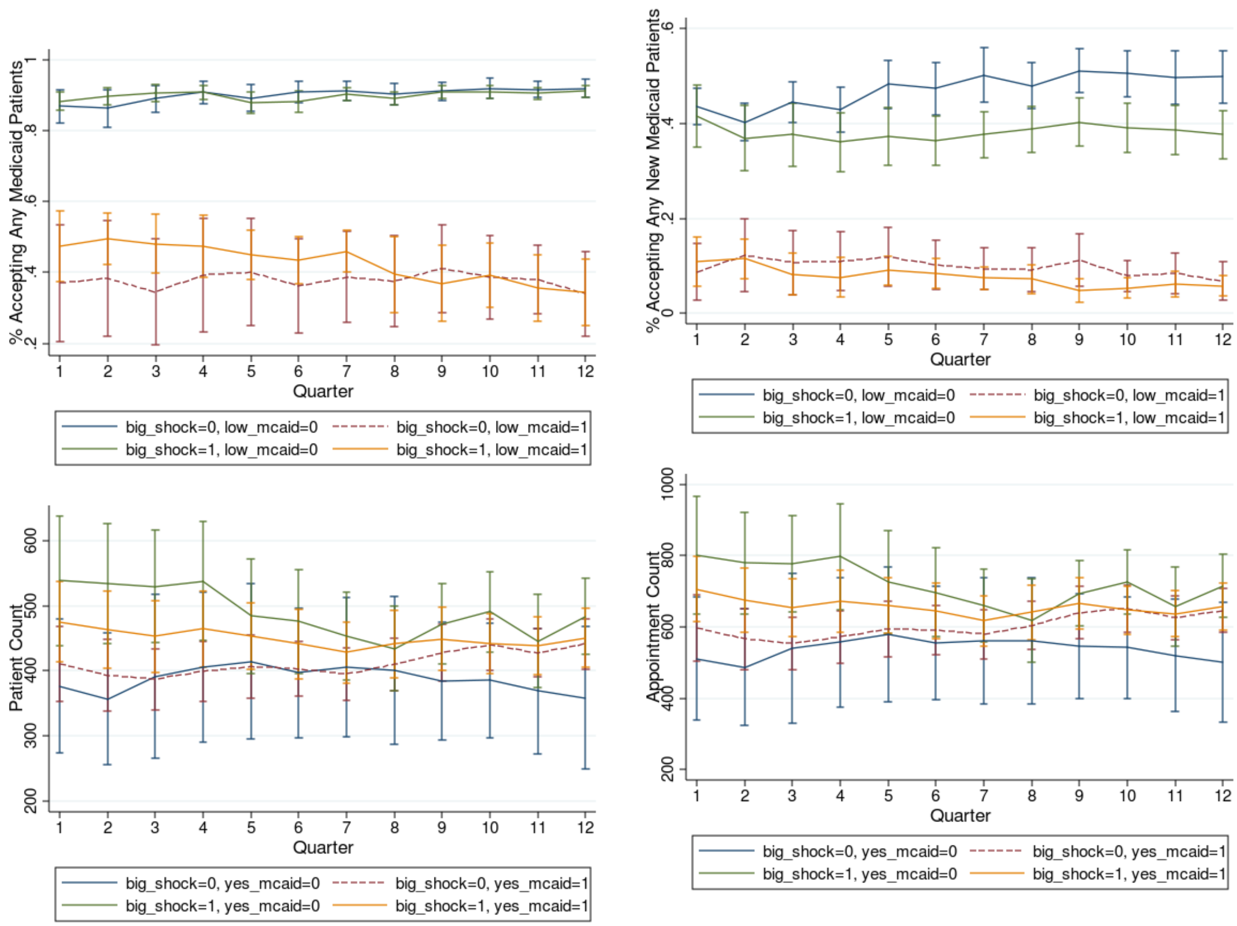
adding in the relevant triple difference term. Here I regress the dependent variables on the full set of interactions between the size of the price shock (above and below median), year-quarter (as a dummy variable), and the two binary indicators described in 4.5.1: an indicator for low pre-period Medicaid participation (relevant for Medicaid participation analyses) and an indicator for any participation in Medicaid during the pre-period (relevant for quantity of services analyses). If trends are different during the pre-period, based on the size of the price shock, this will be reflected in the coefficient on the triple interaction term. Trends appear to be parallel, with the one possible exception of accepting new Medicaid patients, where low Medicaid-participating physicians appear to have been increasing their acceptance of new Medicaid patients in states that would *not* experience a below-median price shock in 2013.

4.6 Results

The conceptual framework in Section 4.3 yields two empirically testable predictions: first, that physicians will respond to a Medicaid price increase by increasing their Medicaid participation, particularly those who saw few or no Medicaid patients before the price increase. Second, that physicians will increase their labor supply, particularly those who saw Medicaid patients after the price increase, and were therefore affected by the policy change. This section presents results testing these predictions for Medicaid program participation, labor supply, and additional measures of access to physician services, including appointment availability and scheduled duration.

All tables present coefficients of interest from regressions including physicians in all states and also regressions including physicians in states that continued the Medicaid primary care payment increase beyond 2014. Physicians in states that kept the primary care payment increase may have found it more salient and therefore it may have had a stronger effect on their behavior. Recall that the coefficient of interest from Equation 4.1 is the interaction term for being in the post-period (2013) and the size of the price shock (defined as $1 - MMR_{2012}$, such that a positive coefficient indicates that states with larger price shocks experienced greater changes in outcomes). The average increase in Medicaid reimbursement was 27.8 percentage points, therefore the effect of the average payment increase from 2012 to 2013 on Medicaid acceptance is the estimated

Figure 4.5: *Pre-Period Trends in Dependent Variables, DDD*



Note: These figures presents the results of individual equations, regressing each dependent variable on a full set of interactions between year-quarter (continuous variable), an indicator for being in a state with an above median price shock, and the DDD variable of interest, including an indicator for being a low-Medicaid physician during the pre-period and an indicator for accepting any Medicaid patients in the pre-period.

coefficient multiplied by the average increase.

4.6.1 The Effect of the Primary Care Payment Increase on Physician Participation in Medicaid

The conceptual model predicts that an increase in the administratively set price should increase physician participation in the public program. Column 1 in the top panel of Table 4.4 reports estimates for Equation 4.1 where the dependent variable equals 1 if a physician billed any claims for a Medicaid patient. For the sample of primary care physicians in all states, the proportion seeing any Medicaid patients did not change with the implementation of the Medicaid primary care payment increase. Interestingly, the coefficient on the triple interaction term in Column 2 suggests that this effect was not driven by low Medicaid participating physicians, who decreased their Medicaid participation in response to the payment increase.

Column 3 in the top panel of Table 4.4 presents estimates from the same estimation, limiting to PCPs in states that continued the payment increase even after it expired in 2014. For this sample of physicians, the proportion seeing any Medicaid patients increased by 6.5 percentage points ($p = 0.010$) with the implementation of the payment increase, or 7.8% relative to the.mean of 81.7%. The payment increase may have been more salient for physicians in states that continued it beyond 2014, either because it was a topic under consideration by local legislators or because they were less concerned about being “stuck" with any Medicaid patients they chose to accept, after the payment increase went away.

Another measure of Medicaid participation is acceptance of any *new* patients covered by Medicaid. Arguably, this measure is of greatest interest to policymakers, as the Medicaid primary care payment increase was intended to incentivize physicians to see newly insured Medicaid patients when the program expanded in 2014. The bottom panel of Table 4.4 reports estimates for Equation 4.1 where the dependent variable equals 1 if a physician billed any claims for a Medicaid patient where the procedure code indicated that it was a new visit. As before, I see a significant effect of the Medicaid payment increase only on PCPs in states that continued the policy beyond 2014. For this sample of physicians, the proportion seeing any new Medicaid patients increased by 5.5 percentage points ($p = 0.005$) - or 15.1% relative to the base rate of 36.4%

Table 4.4: *Effect of the Primary Care Payment Increase on Medicaid Participation, 2010-2013*

	All States (1)	(2)	Permanent Fee Bump States (3)	(4)
	$\geq$ 1 Medicaid patient			
Post $\times$ *PriceShock*	0.0005	0.0007	0.0023***	0.0028***
	(0.0004)	(0.0004)	(0.0009)	(0.0009)
Post $\times$ *PriceShock*		-0.0086***		-0.0101***
$\times$*LowMcaidPre*		(0.0006)		(0.0014)
	$\geq$ 1 new patient from Medicaid			
Post $\times$ *PriceShock*	0.0001	0.0000	0.0020***	0.0020**
	(0.0004)	(0.0004)	(0.0007)	(0.0008)
Post $\times$ *PriceShock*		-0.0073***		-0.0061***
$\times$*LowMcaidPre*		(0.0008)		(0.0014)
Observations	65,783	65,783	13,903	13,903

Note: This table reports the coefficients from fixed effect panel regressions. Unreported covariates include practice indicators, month and year indicators, and county-level controls (uninsurance, unemployment, and median household income). Standard errors are clustered at the practice level. * denotes significance at 10% level, ** denotes significance at 5% level, and *** denotes significance at 1% level.

- with the implementation of the payment increase.

Overall, the results presented in Table 4.4 suggest that a temporary increase in Medicaid payment rates has little effect on physicians' Medicaid participation decisions. However, there is some evidence that physicians in states where the payment increase continued beyond 2014 responded to it by increasing their Medicaid participation, particularly their acceptance of new patients from Medicaid.

4.6.2 The Effect of the Primary Care Payment Increase on Physician Labor Supply

In addition to an increase in physician Medicaid participation, the conceptual framework also predicts that an increase in the administratively set price should increase physicians' total labor supply. Table 4.5 presents estimates for the DD (Equation 4.1) and DDD (Equation 4.3), with three measures of labor supply as dependent variables: appointment count, unique patient count, and total number of minutes scheduled for patient care.

Column 1 shows no overall relationship between the Medicaid primary care payment increase labor supply, while Column 2 presents estimates consistent with the mixed-economy model's prediction of a greater labor supply response among physicians participating in Medicaid. PCPs accepting any Medicaid patients prior to the payment increase increased their labor supply, by an average of 135.7 appointments ($p = 0.002$) and 90.8 unique patients per quarter ($p = 0.003$).

Column 3 shows that PCPs in states that continued the Medicaid primary care increase beyond 2014 responded by increasing their labor supply by an average of 71 appointments ($p = 0.030$) and 49.8 unique patients ($p = 0.023$). This represents a change of 11.1% relative to the average quarterly appointment count and 11.3% relative to the average quarterly patient count. Column 4 reports no significant difference in how physicians responded to the payment increase, based on their pre-period participation in Medicaid. Interestingly, all columns of Panel 3 show no evidence that physicians changed the amount of time scheduled for appointments in response to the Medicaid payment increase, suggesting that appointment duration may have decreased.

Table 4.5: *Effect of the Primary Care Payment Increase on Labor Supply, 2010-2013*

	All States		Permanent Fee Bump States	
	(1)	(2)	(3)	(4)
	Appointment Count			
Post × PriceShock	-0.1058	-0.5515	2.5658**	3.2652**
	(0.5954)	(0.8778)	(1.1757)	(1.3693)
Post × PriceShock		4.8834***		2.7733
×YesMcaidPre		(1.5869)		(2.6687)
	Patient Panel Size			
Post × PriceShock	-0.1155	-0.1619	1.7916**	2.0139**
	(0.4014)	(0.5707)	(0.7823)	(0.8479)
Post × PriceShock		3.2675***		0.9934
×YesMcaidPre		(1.0977)		(1.7971)
Observations	65,783	65,783	13,903	13,903
	Total Minutes Scheduled			
Post × PriceShock	-15.6780	7.7801	-6.1555	10.3150
	(12.9987)	(18.7042)	(25.8487)	(25.7737)
Post × PriceShock		-10.5536		-31.0098
×YesMcaidPre		(35.3157)		(73.6580)
Observations	36,351	36,351	7,996	7,996

Note: This table reports the coefficients from fixed effect panel regressions. Unreported covariates include practice indicators, month and year indicators, and county-level controls (uninsurance, unemployment, and median household income). Standard errors are clustered at the practice level. * denotes significance at 10% level, ** denotes significance at 5% level, and *** denotes significance at 1% level.

4.6.3 The Effect of the Primary Care Payment Increase on Appointment Availability and Duration

While the mixed-economy model in Section 4.3 does not generate predictions about the effect of a Medicaid reimbursement increase on appointment availability, this is a metric of frequent interest to researchers and policymakers. Table 4.6 presents results from the DD and DDD specifications with appointment wait time and duration as the dependent variables. Panel A presents estimates

Table 4.6: *Effect of the Primary Care Payment Increase on Appointment Availability and Duration, 2010-2013*

	All States		Permanent Fee Bump States	
	(1)	(2)	(3)	(4)
	Wait Time, Medicaid			
Post × *PriceShock*	-0.1156***	-0.1130***	0.0168	-0.0129
	(0.0338)	(0.0347)	(0.0641)	(0.0652)
Post × *PriceShock*		0.0502		0.1294
×*LowMcaidPre*		(0.0686)		(0.1951)
	Appointment Duration, Medicaid			
Post × *PriceShock*	-0.0217*	-0.0259**	-0.0211	-0.0222
	(0.0127)	(0.0127)	(0.0211)	(0.0212)
Post × *PriceShock*		0.0297		0.0050
×*LowMcaidPre*		(0.0235)		(0.0249)
Observations	25,281	25,281	4,985	4,985

This table reports the coefficients from fixed effect panel regressions. Unreported covariates include practice indicators, month and year indicators, and county-level controls (uninsurance, unemployment, and median household income). Standard errors are clustered at the practice level. * denotes significance at 10% level, ** denotes significance at 5% level, and *** denotes significance at 1% level.

with appointment wait time (i.e., number of days from appointment scheduling to occurrence), finding that appointment Medicaid wait times decreased in response to the payment increase. On average, wait time decreased by 3.2 days ($p = 0.001$), or 15.8% relative to the mean of 20.2 days.

Panel B presents results from the DD and DDD specifications with scheduled Medicaid appointment duration (in minutes) as the dependent variable. I find that appointment duration decreased by 0.6 minutes, relative to the mean duration of 21.8 minutes, but this was significant only at the $p < 0.1$ level.

4.6.4 The Effect of the Primary Care Payment Increase on Practice Size and Staffing

As an additional analysis, I explore the effect of the primary care payment increase on practice size. While the conceptual framework in Section 4.3 is at the physician level and therefore does not generate practice-level predictions, the topic of physician capacity and the role of mid-level providers is highly policy-relevant. For these analyses, practice size (number of physicians, number of nurses, number of physician assistants) is the dependent variable, regressed on the price shock variable interacted with an indicator for the post-period, as described above.

Table 4.7 shows that practice size and staffing did not change in response to the payment increase. The sign of the coefficient on the interaction term of interest is positive for practices in states that kept the payment increase beyond 2014, but statistically indistinguishable from zero. This is perhaps not surprising, given that staffing decisions may take time and this analysis limits the post-period to one year.

Table 4.7: *Effect of the Primary Care Payment Increase on Practice Size, 2010-2013*

	All States	Permanent Fee Bump States
	Practice Size, Physicians	
Post $\times$ *PriceShock*	-0.1450	0.1376
	(0.2445)	(0.4341)
	Practice Size, Nurses	
Post $\times$ *PriceShock*	-0.0211	0.0272
	(0.0227)	(0.0336)
	Practice Size, Physician Assistants	
Post $\times$ *PriceShock*	-0.0180	0.0262
	(0.0261)	(0.0528)
Observations	11,147	3,503

This table reports the coefficients from six individual regressions. Unreported covariates include month and year indicators. * denotes significance at 10% level, ** denotes significance at 5% level, and *** denotes significance at 1% level.

4.7 Conclusion

A mixed-economy model of physician labor supply predicts that an increase in Medicaid service reimbursement should lead to an increase in physician participation in Medicaid and an increase in total quantity of labor supplied. I find some, but limited empirical evidence to support these predictions. First, I find that primary care physicians did not alter their Medicaid participation decisions in response to the primary increase, except among those PCPs in states that chose to extend the primary care payment increase beyond 2014. These physicians increased their Medicaid participation in response to the payment increase. Second and as predicted, I find that PCPs - particularly those participating in Medicaid - increased their total labor supply in response to the Medicaid payment increase. Results suggest that overall appointment wait times increased as a result of the payment increase, while appointment duration may have fallen slightly.

These results suggest that the temporary increase in Medicaid payments for primary care services may not have been an effective way to increase access for Medicaid patients. To the extent that physicians responded by increasing their Medicaid participation, this was only observed in states that chose to continue the payment increase beyond 2014, when the federal policy expired.

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Appendix A

Table A.1: *Analytic Sample versus National Ambulatory Medicare Care Survey Estimates*

	NAMCS	Analytic Sample
Age		
Category 1 (Youngest)	0.091	0.061
Category 2	0.239	0.225
Category 3	0.352	0.419
Category 4 (Oldest)	0.317	0.268
Female	0.582	0.577
Insurance		
Commercial	0.602	0.602
Medicare	0.249	0.322
Medicaid	0.127	0.048
No Insurance	0.048	0.023
Workers' Compensation	0.014	0.003
Chronic Condition Count		
0	0.449	0.470
1	0.236	0.134
2	0.133	0.129
3+	0.149	0.267
Geography		
Northeast	0.199	0.263
Midwest	0.184	0.194
South	0.396	0.427
West	0.222	0.124
New Patient	0.159	0.137
Practice Size		
Solo	0.340	0.104
2	0.095	0.058
3-5	0.263	0.069
6-10	0.174	0.072
11+	0.123	0.697

Note: This table presents appointment-level descriptive statistics on a nationally representative sample of office visits, compared to the analytic sample of 2013-2014 athenahealth appointments with office-based primary care physicians. NAMCS is the National Ambulatory Medical Care Survey. NAMCS insurance categories are not mutually exclusive and therefore do not sum to one. NAMCS age categories do not match those in athenahealth and are therefore assigned to relative categories. Age category 1 is 15-24 in NAMCS and 20-29 in the analytic sample. Category 2 is 24-44 and 30-49. Category 3 is 45-64 and 50-69. Category 4 is 65+ and 60+.
Source: Authors' analyses and National Ambulatory Medical Care Survey (NAMCS) Summary Tables from the 2012 NAMCS.

Table A.2: *Robustness Check: Alternative Instruments*

	(1) $t-1$	(2) $t-2$	(3) $t-3$	(4) $t-4$	(5) $t-5$
Observed Duration	-0.1821***	-0.0599***	-0.0488***	-0.0400***	-0.0254***
	(0.0079)	(0.0077)	(0.0094)	(0.0103)	(0.0130)
Procedure Count	-0.0081***	-0.0019	0.0009	0.0034	0.0097**
	(0.0015)	(0.0022)	(0.0022)	(0.0037)	(0.0048)
Diagnosis Count	-0.0050***	-0.0017	0.0002	-0.0002	0.0043*
	(0.0011)	(0.0013)	(0.0015)	(0.0019)	(0.0026)
Spending	-0.1489	-0.2568*	0.1931	-0.1467	1.9321
	(0.0985)	(0.1451)	(0.2496)	(0.1585)	(1.2361)
Visit Intensity	-0.0211	-0.0209	0.0003	-0.0101	0.0040
	(0.0434)	(0.0476)	(0.0496)	(0.0512)	(0.0943)
Post-Visit Documentation	0.0017***	0.0007*	0.0011**	0.0004	0.0009
	(0.0004)	(0.0004)	(0.0005)	(0.0006)	(0.0008)
Revisit within 2 Weeks	0.0006**	0.0000	-0.0003	-0.0002	0.0007
	(0.0003)	(0.0003)	(0.0004)	(0.0005)	(0.0007)
Observations	4,253,010	3,843,015	3,011,483	2,665,023	1,370,403

Note: This replicates elements of Tables 1.4 and 1.5, using alternative instruments of patient office arrival time at $t-2$ through $t-5$. Full controls are used. Standard errors are clustered at the physician level. * denotes significance at 10% level, ** denotes significance at 5% level, and *** denotes significance at 1% level.

Table A.3: *Robustness Check: Binary and Log Instrument*

	2SLS (Instrument: Previous Patient Late Y/N)
Observed Duration	-0.2211***
	(0.0140)
Procedure Count	-0.0086***
	(0.0025)
Spending	0.1076
	(0.2030)
Diagnosis Count	-0.0052***
	(0.0019)
Post-Visit Documentation	0.0019***
	(0.0007)
Revisit within 2 Weeks	0.0006
	(0.0005)
First Stage	
Appointment Start Time	1.3466***
	(0.0612)

	2SLS (Instrument: Log of Previous Patient Arrival Time)
Log Observed Duration	-0.4888***
	(0.0512)
Procedure Count	-0.3121***
	(0.0936)
Log Spending	-0.0522**
	(0.0261)
Diagnosis Count	-0.1546***
	(0.0653)
Post-Visit Documentation	0.0707***
	(0.0222)
Revisit within 2 Weeks	0.0176***
	(0.0017)
First Stage	
Appointment Start Time	0.0209***
	(0.0020)

Note: This replicates elements of Tables 1.4 and 1.5, instrumenting for current appointment start time using a) a binary indicator for a previous patient arriving to the office after his or her scheduled appointment start time and b) the log of the previous patient's arrival time. Full controls are used. Standard errors are clustered at the physician level. * denotes significance at 10% level, ** denotes significance at 5% level, and *** denotes significance at 1% level.

Table A.4: *Placebo Test: Subsequent Patient Arrival Instruments*

	Current Appointment (t) Start Time (Minutes Behind)
Primary Instrument	
Patient Arrival for Appointment $t-1$	0.2917***
(Previous Appt)	(0.0094)
Alternative Instruments	
Patient Arrival for Appointment $t+1$	-0.2336
	(0.7476
Patient Arrival for Appointment $t+2$	-0.3162
	(0.7726)

Note: This table presents first stage results of my instrumental variables estimating equation, predicting current appointment start time (minutes behind) as a function of the previous patient's office arrival time ($t-1$), the arrival time of the patients 1 and 2 appointments later. Full controls are used. Standard errors are clustered at the physician level. * denotes significance at 10% level, ** denotes significance at 5% level, and *** denotes significance at 1% level.

Table A.5: *Placebo Test: Revisit Within Two Weeks*

	(1) 2SLS
Revisit Within 2 Weeks	0.0006**
	(0.0003)
Previously Scheduled Revisit Within 2 Weeks	0.0002
	(0.0002)

Note: Full controls are used. Standard errors are clustered at the physician level. * denotes significance at 10% level, ** denotes significance at 5% level, and *** denotes significance at 1% level.

Appendix B

B.1 Metropolitan Statistical Area Inclusion Criteria

The MarketScan database includes inpatient and outpatient claims for a convenience sample of private health plans and self-insured employers. Because MarketScan data varied geographically in representativeness and included an increasing number of employers and health plans over the study period, we limited our analyses to the 323 Metropolitan Statistical Areas (MSAs) where the MarketScan preferred-provider organization (PPO) or point-of-service (POS) population in 2008-2012 represented at least 15% of commercially insured individuals with coverage through a PPO or POS health plan.

Because we used Medicare claims to assess physician-hospital integration, we further limited our sample to include MSAs in the top three quartiles by physician count during 2008 and 2012. We did this to avoid identifying effects off of changes in physician-hospital integration that were driven by random shifts between settings in Medicare claims for small numbers of beneficiaries in small markets. This restriction also likely improved within-MSA overlap between providers contributing to physician-integration assessed with Medicare claims and providers captured by MarketScan data. Specifically, we counted unique National Provider Identifiers (NPIs) for physicians âĂŞ allowing a physician to count twice if they billed under multiple groups, as measured by Tax Identification Numbers (TINs) âĂŞ and included MSAs in the top three quartiles by count of unique NPI-TIN combinations ($\geq$ 219 in 2008 and 221 in 2012).

After these two restrictions, our final study sample included 240 MSAs with an average of 1,318 NPI-TIN combinations billing Medicare in 2008 and a MarketScan PPO population representing, on average, 53% of the fully-insured PPO population in that MSA. Note: the MarketScan PPO or POS population exceeded the Interstudy population in some MSAs âĂŞ likely because self-insured employer PPO or POS offerings were not captured in the Interstudy PPO or POS population measure.

B.2 Measure of Physician-Hospital Integration

Our measure of physician-hospital integration exploited a feature of the Medicare outpatient prospective payment system to calculate a MSA-level variable based on each individual physicianâĂŹs share of outpatient care billed with a hospital outpatient department (HOPD) place of service code. To calculate this, we first reclassified 2-3% of Medicare Carrier file claims in the office setting (place of service code = 11) as occurring in HOPD settings (place of service code = 22) annually. Specifically, we reclassified these Carrier claims when they were found to have a matching claim in the Medicare Outpatient file with a setting code indicating HOPD settings (facility type = 1 and type of service = 3). We considered claims in the two files to refer to the same patient and service if the following matched: A) beneficiary ID, service date, and procedure code, and/or B) beneficiary ID, service date +/- seven days, and NPI of the service provider. We did this in light of recurring findings by the Office of the Inspector General that physicians erroneously record the place of service as an office setting when the service was actually performed in an HOPD or ambulatory surgical center.1 Excluding non-physician NPIs, specialties that do not practice in outpatient settings (anesthesiology, pathology, critical care, emergency medicine), and physicians with small numbers of claims (any NPI in the bottom quartile by annual Carrier file claim count, which is roughly 15 claims), we counted Carrier claims by place of service (i.e., office or HOPD) at the NPI-TIN-MSA level, allowing physicians to bill in multiple MSAs and under multiple TINs. (Most physicians bill under only one TIN, though roughly 15-20% bill under multiple TINs in a given year.) We constructed the measure of physician-hospital integration at the NPI level as:

$$\text{Share HOPD}_{ijm} = \frac{\text{Count of HOPD claims}_{ijm}}{\text{Count of Office Claims}_{ijm} + \text{Count of HOPD claims}_{ijm}} \tag{B.1}$$

Where i indexed physicians, j indexed TINs, and m indexed MSAs. We observed that NPI-TIN-MSA combinations tended to bill predominantly in an office setting (0) or predominantly in an HOPD setting (1). From the NPI-level share variable, we calculated a MSA-level measure as the percent of NPI-TINs billing 100% (or 25%, 75%, 95% - as sensitivity analyses) of their outpatient claims with an HOPD setting code.

To validate our measure, we examined the 10 MSAs that experienced the greatest increase in physician-hospital integration between 2008 and 2012. For each MSA, we conducted web searches for reports (from either the entity's website, local media, or health care trade publications) of major acquisitions or market entry causing greater financial integration between physicians and hospitals. Of the 10 MSAs with the greatest increases in physician- hospital integration according to our measure, we found reports of at least one major physician-hospital merger, acquisition, or market entry causing greater physician-hospital integration in all 10 MSAs.

At the start of our study period (2008), there was considerable variation in physician-hospital integration by physician specialty, with 7% of dermatologists and 45% of diagnostic radiologists exhibiting billing patterns consistent with financial integration with hospitals. From 2008 to 2012, we observed an increase in physician- hospital integration for all major medical specialties. Hematology-oncology/oncology, primary care, and neurology experienced the greatest percentage point change over the study period, while otolaryngology, primary care, and hematology-oncology/oncology experienced the greatest percent change. Primary care, hematology- oncology/oncology, and diagnostic radiology had the highest number of NPI-TIN combinations switch their billing patterns in a manner indicative of integration (Table B.3). We would note that national changes in physician-hospital integration by specialty obscured geographic variation. Examining specialty-specific MSA changes in physician- hospital integration during the study period, we find that diagnostic radiology, cardiology, and primary care had the largest interquartile ranges, with a range of more than 10 percentage points between the 25th and 75th percentile of changes by MSA.

B.3 Measure of Physician Concentration

To control for physician market structure, we constructed a MSA-level physician Herfindahl-Hirschman index (HHI) based on allowed charges for claims with office or HOPD place of services codes in the Medicare Carrier file. Again, we excluded non-physician NPIs, specialties that do not practice in outpatient settings (anesthesiology, pathology, critical care, emergency medicine), and physicians with fewer than roughly 15 claims. We summed all allowed charges for each TIN-MSA combination. Doing so allowed the inclusion of charges billed by the same physician under multiple TINs and charges billed under the same TIN in multiple MSAs. For each TIN-MSA combination, we calculated a market share such that:

$$MarketShare_{ijm} = \frac{\sum AllowedCharges_{jm}}{\sum AllowedCharges_{m}} \tag{B.2}$$

where j indexed TINs and m indexed MSAs. The Herfindahl Index was calculated as:

$$HHI_m = \sum_{j=1}^{N} (MarketShare_{jm})^2 \tag{B.3}$$

B.4 Measures of Plan Benefit Generosity

For every PPO and POS plan in MarketScan, we constructed measures of average inpatient and outpatient benefit generosity. To calculate the annual measure of outpatient generosity, we first summed cost-sharing payments (including copayments, coinsurance, and deductible) for office visit Current Procedural Terminology (CPT) codes (99201-5, 99211-5, and 99241-55) at the claim-day level and calculated an average cost-sharing amount for every plan-CPT combination. We then averaged across CPTs to obtain a summary measure of average out-of-pocket costs at the plan level.

We excluded high-deductible health plans from our analyses to make the deductibles more homogenous across plans. Differences in enrollee illness burden between plans could have contributed to differences in our out-of- pocket spending measure, because with a given deductible, a plan with more sick patients would have more services provided above the deductible with less out-of-pocket spending. Previous research, however, found that our claims- based measures of plan generosity were positively and strongly correlated with copayments listed in health plan benefit guides, suggesting that case-mix did not bias our assessments of plan benefit generosity substantially.2

To calculate the annual measure of inpatient generosity, we first summed cost-sharing payments (including copayments, coinsurance, and deductible) for the 100 most common Diagnostic Related Groups (DRG) at the admission level and calculated an average cost-sharing amount for every plan-DRG combination. We then averaged across DRGs to obtain a summary measure of average out-of-pocket costs at the plan level.

B.5 Commercial Spending: Outpatient and Inpatient

The MarketScan database is a convenience sample of health care claims submitted by employers and health insurers. We included only spending for enrollees enrolled in plans designated as POS or PPO, since claims under other benefit designs may not accurately reflect physician compensation for a service. (The majority of our sample were enrolled in a PPO, with only 14.2% of enrollees in a POS plan.) For any given year, we excluded spending for the few PPO or POS enrollees missing enrollment information, enrolled in a capitated plan, or having a negative claim-day payment during that year (as this may be indicative of partial capitation or a payment framework different from fee-for-service). Despite the MSA inclusion criteria detailed above, there remained considerable fluctuation in MSA-level MarketScan enrollee counts. Roughly half of all MSAs experienced a positive or negative population change exceeding 50% during our sample period (2008-2012). With changes of this magnitude, the provider groups represented in the data may vary over time, generating changes in market-level prices that simply reflect changes in providers seen. To reduce this source of confounding, we restricted our main analysis to the sample of enrollees present in the MarketScan database enrollment files in 2008 and 2012, with the same MSA-of-residence in both years. This restriction made the set of providers assessed in each MSA consistent across years to the extent that these enrollees continued to receive care from the same provider groups (consistency did not require that enrollees stayed with the same specific physicians since prices are negotiated at the group level).

Annual, individual-level outpatient spending was calculated as the sum of all PPO and POS payments for facility and professional claims with an office or HOPD place of service code. PPO and POS enrollees without positive annual spending amounts (roughly 15% of our sample in any given year) were coded as having $0 spending for that year.

Annual, individual-level inpatient spending was calculated as the sum of all PPO and POS facility payments in an inpatient hospital. PPO and POS enrollees without positive annual spending amounts (only 5% of our sample had non-zero inpatient hospital spending in any given year) were coded as having $0 spending for that year.

B.6 Commercial Utilization: Outpatient and Inpatient

Using the same restrictions described in the previous section, we calculated annual, individual-level outpatient utilization equal to the sum of each annual service count multiplied by the national mean of allowed charges for each service (averaged over 2008-2012), with services defined by CPT codes. Before calculating the national average service price, we first summed all spending for a given service (defined by a CPT code) to the enrollee-day levelâĂŤ aggregating all spending for a given person on a given date for a given CPT code. We did this because the MarketScan data frequently have multiple claim lines for a single procedure code on a single day for a single enrollee. Multiple claim lines may represent professional and technical components of payments for the same service (e.g., facility fees for imaging services), may be corrective claims, or may simply be quirks of the billing process. We then calculated national average service prices and multiplied these mean service prices by annual service counts to calculate annual, individual-level outpatient utilization. This claim-day methodology has been used in other research using MarketScan data, including an Institute of Medicine Study on geographic variation in commercial spending.3-5

To calculate annual, individual-level inpatient utilization, we modified this process slightly, with the admission count equal to the count of unique combinations of admission date and DRG for each enrollee in each year. We then multiplied admission counts by the mean price for that DRG (average over 2008-2012) and summed over the year to calculate annual, individual-level inpatient utilization.

Since spending is the product of price and quantity (i.e., utilization), comparisons of changes in spending versus utilization allowed us to deduce the extent to which changes in spending were driven by price. An alternative approach would be to calculate a price index at the MSA level directly instead of decomposing enrollee-level spending into utilization and implied price components. This strategy could be problematic, however, because facility fees for services billed with an HOPD setting codeâĂŤwhile included in our spending totalsâĂŤare frequently bundled across services or otherwise recorded without a CPT code. Direct assessments of prices would therefore tend to underestimate prices for services in hospital-owned physician practices. To illustrate the difficulty this poses in calculating a market-level average service price, imagine a market where service A is performed exactly twice. In the first period, service A is performed in an office for 20*and*30, yielding an average price of $25. In the second period, service A is performed once in an office for 20*andonceinanHOPDfora*$10*professionalfeeanda*$25*facilityfee.IfthefacilityfeeisnotcodedasserviceA*, *t*
To avoid this situation, we decomposed spending into utilization and implied price. Finally, using our approach of decomposing enrollee-level spending into utilization and implied price components allowed us to adjust for important enrollee characteristics that also influence spending and utilization.

B.7 Setting-Specific Office Visit Price Differentials

To calculate the price differential between office visits provided in an office setting or an HOPD setting, we first identified all dollars associated with office visit claims in both settings. Claims in the MarketScan database can be distinguished as provided in an office or HOPD setting based on their place-of-service code. As in Medicare claims, a service with an HOPD setting code frequently has two claims: a professional claim and a facility claim. However, we observed considerable heterogeneity in billing patterns in the MarketScan data for services billed in an

HOPD. Some claim pairs were billed on nearby but different dates, billed with a similar (but non-identical) service code, or billed with the facility component bundled with other services or otherwise without a specific service code. As such, we developed a methodology to match professional and facility claims for services billed in an HOPD setting and to impute missing claim amounts for the roughly 30% of HOPD professional or facility claims for which no matching claim could be identified.

For each year of Marketscan claims data, we selected all professional claims for HOPD office (CPT codes: 99201-5, 99211-5, and 99241-55) visits for an enrollee insured through a PPO or POS plan. We then identified potential facility fee matches for these claims as (1) facility claims with an office visit procedure code in an HOPD or (2) facility claims missing a procedure code in an HOPD. We then paired professional claims to facility fees if the two claims matched on:

1. Enrollee ID, service date, and exact CPT code
2. Enrollee ID, service date, and the first 4 digits of the CPT code
3. Enrollee ID, service date, and the first 3 digits of the CPT code
4. Enrollee ID, service date, a missing CPT code, and a revenue code that indicates an office visit
5. Enrollee ID, service date, a missing CPT code, and missing revenue code.

Once a claim (either professional or facility) matched on one of these successively broader sets of criteria, it was removed from the pool of potential matches. In cases where one professional claim matched to multiple facility fees on the same criteria (or one facility fee matched to multiple professional claims) we summed the matching facility fee dollars and divided equally among the professional claims to which they matched. Claim amounts for the same service and type (professional or facility) in an HOPD were similar, regardless of whether we could identify a matching claim component âĂŞ suggesting that professional and facility payments are truly billed separately and not commonly bundled into one claim.

We then used the group of complete claims (matched professional and facility fees) to estimate the following model, fitting one model for each CPT code. Year interactions were added to adjust for changes across time. We trimmed outlier office visit payment amounts ($\leq$ 5% of payments exceeding \$1000) before estimating coefficients.

$$
\begin{aligned}
FacilityFee = \beta_0 + \beta_1 ProfessionalFee + \beta_2 MSA + \beta_3 PatientAge + \beta_4 PatientGender \\
+ \beta_5 ServiceYear + \beta_6 MSA \times ServiceYear + \beta_7 PatientAge \times ServiceYear \\
+ \beta_8 PatientGender \times ServiceYear + \epsilon \quad \text{(B.4)}
\end{aligned}
$$

Predicted values from the above model were used to impute facility fees for professional claims that did not match with any facility fees and for those with implausibly high payments (exceeding \$1000). Negative claim payments were assumed to be adjustments for incorrect billing and were therefore included in the final dataset.

Finally, to impute professional claims for facility fees that had no matches, the equation was reversed (below), coefficients were estimated from the group of matching professional and facility fees, and used to impute missing and implausibly large professional claims.

$$
\begin{aligned}
ProfessionalFee = \beta_0 + \beta_1 FacilityFee + \beta_2 MSA + \beta_3 PatientAge + \beta_4 PatientGender \\
+ \beta_5 ServiceYear + \beta_6 MSA \times ServiceYear + \beta_7 PatientAge \times ServiceYear \\
+ \beta_8 PatientGender \times ServiceYear + \epsilon \quad \text{(B.5)}
\end{aligned}
$$

Using complete and imputed office visit claims for 2012, we calculated the MSA-level difference between the average payment in MarketScan for established patient office visits (CPT codes: 99211-5) with HOPD setting codes (facility + professional fees) and the average payment for office visits in the office setting (professional fee only). We repeated this process using established patient office visit claims in the Medicare Carrier file (20% sample), matched to facility fees from the Outpatient File (20% sample) on beneficiary ID, service date, and four-digit procedure code (as we found that corresponding professional and facility Medicare claims often differ in the last digit of CPT codes). Comparisons of the office visit price differential across MSAs between Medicare and MarketScan yielded similar results when limited to only complete MarketScan claims (matched professional and facility fees without imputation) (Figure B.1).

B.8 Main Results and Sensitivity Analyses

Regressions were of the form:

$$\begin{aligned} DepVar_{ijmt} = \beta_0 + \beta_1 PhysHospInteg + \beta_2 InsHHI_{mt} + \beta_3 HospHHI_{mt} + \beta_4 PhysHHI_{mt} \\ + \beta_5 X_{mt} + \beta_6 AvgOOP_{jt} + \beta_7 DxCG_{it} + \gamma_t + \delta_m + \epsilon_{ijmt} \end{aligned} \quad \text{(B.6)}$$

where i indexed individual, j indexed plan (specific to each data-contributor in MarketScan), m indexed MSA, and t indexed year. $DepVar_{ijmt}$ was annual individual-level spending or utilization (price-standardized spending). $InsHHI_{mt}$, $HospHHI_{mt}$, and $PhysHHI_{mt}$, were the Herfindahl-Hirschman Indices for the physician, hospital, and insurance markets, respectively. X_{mt} was a vector of MSA-level time-varying characteristics including unemployment rate, percent of population aged 65 and above, percent of population in poverty, physicians per 1000 people, and beds per 1000 people. $AvgOOP_{jt}$ was the plan-specific measure of benefit generosity âĂŞ for inpatient or outpatient services, depending on the type of spending used as the dependent variable. $DxCG_{it}$ was the health risk score created using Verisk Health DxCG Stand Alone Software (v4.1.1 comprising the Budgeting & Underwriting Bundle for the Commercial, Medicaid, and Medicare Populations), which incorporates age, sex, and diagnosis codes from the prior year to predict spending for each enrollee in the current year. γ_t and δ_m are year and MSA fixed effects and ϵ_{ijmt} is an idiosyncratic error term.

The coefficient on $PhysHospInteg_{mt}$ in the following tables indicated the average change in spending (odd-numbered columns) or utilization (even-numbered columns) associated with an increase from 0 (entirely unintegrated) to 1 (fully integrated). Similarly, the coefficient on $InsHHI_{mt}$, $HospHHI_{mt}$, and $PhysHHI_{mt}$ indicated the average change in spending or utilization associated with an increase 0 (perfectly competitive) to 1 (monopolistic). The coefficient on $AvgOOP_{jt}$ indicated the average change in spending or utilization associated with a \$1 increase in average out-of-pocket costs and the coefficient on $DxCG_{it}$ indicated the average change in spending or utilization associated with a one unit increase in the predicted risk score (mean 1 within the MarketScan population, with higher scores indicating higher predicted health care utilization).

We found that an increase from unintegrated to perfect integration between physicians and hospitals was associated with a highly significant $1,445/enrollee increase in outpatient spending (Table B.2). This increase in outpatient spending was driven almost entirely by price increases, as changes in utilization were minimal and insignificant. Changes in physician-hospital integration were not associated with significant changes in inpatient spending (Table B.3). Our findings were robust to multiple alternative variable specifications and MSA inclusion criteria. First, our results remained unchanged when we used a MSA-level measure of physician-hospital integration calculated as the percent of NPI-TINs billing 25%, 75%, and 95% of their outpatient claims with an HOPD setting code (Table B.5). Alternative definitions of physician-hospital integration reduced the increase in inpatient spending by 28-62% but did not appreciably affect estimates for outpatient spending (Table B.6). Second, our results were robust to including only MSAs with large MarketScan populations (greater than 1000 PPO or POS enrollees in 2008-2012) (Table B.6). Third, our results were robust to not weighting observations by the total PPO population in the MSA divided by the MarketScan population in our study sample (i.e., in an analysis giving equal weight to each enrollee in our study sample) (Table B.8). Fourth and finally, our results were robust to use of generalized linear models with a log link and proportional to mean variance function (Table B.8). Holding all other variables constant, changes in other market structure variables were not generally associated with significant changes in outpatient or inpatient spending or utilization, with two notable exceptions. First, we found a significant positive association between changes in hospital concentration and outpatient utilization (Column 2, Table B.2). This could be the result, for example, of larger hospital systems steering patients to settings with more intensive care patterns (e.g., HOPD rather than office) or expanding profitable service lines and thereby inducing patient demand. Second, we found a significant negative association between changes in insurance concentration and outpatient spending, in some specifications (Column 5, Table B.1; Column 1, Table B.6; Column 1, Table B.8). This is consistent with past literature on the relationship between insurer concentration and prices and spending.6

Table B.1: *Physician-Hospital Financial Integration by Specialty, 2008 to 2012*

Specialty	Physician-Hospital Integration (2008)	Physician-Hospital Integration (2012)	Percentage Point Δ (2008 to 2012)	% Δ (2008 to 2012)	# Integrated NPIs (2008)	# Integrated NPIs (2012)	# of NPI Δ (2008 to 2012)
Primary Care	17.5	23.9	6.4	36.3%	32,409	47,824	15,415
Other Low-Volume Medical Specialties	15.8	18.4	2.5	15.9%	9,335	11,777	2,442
Hem-Onc-Onc	24.1	32.2	8.1	33.6%	2,640	4,197	1,557
Diagnostic Radiology	44.6	45.1	0.5	1.1%	21,016	22,036	1,020
Neurology	17.9	21.8	3.9	22.0%	2,516	3,349	833
Cardiology	27.3	28.4	1.1	4.2%	9,842	10,590	748
Orthopedic Surgery	7.6	9.7	2.1	27.8%	1,809	2,399	590
Gastroenterology	10.9	13.6	2.7	24.5%	1,426	1,941	515
Otolaryngology	8.0	11.3	3.3	41.4%	784	1,158	374
Urology	9.4	12.3	2.9	31.1%	1,023	1,379	356
Ophthalmology	7.7	8.7	1.0	13.6%	1,720	1,996	276
Dermatology	6.6	7.6	1.0	15.3%	793	988	195

Note: Table includes high-volume Medicare specialties, with lower-volume specialties under 'Other Low-Volume Medical Specialties'.

Table B.2: *Changes in Outpatient Spending and Utilization Associated with Changes in Physician-Hospital Integration and Physician Market Concentration from 2008 to 2012*

Variables	(1) Spending	(2) Quantity	(3) Spending	(4) Quantity
PhysHospInteg	1,445.03***	263.03	1,373.77***	421.04
	(365.33)	(262.57)	(408.37)	(323.19)
InsHHI	-714.49	-237.73		
	(385.56)	(196.09)		
HospHHI	916.51	636.10*		
	(808.41)	(306.23)		
PhysHHI	1,487.52	-368.06		
	(1,087.18)	(828.61)		
Unemp_rate	33.38	-3,728.66		
	(2,321.77)	(2,404.23)		
Pct_pop_65plus	3,686.35	3,109.75		
	(4,482.94)	(3,720.34)		
Phys_per_1000_pop	128.22	-12.84		
	(125.67)	(112.40)		
Beds_per_1000_pop	66.93	28.76		
	(87.00)	(73.07)		
Pct_in_poverty	-458.08	1,936.64		
	(1,513.40)	(1,043.77)		
AvgOOP_otpt	-5.81***	-5.74***	-5.79***	-5.76***
	(0.69)	(0.57)	(0.67)	(0.56)
DxCG	1,488.77***	1,123.91***	1,488.81***	1,122.88***
	(27.17)	(19.46)	(27.14)	(19.61)
R-squared	0.12	0.13	0.12	0.13
MSA FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

Table B.3: *Changes in Inpatient Spending and Utilization Associated with Changes in Physician-Hospital Integration and Physician Market Concentration from 2008 to 2012*

Variables	(1) Spending	(2) Quantity	(3) Spending	(4) Quantity
PhysHospInteg	427.75	187.71	489.60	323.48
	(229.93)	(210.54)	(267.04)	(279.35)
InsHHI	-92.20	-124.26		
	(190.66)	(174.25)		
HospHHI	377.50	490.63		
	(280.66)	(258.57)		
PhysHHI	847.44	5.86		
	(659.14)	(581.03)		
Unemp_rate	-1,702.27	-3,829.88*		
	(1,612.72)	(1,846.29)		
Pct_pop_65plus	2,816.31	3,160.57		
	(2,675.26)	(2,961.03)		
Phys_per_1000_pop	-77.83	-128.70		
	(72.94)	(83.57)		
Beds_per_1000_pop	81.86	50.96		
	(51.84)	(61.49)		
Pct_in_poverty	2,891.90**	2,400.21*		
	(918.66)	(941.38)		
AvgOOP_inpt	-0.10***	-0.10***	-0.10***	-0.09***
	(0.01)	(0.01)	(0.01)	(0.01)
DxCG	863.87***	809.57***	864.80***	809.64***
	(16.54)	(13.40)	(16.42)	(13.52)
R-squared	0.03	0.04	0.03	0.04
MSA FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

Table B.4: *Changes in Outpatient Spending and Utilization Associated with Changes in Physician-Hospita Integration and Physiican Market Concentration from 2008 to 2012, Alternative Physician-Hospital Integration Specifications*

Variables	(1) Spending	(2) Quantity	(3) Spending	(4) Quantity	(5) Spending	(6) Quantity
PhysHospInteg $\geq$ 95%	1,350.51***	178.01				
	(355.77)	(263.71)				
PhysHospInteg $\geq$ 75%			1,260.62**	40.58		
			(386.30)	(264.77)		
PhysHospInteg $\geq$ 25%					1,617.13**	338.58
					(489.86)	(312.69)
InsHHI	-717.42	-236.16	-708.07	-231.68	-764.42*	-249.2
5	(387.86)	(197.26)	(387.05)	(199.35)	(379.62)	(192.02)
HospHHI	893.98	631.04*	885.74	628.85*	903.33	634.49*
	(806.92)	(306.44)	(795.89)	(306.95)	(770.70)	(302.37)
PhysHHI	1,419.53	-393.22	1,342.99	-421.06	1,481.09	-360.58
	(1,070.91)	(829.98)	(1,051.29)	(830.88)	(1,019.72)	(832.45)
Unemp_rate	27.34	-3,770.78	74.14	-3,850.65	418.49	-3,625.52
	(2,299.22)	(2,384.61)	(2,327.22)	(2,405.98)	(2,282.34)	(2,346.87)
Pct_pop_65plus	3,735.14	3,139.74	4,014.09	3,190.60	4,905.56	3,352.18
	(4,440.96)	(3,708.69)	(4,486.86)	(3,750.03)	(4,558.37)	(3,763.10)
Phys_per_1000_pop	92.04	-18.04	71.29	-15.95	94.89	-19.58
	(128.79)	(113.80)	(136.61)	(115.97)	(127.95)	(112.31)
Beds_per_1000_pop	73.18	29.07	69.88	27.31	69.45	29.57
	(87.71)	(73.74)	(88.45)	(73.89)	(85.36)	(73.05)
Pct_in_poverty	-384.79	1,962.03	-300.52	1,988.66	-414.6	7 1,937.15
	(1,523.12)	(1,038.21)	(1,526.06)	(1,037.87)	(1,521.65)	(1,041.82)
AvgOOP_otpt	-5.79***	-5.74***	-5.79***	-5.74***	-5.78***	-5.74***
	(0.69)	(0.57)	(0.69)	(0.57)	(0.69)	(0.57)
DxCG	1,488.76***	1,123.91***	1,488.74***	1,123.90***	1,488.77***	1,123.91***
	(27.16)	(19.46)	(27.16)	(19.46)	(27.17)	(19.46)
R-squared	0.12	0.13	0.12	0.13	0.12	0.13
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table B.5: *Changes in Inpatient Spending and Utilization Associated with Changes in Physician-Hospita Integration and Physiican Market Concentration from 2008 to 2012, Alternative Physician-Hospital Integration Specifications*

Variables	(1) Spending	(2) Quantity	(3) Spending	(4) Quantity	(5) Spending	(6) Quantity
PhysHospInteg $\geq$ 95%	305.85	149.57				
	(225.09)	(218.79)				
PhysHospInteg $\geq$ 75%			164.03	32.41		
			(232.22)	(211.19)		
PhysHospInteg $\geq$ 25%					218.92	193.24
					(272.88)	(250.21)
InsHHI	-92.20	-124.98	-85.52	-119.47	-95.02	-133.14
	(191.80)	(174.69)	(192.12)	(174.90)	(195.41)	(175.54)
HospHHI	367.17	486.59	363.28	482.98	363.43	487.13
	(283.23)	(259.11)	(286.07)	(260.24)	(283.22)	(256.96)
PhysHHI	812.09	-6.20	774.23	-33.74	794.15	5.06
	(652.94)	(580.18)	(643.76)	(571.63)	(645.03)	(579.23)
Unemp_rate	-1,748.52	-3,841.42*	-1,812.74	-3,904.92*	-1,759.28	-3,782.30*
	(1,607.52)	(1,826.65)	(1,638.37)	(1,848.09)	(1,620.85)	(1,806.62)
Pct_pop_65plus	2,866.05	3,177.92	2,939.77	3,218.52	3,066.40	3,319.60
	(2,676.48)	(2,952.35)	(2,715.23)	(2,994.68)	(2,754.00)	(3,026.54)
Phys_per_1000_pop	-79.61	-129.99	-76.78	-126.46	-74.12	-129.15
	(75.38)	(85.37)	(77.36)	(86.65)	(76.16)	(83.89)
Beds_per_1000_pop	82.71	51.49	80.94	50.24	80.69	50.93
	(52.20)	(61.85)	(52.60)	(61.96)	(52.40)	(61.49)
Pct_in_poverty	2,922.35**	2,411.21*	2,951.82**	2,430.75*	2,934.60**	2,403.50*
	(916.72)	(936.77)	(921.43)	(939.42)	(925.70)	(943.55)
AvgOOP_inpt	-0.10***	-0.10***	-0.10***	-0.10***	-0.10***	-0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
DxCG	863.87***	809.57***	863.86***	809.56***	863.87***	809.57***
	(16.54)	(13.40)	(16.54)	(13.40)	(16.54)	(13.40)
R-squared	0.03	0.04	0.03	0.04	0.03	0.04
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table B.6: *Changes in Outpatient Spending and Utilization Associated with Changes in Physician-Hospital Integration and Physician Market Concentration from 2008 to 2012, MSAs with MarketScan PPO/POS Population Exceeding 1000*

Variables	(1) Spending	(2) Quantity	(3) Spending	(4) Quantity
PhysHospInteg	1,391.64***	169.41	1,256.59**	290.01
	(348.62)	(250.32)	(385.04)	(300.49)
InsHHI	-804.90*	-297.58		
	(387.70)	(188.87)		
HospHHI	859.16	691.57*		
	(733.11	) (274.62)		
PhysHHI	1,434.46	20.11		
	(826.14)	(682.72)		
Unemp_rate	-181.64 -	3,759.08		
	(2,205.20)	(2,308.65)		
Pct_pop_65plus	4,095.25	3,341.65		
	(4,139.74)	(3,411.97)		
Phys_per_1000_pop	89.27	-17.40		
	(124.76)	(105.82)		
Beds_per_1000_pop	86.90	43.36		
	(80.66)	(65.16)		
Pct_in_poverty	168.07	1,962.39*		
	(1,407.60)	(986.27)		
AvgOOP_otpt	-5.23***	-5.23***	-5.22***	-5.24***
	(0.77)	(0.74)	(0.76)	(0.74)
DxCG	1,482.34***	1,123.08***	1,482.33***	1,122.07***
	(26.17)	(18.46)	(26.14)	(18.60)
R-squared	0.12	0.13	0.12	0.13
MSA FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

Table B.7: *Changes in Outpatient Spending and Utilization Associated with Changes in Physician-Hospital Integration and Physician Market Concentration from 2008 to 2012, Unweighted*

Variables	(1) Spending	(2) Quantity	(3) Spending	(4) Quantity
PhysHospInteg	1,335.37**	145.79	1,301.12**	276.65
	(487.78)	(391.92)	(498.59)	(401.38)
InsHHI	-551.42	-94.39		
	(375.83)	(244.26)		
HospHHI	920.29	589.50*		
	(664.87)	(269.93)		
PhysHHI	2,147.67	-199.66		
	(1,187.90)	(909.26)		
Unemp_rate	1,183.45	-2,205.15		
	(2,817.82)	(2,724.23)		
Pct_pop_65plus	4,554.49	2,160.11		
	(4,376.17)	(3,557.15)		
Phys_per_1000_pop	177.14	100.84		
	(170.69)	(156.34)		
Beds_per_1000_pop	-9.99	-40.39		
	(79.00)	(68.60)		
Pct_in_poverty	-94.34	1,218.20		
	(1,444.94)	(1,080.49)		
AvgOOP_otpt	-5.98***	-5.70***	-6.00***	-5.72***
	(0.66)	(0.50)	(0.65)	(0.50)
DxCG	1,532.86***	1,160.46***	1,532.86***	1,159.43***
	(29.02)	(19.56)	(28.95)	(19.65)
R-squared	0.12	0.13	0.12	0.13
MSA FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

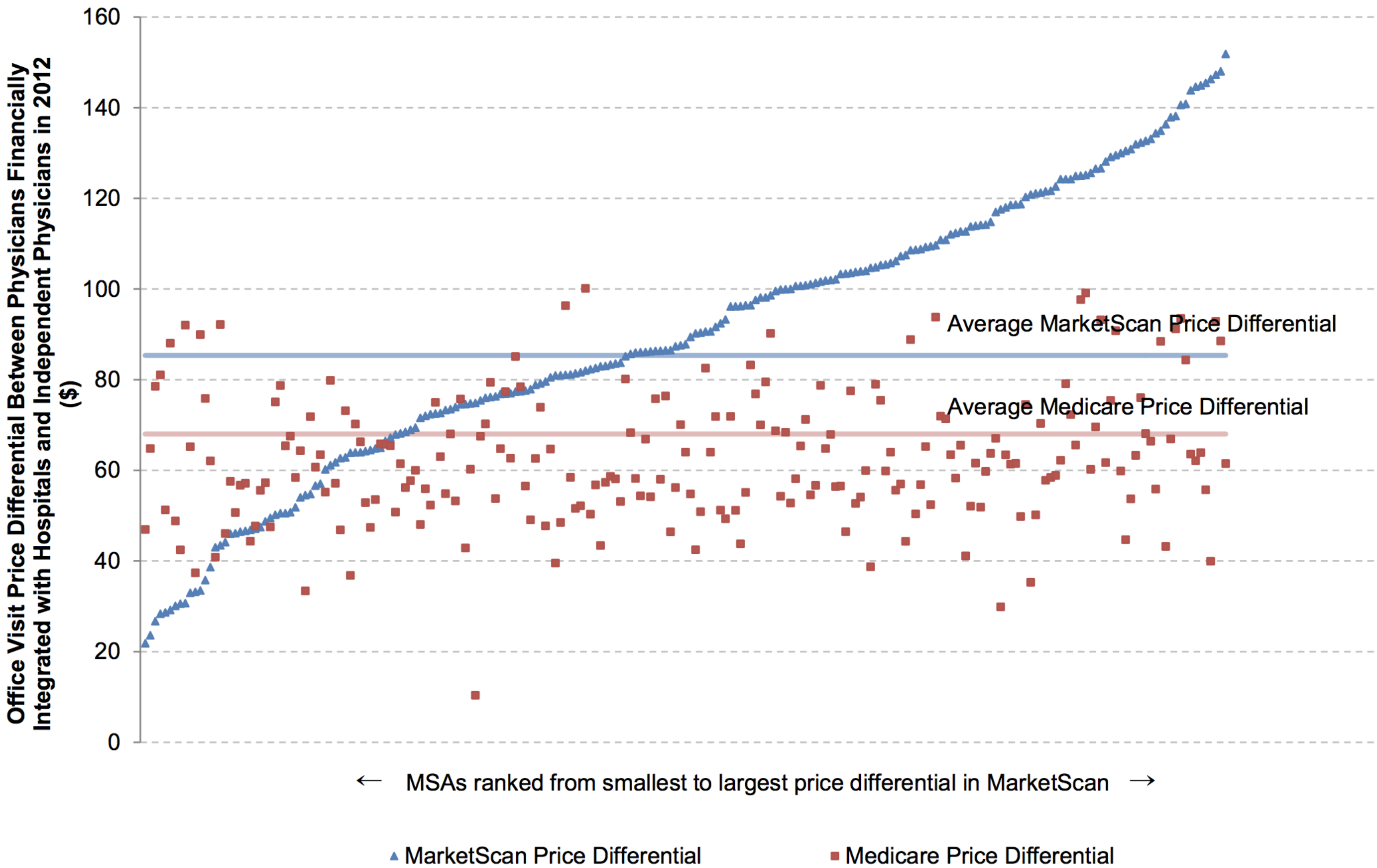
Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05

Table B.8: *Changes in Outpatient Spending and Utilization Associated with Changes in Physician-Hospital Integration and Physician Market Concentration from 2008 to 2012, Generalized Linear Model with Log Link and Proportional to Mean Variance Function*

Variables	(1) Spending	(2) Quantity	(3) Spending	(4) Quantity
PhysHospInteg	0.42**	0.11	0.28*	0.08
	(0.13)	(0.10)	(0.12)	(0.10)
InsHHI	-0.35*	-0.12		
	(0.15)	(0.08)		
HospHHI	0.25	0.20		
	(0.29)	(0.13)		
PhysHHI	0.29	-0.12		
	(0.37)	(0.31)		
Unemp_rate	2.41***	0.32		
	(0.66)	(0.67)		
Pct_pop_65plus	-1.66	-1.00		
	(1.84)	(1.14)		
Phys_per_1000_pop	0.04	0.03		
	(0.03)	(0.03)		
Beds_per_1000_pop	0.03	0.00		
	(0.03)	(0.02)		
Pct_in_poverty	-0.69	0.03		
	(0.52)	(0.42)		
AvgOOP_otpt	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
DxCG	0.11***	0.10***	0.11***	0.10***
	(0.00)	(0.00)	(0.00)	(0.00)
MSA FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

Figure B.1: *Difference in Mean Office Visit Prices Between Physicians Financially Integrated with Hospitals and Independent Physicians, by MSA for Medicare and MarketScan Populations, Complete Claims Analysis*



Note: The average difference between office visit prices with a hospital outpatient department (HOPD) setting code and office visit prices with an office setting code (HOPD setting price - office setting price) is plotted for each MSA in the Medicare and MarketScan population (after trimming outfitters above the 95th percentile of Medicare and MarketScan price differences), with MSAs ordered based on the price differential in the MarketScan population. Calculations for this figure rely solely on HOPD claims where we can match professional and facility claims, without any necessity for claim imputation.

Appendix C

C.1 Metropolitan Statistical Area Inclusion Criteria

Because we used Medicare claims to assess physician-hospital integration, we limited our sample to include MSAs with at least 150 physicians billing Medicare annually between 2008 and 2013. We did this to avoid identifying changes in physician-hospital integration driven by random shifts between settings in Medicare claims for small numbers of beneficiaries in small markets. This restriction also likely improved within-MSA overlap between providers contributing to physician-integration assessed with Medicare claims and providers captured in MarketScan. This restriction resulted in a sample of 289 MSAs.

For our analyses where construction of the dependent variable relied on the MarketScan databases, we further limited our sample of MSAs. The MarketScan database includes inpatient and outpatient claims for a convenience sample of private health plans and self-insured employers. Because MarketScan data varied geographically in representativeness and included an increasing number of employers and health plans over the study period, we limited our analyses to the MSAs where the MarketScan preferred-provider organization (PPO) or point-of-service (POS) population in 2008-2013 represented at least 15% of commercially insured individuals with coverage through a PPO or POS health plan, according to the InterStudy HealthLeaders data. For the analyses using inpatient and outpatient price indices as the dependent variable, this restriction resulted in a sample of 226 MSAs.

C.2 Medicare ACO Penetration

To calculate a measure of ACO penetration at the MSA level, we divided the number of ACO-assigned Medicare beneficiaries in each MSA by the count of assignment-eligible Medicare beneficiaries in the MSA. Assignment-eligible beneficiaries are those continuously enrolled in Parts A and B (while alive) with at least one qualifying service.

C.3 Measure of Physician-Hospital Integration

Our measure of physician-hospital integration exploited a feature of the Medicare outpatient prospective payment system to calculate a MSA-level variable based on each individual physicianâĂŹs share of outpatient care billed with a hospital outpatient department (HOPD) place of service code. To calculate this, we first reclassified 2-3 percent of Medicare Carrier file claims in the office setting (place of service code = 11) as occurring in HOPD settings (place of service code = 22) annually. Specifically, we reclassified these Carrier claims when they were found to have a matching claim in the Medicare Outpatient file with a setting code indicating HOPD settings (facility type = 1 and type of service = 3). We considered claims in the two files to refer to the same patient and service if the following matched: A) beneficiary ID, service date, and procedure code, and/or B) beneficiary ID, service date +/- seven days, and NPI of the service provider. We did this in light of recurring findings by the Office of the Inspector General that physicians erroneously record the place of service as an office setting when the service was actually performed in an HOPD or ambulatory surgical center.1

We excluded non-physician NPIs and physicians with primary specialties (the most frequently billed HCFA specialty code in any given year) that were primarily inpatient-based and did not practice in outpatient settings - including anesthesiology, pathology, critical care, and emergency medicine. We identified and excluded hospitalists as any primary care specialty (internal medicine, family practice, general practice, geriatric medicine, pediatric medicine, osteopathic manipulative medicine, preventive medicine, or hospice and palliative care) for whom inpatient claims made up at least 90 percent of their allowed charges in the Medicare Carrier File.2 Finally, we excluded physicians with fewer than 15 Carrier File claims. For the remaining physicians, we counted Carrier claims by place of service (i.e., office or HOPD) at the NPI-TIN-MSA level, assigning physicians to a primary TIN-MSA combination based on the plurality of their allowed charges in any given year. (In any given year, roughly 10 percent of physicians billed more than 15 Carrier file claims under two or more TINs, and 3 percent bill in two or more MSAs.) We constructed the measure of physician-hospital integration at the NPI level as:

$$\text{Share HOPD}_{ijm} = \frac{\text{Count of HOPD claims}_{ijm}}{\text{Count of Office Claims}_{ijm} + \text{Count of HOPD claims}_{ijm}} \tag{C.1}$$

where i indexed physician, j indexed TIN, and m indexed MSAs. A physician was considered financially integrated with a hospital if he/she billed >=90% of outpatient services in an HOPD. Given the well- documented errors in place-of-service coding, we classified a physician as financially integrated with a hospital under two additional circumstances. First, if a physician billed primarily under a TIN identified as a hospital. To identify hospital TINs, we created a list of TINs with nine or more unique NPIs and five or more office visits in the Carrier file, for any given year. We then searched the subscription TIN database, einfinder.com, and retrieved all names associated with each TIN. We considered a TIN to be a hospital if any of its names contained at least one of the following keywords: hospital, medical center, or systems. We identified 1784 TINs as hospitals. Second, we considered a physician integrated with a hospital when billing in a large (>=10 NPIs) TIN with at least 50% of NPIs billing $\geq$ 90% of outpatient services in an HOPD.

From the NPI-level share variable, we calculated a MSA-level measure as the percent of NPI-TINs billing >=90 percent (or 25, 75, 100 percent âĂŞ as sensitivity analyses) of their outpatient claims with an HOPD setting code.

C.4 Hospital and Physician Four-Firm Concentration Ratio

To supplement our analysis of hospital and physician concentration using the Herfindahl Hirschman Index, we also calculated a four-firm concentration ratio. This is another frequently used measure of market structure that captures the total market share of the largest four firms in a market.

C.5 Physician Group Specialty Mix

C.6 Irving Levin Mergers & Acquisition Database

Using the Irving Levin AssociatesâĂŹ Health Care Mergers and Acquisitions Database from 2008- 2015, we were able to identify instances of provider consolidation directly. Specifically, for every acquired physician group, we identified the TIN(s) associated with each group name using the Employer Identification Number Database.3 This allowed us to link acquired practice names to TINs for 79.2 percent of transactions. Practices that could not be linked to a TIN were disproportionately small (1-2 physicians) and for-profit.

C.7 Price Indices

We calculated a price index, designed to capture the mean prices for a basket of services in a MSA, relative to national prices. To construct this measure, we first computed the mean price for every service-MSA combination: $\bar{P}_{imt}$ where i indexed service (DRG or CPT code for inpatient or outpatient indices, respectively), m indexed MSA, and t indexed year. We then calculated the national mean service price over all MSAs: $\bar{P}_{imt}$. For each MSA, we computed total actual spending as the number of procedures in a given service, multiplied by the MSA average price for that service, and summed over all services in the county: $S_{mt} = \sum_{i=1}^{n} N_{imt} \times \bar{P}_{imt}$. We also calculated spending as if the service had been paid at the national mean price: $\hat{S}_{mt} = \sum_{i=1}^{n} N_{imp} \times \bar{P}_{it}$. The price index was then: $Index_{mt} = \frac{S_{mt}}{\hat{S}_{mt}}$. An index above one indicated a MSA where mean service prices paid exceeded the national mean and vice versa for an index below one. We computed price indices annually, fixing the national mean service price at the value in 2013, so that the change in the index from 2008-2013 included both variation across markets and growth in average service prices over time.

The market basket included services that represented a large share of spending in both the pre- and post-periods.4 Specifically, we included:

- The top 200 DRGs by spending
- The top 200 outpatient CPTs by spending

Limiting to services that met the above criteria in both the pre- and post-periods (to create a stable market basket over time), we had 171 services in the inpatient market basket and 143 services in the outpatient market basket.

C.8 Time Trend and Trend Break Analysis

For all market-level measures of consolidation and prices, we tested for time trends and a change in trends from the pre-period to the post-period, holding other market factors constant. To quantify time trends, we estimated the following model:

$$T_{mt} = \beta_0 + \beta_1 Year_t + \delta_m + \epsilon_{imt} \tag{C.2}$$

where m indexed MSA and t indexed year. Y_{mt} was our claims-based measure of physician-hospital integration, average TIN size, physician HHI, hospital HHI, and market-level price index (inpatient and outpatient). β_1 was the coefficient of interest, indicating a time trend during our study period.

To quantify any break in time trends from the pre-period to the post-period, we estimated the following model:

$$T_{mt} = \beta_0 + \beta_1 Year_t + \beta_2 Year_t \times Post + \delta_m + \epsilon_{imt} \tag{C.3}$$

where m indexed MSA and t indexed year. Y_{mt} was our claims-based measure of physician-hospital integration, average TIN size, physician HHI, hospital HHI, and market-level price (inpatient and outpatient). β_2 was the coefficient of interest, indicating a time trend during the post-period that differed from the pre-period trend.

Table C.1: *Annual Changes in Measures of Consolidation and Prices, Pre- to Post-Period*

Variables	(1) Physician-Hospital Integration	(2) Physician HHI	(3) Weighted Average TIN Size	(4) Hospital HHI	(5) Inpatient Price Index	(6) Outpatient Price Index
Year	0.01***	17.18***	4.70***	53.86***	0.04***	0.02***
	(0.00)	(4.88)	(0.99)	(9.04)	(0.00)	(0.00)
Observations	1,734	1,734	1,734	1,734	1,356	1,356
R-squared	0.95	0.98	0.94	0.98	0.93	0.98
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
F Statistic	110.2	12.40	22.37	35.49	933.8	583.8

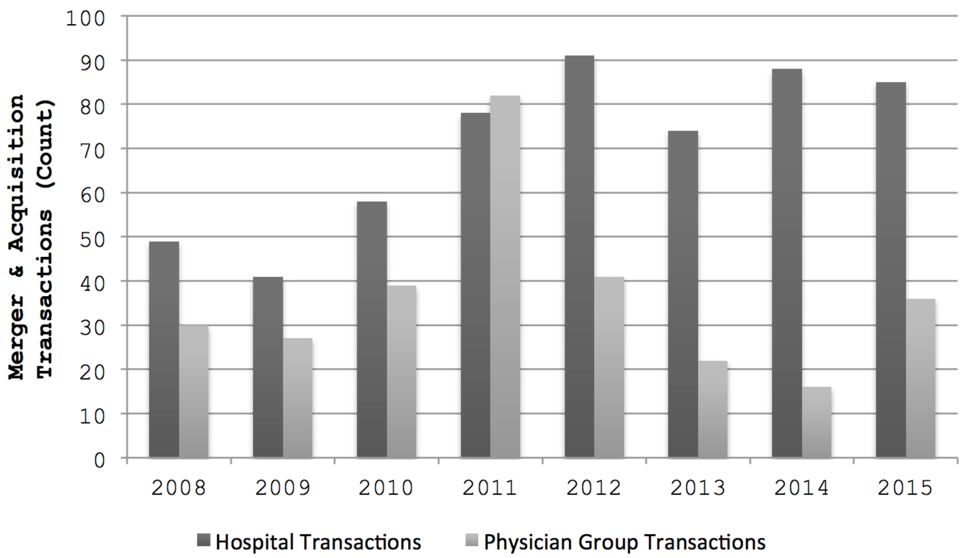
Source: AuthorsâĂŹ analysis of data from the Centers for Medicare and Medicaid and Irving Levin Associates.
Note: All columns present results from separate between-market analyses, clustering standard errors at the MSA level. PhysicianâĂŹs average group size is calculated as the average count of physician billing for outpatient care within a TIN, weighting each TIN by its share of total physicians in the MSA. MSA is Metropolitan Statistical Area. TIN is Tax Identification Number. HHI is Herfindahl Hirschman Index. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.2: *Trend Breaks in Measures of Consolidation and Prices, Pre- to Post-Period*

Variables	(1) Physician-Hospital Integration	(2) Physician HHI	(3) Weighted Average TIN Size	(4) Hospital HHI	(5) Inpatient Price Index	(6) Outpatient Price Index
Year	0.011***	9.596	2.513**	51.860***	0.049***	0.023***
	(0.001)	(6.343)	(1.236)	(12.018)	(0.002)	(0.001)
Year*Post	0.002**	5.418	1.559*	1.428	-0.006***	0.000
	(0.001)	(3.828)	(0.935)	(6.539)	(0.001)	(0.001)
Observations	1,734	1,734	1,734	1,734	1,356	1,356
R-squared	0.948	0.976	0.941	0.981	0.927	0.976
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
F Statistic	56.62	6.377	11.31	17.88	508.2	292.2

Source: AuthorsâĂŹ analysis of data from the Centers for Medicare and Medicaid and Irving Levin Associates.
Note: All columns present results from separate between-market analyses, clustering standard errors at the MSA level. PhysicianâĂŹs average group size is calculated as the average count of physician billing for outpatient care within a TIN, weighting each TIN by its share of total physicians in the MSA. MSA is Metropolitan Statistical Area. TIN is Tax Identification Number. HHI is Herfindahl Hirschman Index. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure C.1: *Estimated Percentage of Medicare Fee-For-Service Beneficiaries Participating in Accountable Care Organizations (ACOs), by Core-Based Statistical Area, 2014*



Source: Authors' analysis of data from Irving Levin Associates

C.9 Main Results and Sensitivity Analyses

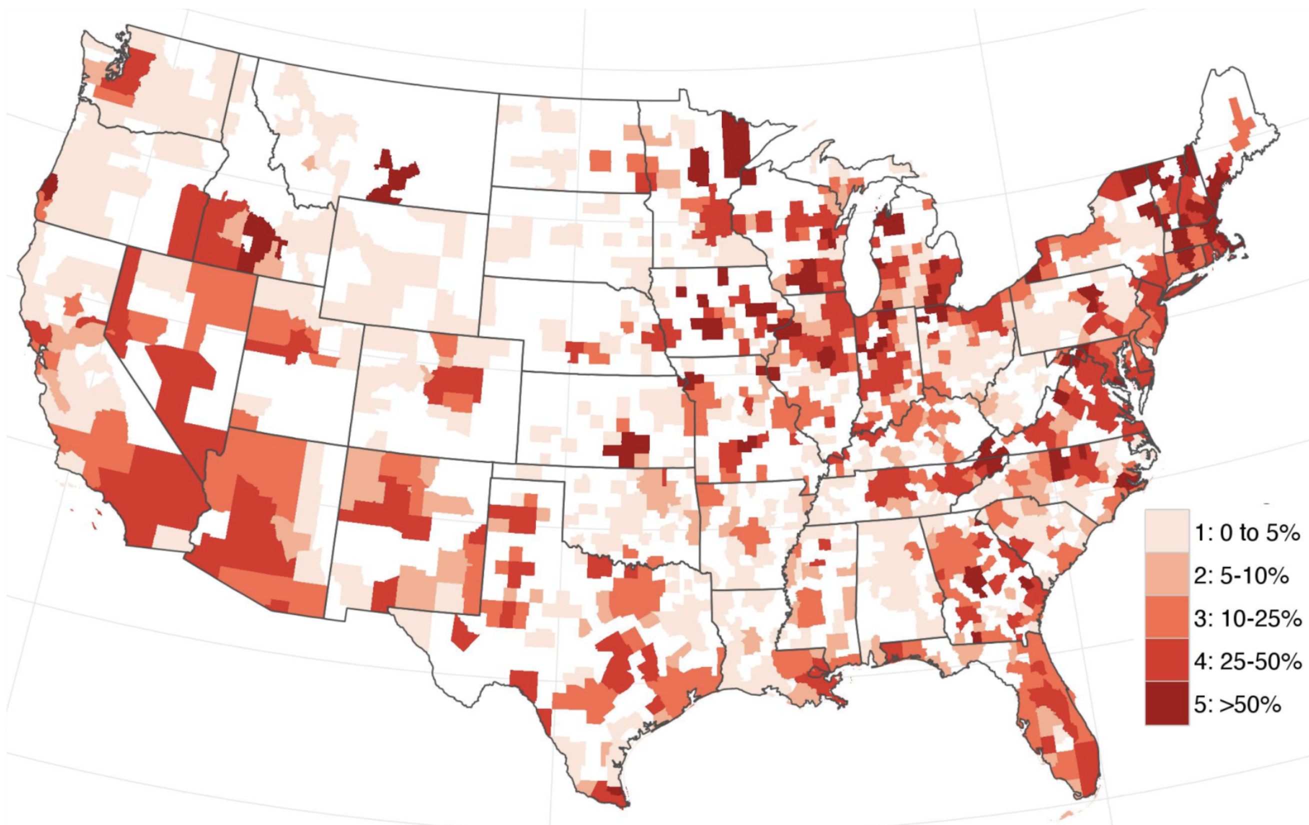
MSA-level regressions were of the form:

$$Y_{mt} = \beta_0 + \beta_1 Post + \beta_2 ACOpenetration2014_m \times Post + \beta_3 InsMkt_{mt} + \delta_m + \epsilon_{mt} \tag{C.4}$$

where m indexed MSA and t indexed year. Y_{mt} was physician-hospital integration, average TIN size, Physician HHI, Hospital HHI, inpatient commercial price index, and outpatient commercial price index. $ACOPenetration2014_m$ was a continuous variable quantifying the percent of eligibile beneficiaries enrolled in an ACO. $Post$ was an indicator equal to one in 2011-2013. $InsMkt_{mt}$ was a vector of insurnace market characteristics including commercial insurance HHI, Medicare Advantage HMO share, and commercial insurance HMO share. γ_m was a vector of MSA fixed effects and ϵ_{mt} was an indiosyncratic error term.

Physiican- and physician group-level regressions were of the form:

Figure C.2: *Healthcare Merger and Acquisition Count*



Source: Authors' analysis of data from the Centers for Medicare and Medicaid Services.
Note: Estimated percentage of Medicare FFS beneficiaries participating in an ACO is only shown for micropolitan and metropolitan statistical areas. Areas not included in either category due to small population size are blank.

$$Y_{imt} = \beta_0 + \beta_1 Post + \beta_2 ACOparticipant_i + \beta_2 Post + \beta_3 ACOparticipant_i \times Post + \delta_m + \epsilon_{imt} \quad \text{(C.5)}$$

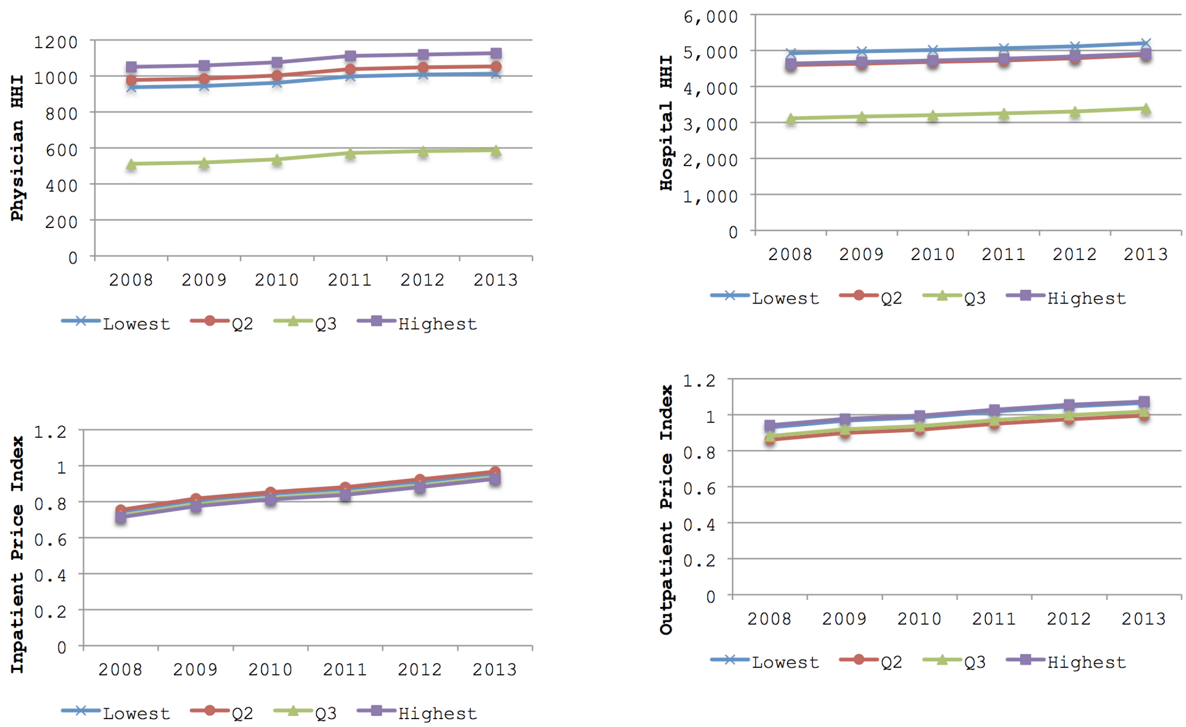
where i indexed physician NPI or physician group TIN, m indexed MSA, and t indexed year. Y_{mt} wasan indicator for ownership or employment by a hospital, an indicator for merge or acquisition participation, and physician group size. $ACOparticipant_i$ was an indicator for whether the NPI ever billed Medicare Carrier File claims under a TIN with a Medicare ACO contract in 2012 or 2013. $Post$ was an indicator equal to one in 2011-2013. γ_m was a vector of MSA fixed effects and ϵ_{mt} was an indiosyncratic error term.

Table C.3: *Association Between MSA-level 2014 ACO Penetration and Provider Market Structure*

Variables	(1) Physician-Hospital Integration	(2) Physician HHI	(3) Weighted Average TIN Size	(4) Hospital HHI	(5) Inpatient Price Index	(6) Outpatient Price Index
Post	0.04***	28.75	6.44	154.24***	0.11***	0.06***
	(0.01)	(24.18)	(6.23)	(35.93)	(0.01)	(0.01)
Post*ACOpenetration2014	-0.02	130.68	27.02	-143.73	-0.04	0.03
	(0.02)	(72.53)	(17.68)	(125.43)	(0.02)	(0.01)
Insurance HHI	-0.00	0.02	-0.00	-0.06	0.00	0.00
	(0.00)	(0.02)	(0.00)	(0.04)	(0.00)	(0.00)
MA HMO Share	-0.11	155.24	38.00	584.89	0.50*	-0.01
	(0.08)	(273.28)	(59.46)	(1,118.46)	(0.20)	(0.09)
Commercial HMO Share	-0.09*	-37.08	-42.44	-643.11*	-0.26***	-0.14*
	(0.04)	(214.58)	(34.03)	(323.17)	(0.07)	(0.05)
Observations	1,734	1,734	1,734	1,734	1,356	1,356
R-squared	0.95	0.98	0.94	0.98	0.88	0.97
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
F Statistic	21.31	4.25	1 5.676	7.069	128.6	129.0

Source: AuthorsâĂŹ analysis of data from the Centers for Medicare and Medicaid and Irving Levin Associates.
Notes: All columns are the results of separate between-market analyses, clustering standard errors at the MSA level. PhysicianâĂŹs average group size is calculated as the average count of physicians billing for outpatient care within a TIN, weighting each TIN by its share of total physicians in the MSA. MSA is Metropolitan Statistical Areas. ACO is Accountable Care Organization. HMO is Health Maintenance Organization. HHI is Herfindahl Hirschman Index. Robust standard errors in parentheses.*** p<0.001, ** p<0.01, * p<0.05

Figure C.3: *Provider Market Structure by Quartile of 2014 ACO Penetration, 2008-2013*



Source: Authors' analysis of data from the Centers for Medicare and Medicaid, the American Hospital Association, and Irving Levin Associates.
Notes: All panels result from separate between-market analyses, presenting the average annual value of the dependent variables, by quartile of 2014 ACO penetration. Physicians' average group size was calculated as the average count of physicians billing for outpatient care within a TIN, weighting each TIN by its share of total physicians in the MSA. ACO is Accountable Care Organization. HHI is Herfindahl Hirschman Index.

Table C.4: *Association Between ACO Participation (2012, 2013, or 2014) and Physician-Hospital Integration and Physician Group Acquisition*

Variables	(1) Financiall Integrated with a Hospital	(2) Acquired
ACOparticipant	0.033	0.002
	(0.024)	(0.002)
Post	0.024***	0.001
	(0.003)	(0.001)
ACOparticipant*Post	0.011	-0.002
	(0.009)	(0.003)
Observations	1,729,494	1,729,494
R-squared	0.112	0.014
MSA FE	Yes	Yes
F Statistic	23.15	1.064

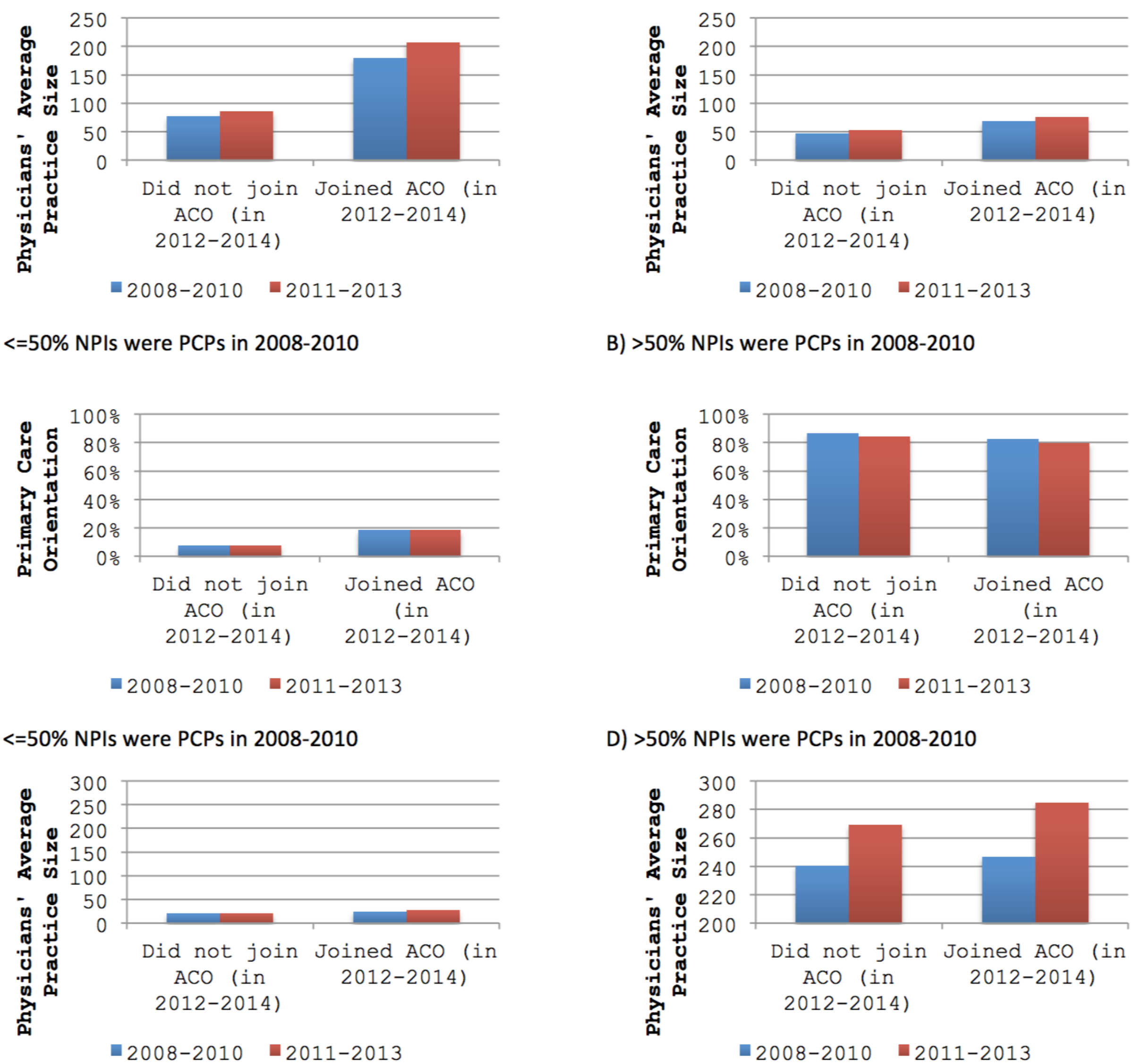
Source: AuthorsâĂŹ analysis of data from the Centers for Medicare and Medicaid and Irving Levin Associates.
Notes: Separate within-market analyses clustered standard errors at the MSA-level. Percent of physicians acquired was calculated as the share of physicians billing under a TIN that was identified as the target of a merger or acquisition in any given year. ACO is Accountable Care Organization. MSA is Metropolitan Statistical Area. Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05

Table C.5: *Association between ACO participation (2012, 2013, or 2014) and Physician Group Size*

Variables	(1) TIN Size
ACOparticipant	61.31**
	(19.77)
Post	7.93***
	(1.62)
ACOparticipant*Post	11.40**
	(3.65)
Observations	569,955
R-squared	0.43
MSA FE	Yes
F Statistic	25.00

Source: AuthorsâĂŹ analysis of data from the Centers for Medicare and Medicaid.
Note: Within-market analyses clustered standard errors at the MSA-level. ACO is Accountable Care Organization. TIN is Tax Identification Number. MSA is Metropolitan Statistical Area.. Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05

Figure C.4: *Physician Group Size by 2014 ACO Participation, 2008-2013, Stratified by Baseline Primary Care Orientation and Baseline Size*



Source: Authors' analysis of data from the Centers for Medicare and Medicaid.
Note: All panels result from separate within-market analyses, presenting the average pre- and post-period value of the dependent variable, by 2012, 2013, or 2014 ACO participation. Physician's average group size was calculated as the average count of physicians billing for outpatient care within a TIN, weighting each TIN by its share of total physicians in the MSA. Primary care orientation was calculated as the share of physicians billing under a TIN with a primary care specialty. ACO is Accountable Care Organization.