Three Essays on

Healthcare Provider Behavior

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THREE ESSAYS ON HEALTHCARE PROVIDER BEHAVIOR

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This dissertation consists of three essays:

Essay 1

In recent years, the physician practice landscape has been characterized by a shift away from small, single specialty physician practices and towards larger, more integrated providers. Responses to this trend have been mixed, with some hailing it as a cost saving cure-all and others warning about the dangers of increased market power and the potential for anti-competitive behavior. This trade-off has been debated by health care professionals, economists and government agencies in boardrooms, academia and courts. The discussion of integration has been impeded by a failure to carefully define terms and distinguish between two distinct components of integration: administrative and behavioral. Administrative, or financial, integration happens when providers merge, or hospitals purchase physician practices. This type of integration is associated with increased bargaining power and higher reimbursements. Furthermore, through profit sharing, financial integration can create an incentive for providers to refer patients to other specialists for more tests or more care, some of which may be unnecessary. In contrasts, behavioral integration refers to doctors working together and coordinating care. It has been associated with decreased waste and more efficient care. Previous work has often used measures of administrative integration, such as the share of physician practices owned by hospitals, to proxy for behavioral integration. Those modeling decisions are understandable as, up to this point, a metric which separately captures behavioral integration in a systematic way has not existed.

The lack of a metric has been a hurdle to evaluating these two components separately. In this paper, I use Medicare data on physician patient sharing patterns to develop metrics that capture physician practice integration at the behavioral level. I compare these behavioral integration metrics to a more standard organizational level integration metric. The low correlation, only 0.30, demonstrates that these metrics are distinct. Using all these metrics, I examine the impact of these two types of physician integration on the utilization of medical care. With national data over time, I use changes in integration and utilization within regions to estimate how the different types of integration impact the ability to provide quality care at a low cost, which I refer to as efficiency. As a model of physician behavior predicts, I find that behavioral integration reduces cost while improving quality. In contrasts, financial integration appears to increase cost without having an impact on quality. These results are robust to different measures of behavioral integration and different identification strategies.

Essay 2

When health care providers and managed care organizations (MCOs) bargain, the main tool providers have is the threat to refuse to be in the MCO's network. In fact, anecdotal evidence indicates that a major mechanism that practices employ to maximize profits in the face of differing insurer reimbursements, limited capacity and stochastic demand is to choose insurers discriminately. Providers do not accept patients from every MCO, however, providers do not exclusively accept the most profitable MCO. In this paper, I apply these institutional facts to a Nash cooperative bargaining framework to develop a bargaining model that explicitly models the provider's disagreement point with the MCOs. In doing this, I am able to solve analytically for the interdependence of prices between MCOs and add to previous bargaining models by making the value of a MCO to a provider more explicit. This model shows the impact of MCO market structure on prices. By introducing provider capacity constraints, I am able to model two important provider-side considerations: the risk capacity will be unused, and the risk that a low-paying patient will displace a higher-paying patient. Neither of these two effects have been previously captured in the bargaining literature, which typically has featured marginal costs as the limiting factor for providers contracting with MCOs. I also show how predictions in my model match empirical observations and estimates from other work. I demonstrate a strong negative association between MCOs' market power and negotiated prices, and show that the degree of market level price differences predicted by this model is similar to what has been observed. Finally, recent empirical work has found that that price increases for Medicare are positively associated with private MCOs' prices and that this impact is stronger in areas with more concentrated insurers, and areas in which Medicare patients represent a larger share of the market. My model analytically makes these predictions and can explain the underlying mechanisms.

Essay 3

This paper examines how primary care providers (PCPs) change their referral patterns to specialists after they join a Medicare Shared Savings Program Accountable Care Organization (ACO). We find that primary-care providers respond differently to ACO formation depending on the degree to which the providers have a pre-existing relationship with specialists in the ACO. Relatively speaking, the smaller the previous PCP-specialist relationship, the bigger the response. We also find that primary-care providers without a pre-existing relationship with ACO specialists make up a large share of the ACOs PCPs and referrals. PCPs that sent a large share of referrals to specialists that join an ACO in the years prior to ACO formation decrease the number of patient they refer to those specialists.

BIOGRAPHICAL SKETCH

Daniel Ludwinski did his undergraduate work at Colgate University (2007) where he completed dual concentrations in economics and mathematics. After completing his undergraduate education and prior to matriculating at Cornell University, Daniel worked in San Francisco for MarketBridge, a sales and marketing consulting firm. Upon completion of his PhD, Daniel returned to his alma mater, Colgate University, as a professor.

DEDICATION

This dissertation is dedicated to my wife, Ashley Ludwinski, who supported me through six challenging years of graduated work and made countless sacrifices to allow me to finish my degree. Thank you for making this achievement possible. Thank you for leaving your life and friends in San Francisco, for putting your career goals on hold, for working so many odd jobs that helped our family get by, for helping me continue on when I did not think I could finish. It is also dedicated to my two daughters, Madelyn and Mikaela.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Efficiency Implications of Physician Integration
Behavioral vs Administrative

Abstract

In recent years, the physician practice landscape has been characterized by a shift away from small, single specialty physician practices and towards larger, more integrated providers. Responses to this trend have been mixed, with some hailing it as a cost saving cure-all and others warning about the dangers of increased market power and the potential for anticompetitive behavior. This trade-off has been debated by health care professionals, economists and government agencies in boardrooms, academia and courts. The discussion of integration has been impeded by a failure to carefully define terms and distinguish between two distinct components of integration: administrative and behavioral. Administrative, or financial, integration happens when providers merge, or hospitals purchase physician practices. This type of integration is associated with increased bargaining power and higher reimbursements. Furthermore, through profit sharing, financial integration can create an incentive for providers to refer patients to other specialists for more tests or more care, some of which may be unnecessary. In contrasts, behavioral integration refers to doctors working together and coordinating care. It has been associated with decreased waste and more efficient care. Previous work has often used measures of administrative integration, such as the share of physician practices owned by hospitals, to proxy for behavioral integration. Those modeling decisions are understandable as, up to this point, a metric which separately captures behavioral integration in a systematic way has not existed. The lack of a metric has been a hurdle to evaluating these two components separately. In this

paper, I use Medicare data on physician patient sharing patterns to develop metrics that capture physician practice integration at the behavioral level. I compare these behavioral integration metrics to a more standard organizational level integration metric. The low correlation, only 0.30, demonstrates that these metrics are distinct. Using all these metrics, I examine the impact of these two types of physician integration on the utilization of medical care. With national data over time, I use changes in integration and utilization within regions to estimate how the different types of integration impact the ability to provide quality care at a low cost, which I refer to as efficiency. As a model of physician behavior predicts, I find that behavioral integration reduces cost while improving quality. In contrasts, financial integration appears to increase cost without having an impact on quality. These results are robust to different measures of behavioral integration and different identification strategies.

1 Introduction

The move towards larger, more integrated physician practices has been well documented. The risk of higher prices has been documented as well. The government seems to echo this tension, as on one hand they encourage coordination, but on the other they try to avoid the negative impacts. One way they've promoted coordination is through the push for Accountable Care Organizations (ACOs), collections of providers that join together to take some financial responsibility for a set of beneficiaries. The government has, however, opposed large consolidation among physician practices by challenging mergers and acquisitions on antitrust grounds such as St. Luke's health system in Idaho. A major driver towards larger, more integrated practices is the desire for efficiency and the belief that a "siloed-approach" to medicine is ineffective and wasteful.

In this paper, I address this empirical question by examining the impact of integration on quantity. I look at both physician practice structure and treatment patterns and relate them to healthcare efficiency and outcomes. I explore competing definitions of integration and develop innovative metrics to capture different aspects of vertical integration.

In his New Yorker article, The Cost Conundrum, Atul Gawande illustrated the disparities in treatment costs across regions, the lack of a correlation with health outcomes, and pointed to integrated care as a solution. The belief in coordinated care as a driver of efficiency was a driver in some of the provisions of the 2010 Affordable Care Act. Accountable Care Organizations are a group of hospitals, physicians and other providers that are assigned a particular set of patients. The Medicare Shared Savings Program rewards ACOs that provide care to their assigned patient population at less than expected cost, while maintaining quality.

The idea behind this program is that by working together and sharing information the ACOs can lower the cost of care.

The Institute of Medicine was tasked with investigating whether the Center for Medicare and Medicaid Services (CMS) should change their reimbursement policies to reward lower utilization areas. However, in their comprehensive report they were not able to find evidence of efficiency differences across areas. In fact, they found that "after accounting for differences in age, sex, and health status, geographic variation is not further explained by other beneficiary demographic factors, insurance plan factors, or market-level characteristics." (Institute of Medicine 2013). The conclusion of their 207-page report was that the Center Medicare and Medicaid Services should not alter payments for regional efficiency, but should instead seek to "incentivize the clinical and financial integration of health care delivery systems". This advocacy of coordinated care stands out because it was not supported by any of the analyses in the report.

The promotion of vertical integration and the promotion of coordinated care is not without risks, such as higher prices or physician induced higher quantities. These risks have been recognized by the Federal Trade Commission (FTC), and acknowledged by the guidelines put out by the Department of Justice and the Federal Trade Commission regarding the formation of Accountable Care Organizations and antitrust concerns. The government demonstrated they were willing to enforce antitrust

However, antitrust law and economic theory differentiates between horizontal integration and vertical integration. The effect of horizontal integration both theoretically and empirically is to increase prices. Vertical integration is less straightforward as in some industries there can be efficiencies gains both through changing the production function but also by eliminating transactional inefficiencies such as double marginalization. Furthermore, in the medical services market prices are set through bargaining between providers and insurance companies. Two providers looking to vertically integrate, operating in different sectors with different market power can potentially merge and use bargaining power in one sector to raise prices in another. The early empirical work looking at the price impacts indicates that this is happening.

But while the price impacts of integration are important, the quantity impacts of integration matter as well. This concern is especially pronounced in the medical services sector as physicians often have a lot of control over the quantity of medical care that a patient receives. The concern over physician induced demand shows up in legislation through STARK laws, which prohibit certain types of physician self-referrals, and anti-kickback measures, which prohibit other providers from paying for referrals. But these laws are limited in their application as they do not apply to certain physician group arrangements, or physicians who are employed. Furthermore, Accountable Care Organizations are eligible to apply for waivers, the justification being that these are needed to effectively coordinate care.

In an integrated system, the profits from increasing quantity are internalized. If the general practitioner and the cardiologist are in the same practice, then whenever the GP refers a patient to the cardiologist for extra work this increases the practices profitability.

Many recent organizational changes and policies have been undertaken with the assumption that there are large benefits to coordinated care and integration. The risk of increased prices is known, but the prediction about changes in the quantity of care is ambiguous as we have two competing narratives. The optimists from the medical profession and the policy realm believe that integration means efficiency and should be encouraged and pursued. The pessimistic economist warns about perverse incentives and the potential of vertically integrated providers to increase the quantity of care.

2 Previous Literature

The increasing prevalence of large practices, and hospital owned practices has been documented in several sources. According to Kocher et al, between 2000 and 2008 hospital ownership of physician practices doubled (2011). Other authors have demonstrated that this pattern has continued. For example, Neprash et al find that hospital ownership increased from 18.0% to 21.3% between 2008 and 2012 (Neprash, Chernew, Hicks, Gibson and McWilliams 2015). Using a different data source Burns et al observes a similar, but more pronounced rise is hospital ownership from 17% of physicians to 33.8% (2013), between 2003 and 2012. The same article also documents a rise in the average practice size, with physician-owned groups rising from 16.4 to 21.3 and hospital-owned groups doubling in size from 64.3 to 120.6 during the same period.

The impact on efficiency of this consolidation is not clear theoretically or empirically. The literature on vertical integration is mixed in terms of its impact, and Gaynor's survey of vertical integration in healthcare ignored the potential quantity effects (Gaynor 2006). Vertical integration in the healthcare sector is potentially more problematic than in other sectors due to the potential for providers to induce demand. There is a substantial body of literature that documents physicians' responses to financial incentives. It has been shown that physicians who own MRI machines order more test (Baker et al 2010), those whose can make profits by prescribing drugs order more expensive name brand drugs (Iizuka 2012), and physicians practices which are owned by hospitals are more likely to refer patients to those hospitals (Baker 2014). Hospital consolidation has also been shown to lead to an increase in referrals for advanced procedures (Nakamura 2007).

Other empirical literature shows efficiency gains from integration and size, while showing increasing prices with vertical integration. Weeks et al (2010) find that large multi-specialty groups associated with both higher quality and lower cost of care, finding savings of $272 per patient (3.6 percent) for physicians in integrated groups. Neprash did not find a utilization or spending benefit when physician practices were acquired, but did find a price increase for outpatient services. Similar price increasing effects were found by Baker et (2014). More recently, studies on the efficacy of ACOs have found modest gains to integration (Nyweide 2015).

A theoretical basis for promoting vertical integration stems from the idea that there are increased efficiencies available through information sharing and the coordination of care. A 2008 synthesis of the literature relating physician organization to quality and efficiency supported this view concluding that concludes that "Evidence increasingly shows that improved "systemness" drives quality and efficiency" (Tollen 2008). This efficiency does not need to involve the transfer of physical goods, as Atalay (2014) demonstrated. The principal result of vertical integration can be the intrafirm transfers of intangible inputs.

There also is reason to believe that larger firms may promote efficiency in terms of patient outcomes. One role of firms is to manage within-firm capital and labor allocation, empowering each means of production to maximize its contribution. It has been shown, using data on obstetricians, that physician group practices perform a similar role in efficiently matching patients with specialists (Epstein, Ketcham and Nicholson 2010).

Not all studies find a positive relation between practice size and patient outcomes. In a study on 1,045 primary care based practices, Casalino et al find that small practices have fewer preventable hospital admissions (2014). However, they also find that physician-owned practices had fewer preventable admissions, and they only looked at practices with less than 19 physicians.

Empirical studies at the patient level have consistently indicated that increasing the continuity of care leads to lower costs and better outcomes (Maarsingh 2016). Furthermore, it has been shown that when there is a strong link between hospitals and SNF readmissions were lower (Rahman 2013), and highly integrated SNF have lower spending (Afendulis 2011). Casalino points to the integrated system's ability "to create organized processes to proactively improve care" as one driver of increased efficiency (Casalino 2003).

One point of potential inefficiency is the transfer of patient information as patients move between practices. Studies have documented that "many referrals... often contain insufficient data for medical decision making" (Mehrotra et al. 2011). This loss of data can lead to inefficiencies in terms of unnecessary or inappropriate care.

A potential indicator of inefficiencies in the healthcare sector is the regional variation in per capita spending for Medicare patients. Since 1988 Dartmouth Atlas has been cataloging these stark differences, and researchers have tested a variety of explanations. It has been shown that there is an association between the number of health resources (doctors, hospital beds, etc.) and the amount of spending. The degree to which this relationship is causal (hospitals want to fill their beds) or incidental (sicker patients need more hospitals) is not clear. It has also been demonstrated that patient preferences only explain a small portion of variation (Baker 2014b).

Medicare's reimbursements are not uniform across regions, which has led some to question whether regional differences were truly reflective of differences in utilization or an artifact of reimbursement methodology. However, Gottlieb et al (2010) carefully analyzed Medicare's reimbursement system and constructed standardized measures of utilization that removed differences in the reimbursement rates. Even with that source of variation removed, large regional differences in utilization remain. However, whether this remaining variation reflects differences in efficiencies has not conclusively been established.

3 Theoretical Framework

What follows is a stylized model of physician behavior that formalizes the expected relationship between the quantity of care provided and integration. Prior to proceeding, it is critical to establish a working definition of integration. Integration colloquially means the joining of separate parts into a combined entity. Previous literature has used legal relationship between providers such as hospital ownership (see Neprash et al 2015, Afendulis 2011) or group practice size (Weeks et al 2010) as proxies for integration. However, this legal and administrative connection is not usually what the medical profession and the policy makers are referring to when they advocate increased integration. Instead, they are talking about increased information sharing and moving towards a system where providers work together seamlessly. This could take the form of lower transaction costs for patient hand-offs, better information sharing, the alignment of practice patterns and strategies or better matching of patient needs with specialists

Therefore, it is useful to think of integration as having two separate components: administrative/financial integration and behavioral integration. Administrative integration occurs when physicians form large groups, or hospitals purchase physician practices. Behavioral integration may occur with administrative integration, but it is a separate concept. It is providers seamlessly working together to provide patient care. The expectation from policy makers and the public health community is that this behavior change is what leads to more efficient care. An ownership change will not necessarily be accompanied by a change in information sharing or patient sharing. Hospitals acquire practices for other reasons than increasing efficiency. If the goal of the acquisition is to or to increase market share and market power, then there is no reason to think integration will increase at all. I will show below how administrative integration and efficiency (through behavioral integration) have different expected impacts on utilization.

Through the following model, I highlight how increased efficiency and altered financial incentives have competing effects. This model is an adaptation of the model developed in Chandra and Skinner (2012), my main addition is including parameters to capture changes in efficiency (z) and changes in the physicians' return to quantity (y).

In this model, physicians receive utility from two outputs: the health of their patients and their income. They receive income based upon the quantity of services provided, however physicians vary on how much they receive for different procedures, both because of prices and because of differing levels of financial integration. A solo practicing primary care provider will not receive a monetary benefit if one of his patients needs to visit the urologist.

While an important component, I abstract away from the exact method through which providers receive compensation. The model holds as long as integration leads to the physician having a financial stake in a broader set of services and procedures – even if this impact is indirect. I capture the relationship with the parameter $y_{k,i,j}$ below where k indexes procedures, i indexes patients and j indexes physicians. Physician j's profit function from patient i is given by:

$$\Pi_{ij}(\boldsymbol{x}, \boldsymbol{p}, \boldsymbol{y}) = \sum_{k} y_{k,j} \pi_{k,j} x_{k,i}$$

where $\boldsymbol{x_{k,i}}$ represents the quantity of procedure k performed for patient i, $\pi_{k,j}$ is the profit from procedure k, and $\boldsymbol{y_{k,j}}$ represents the share of the profits that go physician j when procedure k is performed. The parameter $\boldsymbol{y_{k,j}}$ varies from 0 to 1 and captures the degree to which a physician j is financially rewarded for patient i receiving procedure k. The parameter for patient (i) who has an office visit (k) to a solo-practicing primary care physician (j) would be 1 for that physician/patient/procedure combination. For that same primary care physician and patient, an antegrade pyelogram performed by a urologist would have a parameter of 0. If those physicians were to join into a multispecialty practice, the y-parameter would be somewhere between 0 and 1.

Physicians also care about the value of health care for patients, which is given by $\Psi s(zx)$. The parameter Ψ represents the patient's willingness to pay for that level of health, and $s(*)$

is the health production function, which takes x as an input and produces health at a positive but decreasing rate ($s''(*) < 0$). Adding procedures at first increases patient well-being, however, at some point the extra procedures have a negative impact ($s'(*) < 0$). I have included an efficiency factor, z, which captures the effectiveness of the inputs. Unnecessary test and procedures, due to incomplete information or misaligned incentives, would lead to a low z. Physicians face a simple constraint in terms of demand or capacity, which I simply summarize by the parameter $\bar{x}$. The parameter ω represents the relative value a physician puts on income. The objective function is given by:

$$\max_{x} \Psi \mathrm{s}(\mathrm{zx}) + \omega \mathrm{pyx}$$

$$s.t. \quad x \leq \bar{x}$$

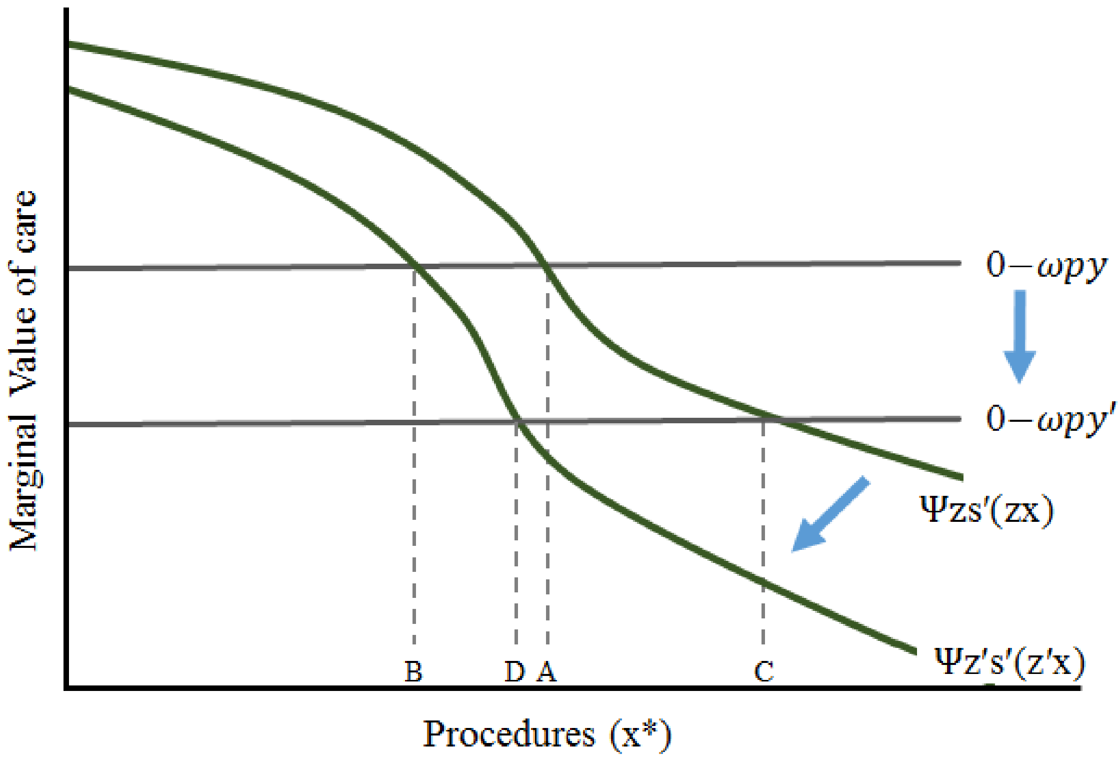
The corresponding first order condition is therefore:

$$\mathrm{z}\Psi s'(zx) + \omega py = 0$$

The first term is the marginal value (to the patient) of care and the second term is the marginal dollar that the physician receives. I must note that in this very simplistic model without the constraints, the physician would like to continue to provide care until marginal value of care is negative.

The figure below illustrates the relationship between these variables and the physician's optimal quantity. Since s' is decreasing in x, the effect of an increase in z is a decrease in x*. This is shown by a move from point A to B. An increase in financial integration is an increase in the procedures for which the provider has a financial interest and represented by a change in y. This will increase x, shown by a move from B to D (or A to C).

Figure 1: Theoretical Impact of Integration



In this model, the theoretical net effect of integration is ambiguous; it depends on the magnitude of the efficiency gains, the change in financial integration, and the health production function. I show in Appendix A that a change in y will increase x* if the percent change in z (efficiency) is less than the percent change in y (the revenue share). As is detailed below, I will estimate the relationship between utilization (x) my measure of behavioral integration (which integration proponents argue positively impacts z) and administrate/financial integration (y).

4 Integration Definition

As demonstrated above, it is important to be able to measure integration as provider behavior in addition to observing organizational structure. One possible reason that previous empirical work has not distinguished between administrative and behavioral integration is that behavioral integration is hard to quantifiably measure and there is no well-established methodology. In contrast, administrative/financial integration is fairly easy to quantify and measure. Both hospital ownership of practices and average group size capture this.

A contribution of this paper is the development of easily calculable summary metrics for behavioral integration. My metric features reasonable data requirements and is suitable for aggregation and comparison compared across regions and time. It captures the degree to which physicians consistently work together, and serves as a good proxy for their ability to seamlessly work together, share information, and align practice patterns and patient care patterns.

I propose two complementary metrics for behavioral integration which I construct using the patient sharing data from CMS (detailed below). Both metrics are built at the level of an individual physician and can be easily aggregated to the geographical level for analysis purposes.

My first metric I term the “share in-group”. To compute this for physician j in group A, I calculate the total number of patients seen, the total number of patient visits (within 30 days) to other providers, and of those other visits, the number that were in group A. On a patient level, this metric approximates the share of care a patient can expect to receive in provider j's group. Mathematically, the integration metric is:

$$Integration_j = [Share\ in\ Group]_j$$

$$= \frac{[Provider\ j's\ Patient\ Visits] + [Provider\ j's\ patients'\ visits\ to\ other\ providers\ in\ group\ A]}{[Provider\ j's\ Patient\ Visits] + [Provider\ j's\ patients'\ visits\ to\ other\ providers]}$$

This approximates the share of a physician's patient's care that the patient receives from the physician's practice for an episode of care under the following simplifying assumptions: each visit to a provider receives equal weight, and the episode of care extends 30 days out from the first visit.

In a non-integrated system, the patient will see a large number of disconnected providers. If that disconnection is related to being in different practices, the above "share in-group" metric will capture this. In this type of system, the transfer of patients between providers can often lead to lost or incorrect patient information. On top of the inconvenience of missing information, and the potential disasters caused by incorrect information, studies have consistently shown that care that is more closely tailored to patient-specific circumstances generally leads to better care (Weiner et al 2013, Barry, Edgman-Levitan 2012). In a fully integrated system, the patient receives the entirety of their care in that system, and all information about the patient is shared between all the patient's healthcare providers, perhaps with the help of a unified electronic medical record system (EMR). In this case, the integration measure "share in-group" will be high (100%).

It is also possible, however, that providers can be behaviorally integrated, in the sense that they effectively share data and work as a unit, without being in the same practice. To deal with this possibility I create a separate metric that captures the level of concentration in a provider's referral network. The idea is that a more concentrated network should be correlated with better information sharing as it potentially reflects relationships that are more established and purposeful. For each physician, I calculate the Herfindahl-Hirschman Index (HHI) of the physician's referrals for each specialty (s). HHI is a metric which is commonly used to measure market concentration and is defined as the sum of the squared market shares times 10,000. The HHIs for the physician specialties are aggregated to the physician level by taking an average weighted by the number of referrals.

$$Integration_j = Referral\ Concentration = \sum_s w_s * HHI_{j,s}$$

$$= \sum_s \left[\left(\frac{\sum_{k \in s} Ref_{k,j}}{\sum_k Ref_{k,j}} \right) \left(\sum_{k \in s} \left(\frac{Ref_{k.j}}{\sum_{k \in s} Ref_{k,j}} \right)^2 * 10{,}000 \right) \right]$$

Where in the above equation j indexes the physician, k indexes all other physicians and s indexes other physician's specialties.

One may worry that these measures could mechanically relate increased utilization with decreased integration. This would be the case if sicker patients needed to see a wider range of specialists. This would change the level of integration for the share-in-group measure by changing the amount of the patients care that could be provided within the group. However, this would not be a change in integration as the group's ability to provide care has not changed. With the referral-network-concentration measure, this could change the level of integration if it increased the share of patients who received care in specialties the physician had less of a relationship with, that is specialties where the patient referral pattern is more dispersed and thus has a lower HHI.

To control for both of these possibilities, I also created weighted versions of these metrics where I hold fixed across time and across regions the weight given to each specialty from each specialty. That is, the level of integration for the referrals from a primary care provider to a urologist in Nebraska in 2012 will receive the same weight as a primary care provider to a urologist in New York City in 2014. This eliminates the potential for mechanical correlation between the level of care needed for patients and the integration metrics. Results are reported with and without the specialty weights.

5 Data Sources

I use data on physician relationships and patient sharing patterns from Medicare patient referral data to create my behavioral integration metrics. While Medicare refers to this as “patient referral” data, it is more properly termed “shared patient” data as the dataset records any patient sharing relationship between providers of health services within a certain time frame (either 30, 60, 90 or 180 days) regardless of whether or not a formal referral exist[1]. A patient visiting one specialists then choosing to get a second, independent opinion from another specialist would be recorded as being “referred”, whereas, in fact, the two physicians only shared a common patient. This dataset is based on the National Claims History (NCH) database which includes most Medicare claim types: Inpatient, Outpatient, Home Health Agency (HHA), Skilled Nursing Facilities (SNF), Carrier claims and Durable Medical Equipment Regional Carrier (DMERC) claims. This data set extends from 2009 through part of 2015, allowing me to observe changing patterns over time.

The dataset includes a source National Provider Identifier (NPI), a target NPI and the number of shared connections and the number of shared patients. The “source” physician is the

[1] Following the Center for Medicare and Medicaid Services, I use the terms “shared patient” and “referral” interchangeably in this text.

physician that the patient saw first in the dataset, and the “target” physician is the physician seen later. I use this data set to construct my measures of physician behavioral integration, and explain my methodology below. One limitation of this data set is that it omits connections that share fewer than 10 patients. To illustrate how this data is constructed: if a patient visits physician A on March 1, and physician B on April 15 (46 days), this connection will be counted in the datasets including the 60, 90 and 180-day window, but not the 30-day window. If that a patient visits physician A on September 1 and physician B on September 12, then that connection will be included in all four datasets.

In order to assign physicians to practices, I use the Provider Enrollment, Chain, and Ownership System (PECOS) organization identifier taken from the Center for Medicare and Medicaid Services (CMS) Physician Compare database. I use this identifier both to create my measure of in-practice patient sharing and to create a measure of regional physician practice concentration.

Using the Medicare Provider Utilization and Payment Data (MPUP) file, I also construct another commonly used measure of vertical integration: the share of physician practices owned by a hospital. I follow the method, explained in Neprash, et al (2015), of identifying hospital ownership through the use of the place of service field. I validate that the estimates using the MPUP data closely tracked with those in their paper and the paper’s technical appendix. Ownership is one definition of vertical integration and I below contrast this measure with the physician connection-based metric of integration.

My main dependent variable comes from The Dartmouth Atlas of Health Care. I use market level race, age, gender and price adjusted per capita Medicare spending as a measure of utilization. Dartmouth Atlas breaks spending into five categories of spending: hospital and SNF, physician, outpatient, hospice and equipment.

The Geographic Variation Public Use File from the Center for Medicare and Medicare Cervices (CMS) includes different utilization measures that are unadjusted, standardized using methodology that differs from Dartmouth Atlas, and adjusted for patient health-risk. Finally, as a check on health outcomes I use readmission rates from the CMS's Medicare Hospital Compare dataset.

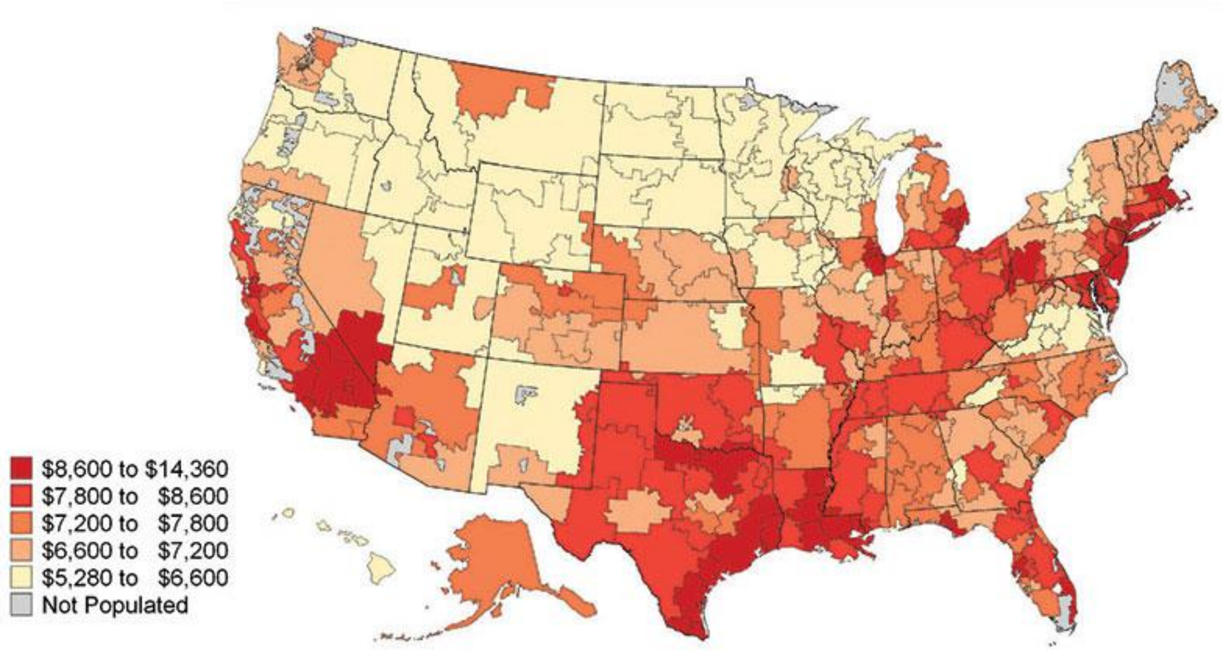
For a full list of data sources and some brief descriptions about the construction of each measure, see Appendix B:Data Sources and Technical Notes.

6 Descriptive Statistics

For reasons described below (7 Estimation Strategy), I perform my analysis at the region level; specifically I use Dartmouth Atlas' Health Referral Region (HRR) as my unit of analysis[2]. Health Referral Regions (HRRs) are used often in the literature on regional variation in health expenditures. They have been constructed by Dartmouth Atlas to capture distinct, but complete regional markets for medical care. The defining requirement for a HRR is that it contains at least one hospital where patients can receive major cardiovascular procedures. HRRs are made up of a collection of Hospital Service Areas (HSAs). HSAs are areas built to contain the area from which a hospital's patients are primary drawn and are constructed using patient flow data. There are 306 HRRs and 3,436 HSAs. A map of the HRRs shaded by total spending follows.

[2] I also examined using Metropolitan Core Based Statistical Areas (CBSAs) and the older Metropolitan Statistical Areas (MSAs). My results are robust to using these other measures.

Figure 2: HRR by Adjusted Total Medicare Spending[3]



The tables below contain basic summary statistics of the analysis data at the HRR level and the HSA level. The first two tables (Table 1, Table 3) for HRRs and HSAs, respectively, show for each variable that will be used as the dependent variable the means, standard deviations, minimums, maximums, coefficients of variation, and correlations between each respective variable and the main dependent variable - Age, Sex, Race & Price Adjusted spending per beneficiary. The tables following those (Table 2 and Table 4) show the means, standard deviations, minimums, maximums for the dependent variables.

Average adjusted per beneficiary overall Medicare spending in a HRR is $9,427, and the standard deviation across HRRs is $1,241. The variations across time are much smaller with

[3] Reproduced from Dartmouth Atlas of Health Care © 2017 The Trustees of Dartmouth College

the average absolute change between 2009 and 2014 being $348 and the average overall change between 2012 and 2014 being $192. The alternative utilization measures have similar means and standard deviations with the exception of the risk-adjusted measure of utilization which is less variable than the other measures.

Hospital/SNF spending is the largest category, making up about 45% of the total – approximately equal to the next two highest: physician services (~27%) and outpatient services (~16%). Most of the components move together and are fairly correlated with overall spending across HRRs. The exception is outpatient services which is negatively correlated with the main explanatory variable. The coefficient of variation is much smaller for the sum of physician and outpatient than for either component individually, which is an indicator of the negative correlation between these two components (correlation = -0.63). Based on the coefficient of variation, home health care is the most variable of the components, but only makes up a small share of total spending (~6%).

As my metrics for behavioral integration are new, it is necessary to check to see first, whether they are capturing behavioral integration, and second, whether they are different from previous metrics such as the share hospital owned practices, as well as the standard measure of horizontal concentration, HHI[4] (Herfindahl-Hirschman Index) and group practice size.

As a test of my metrics validity I examined the areas which score high on the measure, and looked to see if there are reasons to believe that these areas are highly integrated. For reference, at the HRR level, the average level of in-practice referral percent is about 50%,

[4] HHI is defined for a particular market as the sum of the square of the market shares of each firm. I use the PECOS practice indicators to associate providers with practices and use practice as the firm. I created HHIs measures based on both on the number of physicians and the share of Medicare allowed amounts, using MPUP data. Results did not substantially differ between the two versions.

and the standard deviation is 6.5%. By the measure, the least integrated HRR is Harlingen, TX with an integration measure of 32.0% and the highest is Rochester, MN with 78.8%. Many other highly behaviorally integrated HRRs are also in the Midwest, with La Crosse, WI (72.6%), Grand Forks, ND (70.5%), Minneapolis, MN (59.6%) and Madison, WI (64.7%). Other regions which are noted for their integrated providers also score high with my integration metric, such as Cleveland, OH (Cleveland Clinic – 59.8%), Danville, PA (Geisinger – 54.6%) Boise, ID (St. Luke's – 56.3%).

Having one large, integrated practice is not the only way to achieve a high integration score. If a region is populated with smaller players that keep their patients "in house", those regions will also show a high level of integration. Some notable examples of that are Urbana, IL (physician HHI 1,280, integration 67.3%), Madison, WI (physician HHI 980, integration 64.7%), and Seattle, WA (physician HHI 170, integration 64.2%).

Below, I compare my behavioral integration metric to the share of practices that are owned by a hospital, a frequently used measure of vertical integration that mainly captures administrative integration. The HRR level correlation between the two metrics is fairly low, only 0.30. The following maps contrast the areas that are more behaviorally integrated (in red) and less integrated (green)[5]. In some regions, they agree – such as the Northwest and Southeast, but in other areas there is significant disagreement. The difference is starkest in the Midwest. I have included a close view to illustrate this contrast (Figure 6).

Another commonly used measure of integration is HHI. The correlation between physician HHI and my measure of behavioral integration is 0.49. This reflects the fact that they are

[5] Note: These maps display CBSAs. The HRR map is similar.

codetermined in that a very highly horizontally integrated system will by construction also measure as highly vertically integrated, and there will be a similar correspondence at the other end of the spectrum. However, there is a good deal of variation in the middle, as demonstrated by some of the examples highlighted above.

The final two metrics I examine are simpler: the average size of a practice in a region and the share of providers that are solo practitioners. Both correlate strongly with my measure of vertical integration, with average practice size correlating 0.45 and the share of solo practices correlating -0.57 across regions. To determine whether my metric is capturing a different phenomenon than these two measures, I will run my regression specifications with and without these measures as covariates.

To be useful, my behavioral integration should be able to capture not only differences between regions, but also changes across time. In response to Atul Gawande's piece in The New Yorker, and along with the implementation of the Affordable Care Act's Accountable Care Organizations there was a recognized push towards integrated care in McAllen, TX. This push has widely been recognized as successful[6]. While McAllen is still one of the most expensive HRRs, average costs have dropped from $14,750 in 2009 ($5,273 above the US average) to $12,654 in 2014 ($3,066 above average). The third highest spending HRR is Monroe, LA. Over the same time period, spending was virtually unchanged, from $12,914 to $12,435. My metric captures the large change behavioral integration: between 2009 and 2014 behavioral integration increased by 14% in McAllen. There was very little change in

[6] See the Kocher & Mostashari in New York Times: A Health Care Success Story, https://www.nytimes.com/2014/09/24/opinion/a-health-care-success-story.html?_r=3&assetType=opinion

Monroe (2%). The figure below shows the changes in behavioral integration and spending in those two regions.

Figure 3: McAllen, TX and Monroe, LA – Integration and Medicare Spending over Time

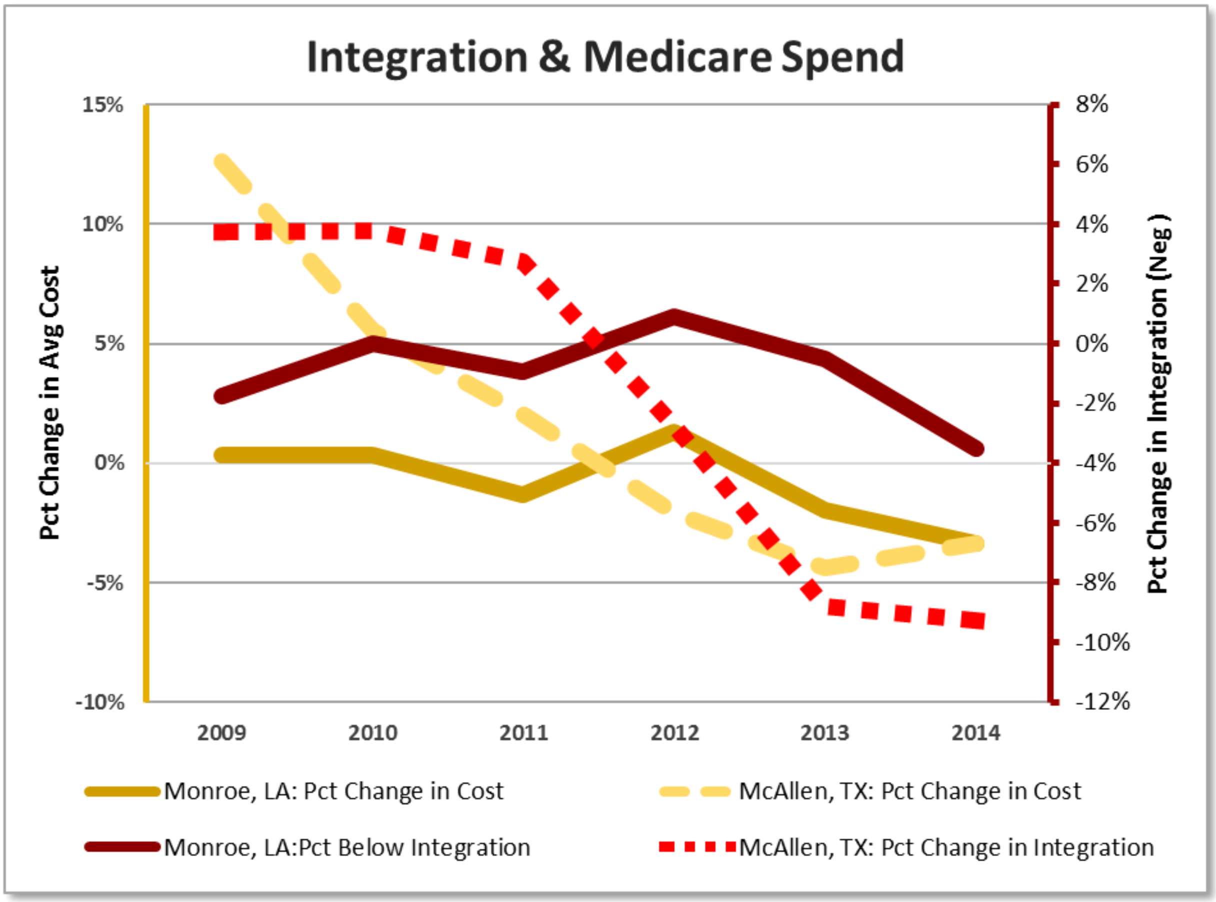


Figure 4: Share of Practices Owned by a Hospital by Region

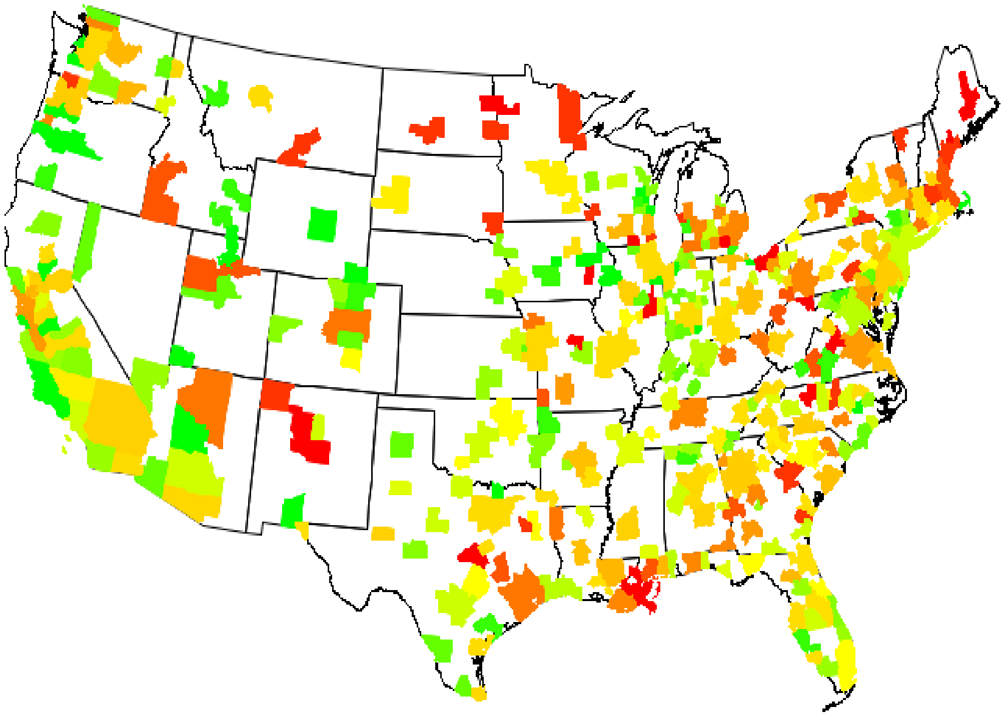


Figure 5: Level of behavioral integration by Region

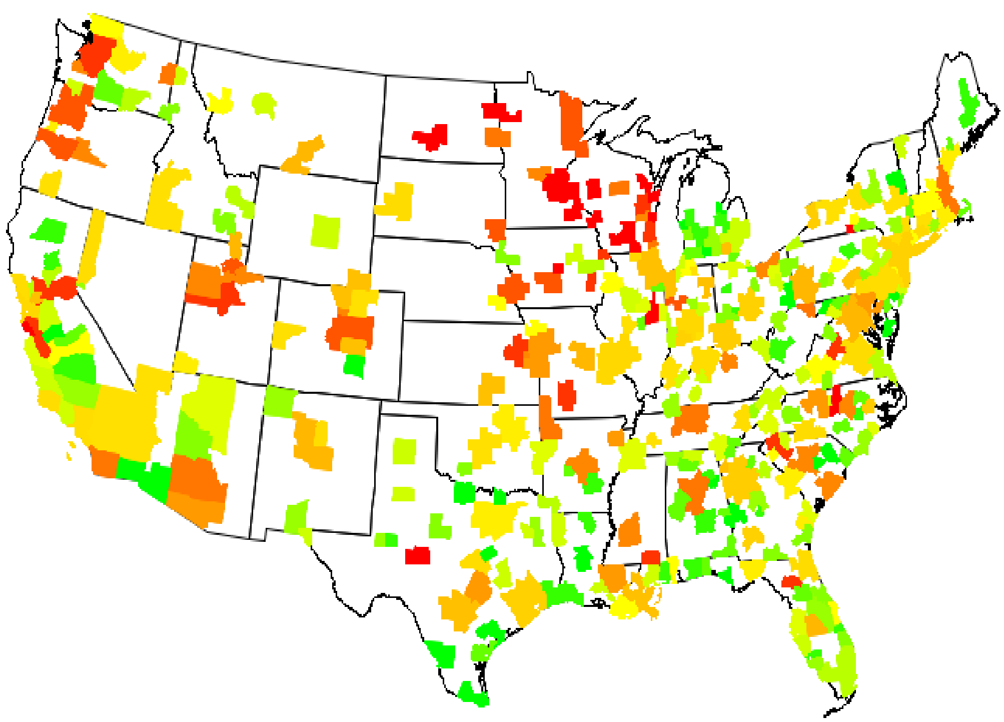


Figure 6: Contrasting Hospital Owned Practices and Behavioral Integration in the Midwest

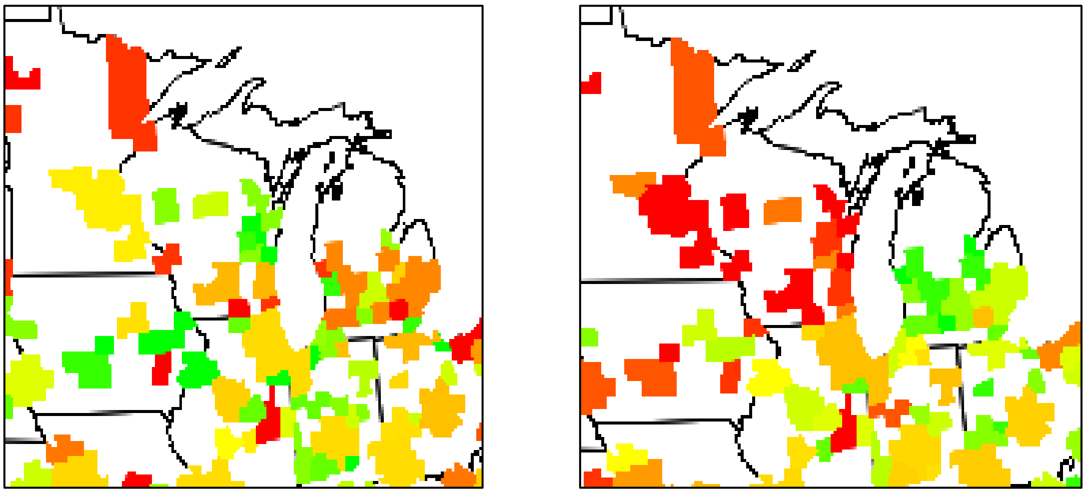


Table 1: Sample Statistics of Dependent Variables - HRR

	Avg	StD	Min	Max	COV	Corr w/main utilization metric
Readmission Rate	17.47	2.03	11.16	25.39	0.12	62.9%
Age, Sex, Race & Price Adjusted	$9,427	$1,241	$6,724	$13,596	0.13	100.0%
Alternative Utilization Metrics						
No Price Adjustment	$9,251	$1,204	$6,877	$14,165	0.13	75.7%
Raw Spending	$9,129	$1,364	$6,341	$15,364	0.15	72.0%
CMS Standardized	$8,775	$1,294	$5,686	$13,965	0.15	96.1%
CMS Risk-Adjusted	$9,354	$827	$6,334	$11,677	0.09	78.5%
Spending Category:						
Hospital/SNF	$4,268	$669	$2,523	$6,237	0.16	90.5%
Physician	$2,515	$541	$1,181	$4,359	0.22	59.6%
Outpatient	$1,516	$334	$584	$2,803	0.22	-2.2%
Physician+Outpatient	$4,030	$437	$2,882	$5,682	0.11	72.2%
Home Health Care	$528	$302	$65	$2,145	0.57	77.1%
Hospice	$382	$156	$55	$899	0.41	40.5%
Equipment	$218	$45	$90	$409	0.21	34.4%

Note: N = 306 HRRs x 3 Years = 918

Table 2: Sample Statistics of Independent Variables - HRR

	Avg	StD	Min	Max
Share in-group	50.3%	6.4%	32.6%	78.8%
SPC Wtd Share in-group	40.7%	5.5%	26.8%	68.1%
Physician Network Concentration	3,092	473	2,016	4,718
SPC Wtd Network Concentration	1,964	417	1,090	3,405
Share Phy Hosp Owned	29.1%	7.3%	13.7%	60.1%
Physician HHI	542	563	49	4,264
Hospital HHI	2,676	1,727	185	9,053
Avg Group Size	90.4	122.6	4.0	1,502.6
Share Solo Practitioner	20.3%	5.8%	7.9%	51.7%
Num Docs	2,273	2,424	279	16,093
Num Enrollees	85,035	78,715	12,283	499,734

Docs/Enrollee	32.61	11.97	2.97	109.41

Notes: N = 306 HRRs x 3 Years = 918

Table 3: *Sample Statistics* of Dependent Variables - HSA

	Avg	**StD**	**Min**	**Max**	**COV**	**Corr w/main utilization metric**
Readmission Rate	17.26	1.84	11.16	24.17	0.11	46.0%
Age, Sex, Race & Price Adjusted	$9,479	$1,516	$5,395	$19,170	0.16	100.0%
Spending Category:						
Hospital/SNF	$4,336	$921	$1,674	$12,283	0.21	90.5%
Physician	$2,279	$628	$801	$5,248	0.28	47.9%
Outpatient	$1,801	$618	$718	$6,588	0.34	8.7%
Physician+Outpatient	$4,080	$537	$2,435	$7,786	0.13	66.0%
Home Health Care	$511	$361	$21	$3,119	0.71	64.1%
Hospice	$372	$210	$30	$2,313	0.57	36.8%

Notes: N=3,428 HSAs with no missing data x 3 Years = 10,284
The omitted other dependent variables were not available at the HSA level

Table 4: Sample Statistics of Independent Variables - HSA

	Avg	**StD**	**Min**	**Max**
Share in-group	46.8%	9.6%	6.6%	100.0%
SPC Wtd Share in-group	36.3%	9.5%	0.0%	100.0%
Physician Network Concentration	4,320	1,404	293	10,000
SPC Wtd Network Concentration	3,158	1,547	0	10,000
Share Phy Hosp Owned	28.1%	16.1%	0.0%	100.0%
Physician HHI	1,938	1,880	116	10,000
Hospital HHI	9,211	1,906	629	10,000
Avg Group Size	15.6	50.5	1.0	1,678.7
Share Solo Practitioner	37.9%	19.6%	0.0%	100.0%
Num Docs	128	323	1	5,694
Num Enrollees	7,624	12,949	66	190,548
Docs/Enrollee	23.99	24.29	0.27	712.51

Notes: N=3,428 HSAs with no missing data x 3 Years = 10,284

Table 5: HRR Level Correlations for Dependent Variables

	Share in-group	SPC Wtd Share in-group	Physician Network Concentration	SPC Wtd Network Concentration	Share Phy Hosp Owned	Physician HHI	Hospital HHI	Avg Group Size	Share Solo Practitioner	Num Docs	Num Enrollees	Docs/Enrollees
Share in-group	100.0%											
SPC Wtd Share in-group	90.2%	100.0%										
Physician Network Concentration	25.8%	13.6%	100.0%									
SPC Wtd Network Concentration	33.0%	19.3%	95.5%	100.0%								
Share Phy Hosp Owned	30.0%	28.1%	6.8%	8.2%	100.0%							
Physician HHI	49.0%	58.0%	14.7%	14.8%	19.2%	100.0%						
Hospital HHI	1.7%	11.0%	-2.7%	-5.1%	-13.2%	49.0%	100.0%					
Avg Group Size	45.4%	40.9%	0.7%	6.4%	37.0%	24.0%	-21.4%	100.0%				
Share Solo Practitioner	-57.7%	-51.7%	-7.6%	-15.6%	-33.7%	-20.9%	11.9%	-41.1%	100.0%			
Num Docs	7.3%	-2.5%	-12.4%	-11.5%	17.4%	-33.3%	-59.2%	47.0%	-22.7%	100.0%		
Num Enrollees	-0.9%	-7.3%	-17.2%	-16.9%	8.5%	-38.3%	-62.0%	36.1%	-16.5%	95.5%	100.0%	
Docs/Enrollees	44.0%	27.7%	6.9%	14.5%	32.5%	5.0%	-15.0%	57.7%	-41.1%	33.1%	14.7%	100.0%

Table 6: HRR Level Correlations for Independent Variables

	Readmission Rate	Age, Sex, Race & Price Adjusted	No Price Adjustment	Raw Spending	CMS Standardized	CMS Risk Adjusted	Hospital/SNF	Physician	Outpatient	Physician+Outpatient	Home	Hospice	Equipment
Readmission Rate	100.0%												
Age, Sex, Race & Price Adjusted	62.9%	100.0%											
Alternative Utilization Metrics													
No Price Adjustment	68.2%	75.7%	100.0%										
Raw Spending	70.1%	72.0%	96.8%	100.0%									
CMS Standardized	63.9%	96.1%	78.4%	80.3%	100.0%								
CMS Risk Adjusted	25.2%	78.5%	43.6%	42.7%	78.2%	100.0%							
Spending Category:													
Hospital/SNF	69.1%	90.5%	67.0%	61.8%	82.8%	62.5%	100.0%						
Physician	46.5%	59.6%	71.3%	69.4%	63.7%	45.5%	38.9%	100.0%					
Outpatient	-12.2%	-2.2%	-26.7%	-23.0%	-5.6%	7.8%	3.2%	-59.2%	100.0%				
Physician+Outpatient	48.3%	72.2%	67.9%	68.4%	74.7%	62.4%	50.7%	78.7%	3.2%	100.0%			
Home	35.2%	77.1%	56.3%	53.4%	76.7%	61.5%	59.0%	36.3%	-13.3%	34.8%	100.0%		
Hospice	-5.0%	40.5%	8.4%	5.9%	38.1%	50.4%	22.0%	12.7%	-10.2%	8.0%	49.4%	100.0%	
Equipment	8.7%	34.4%	2.8%	-3.4%	24.3%	39.6%	36.2%	4.2%	-9.5%	-2.0%	30.2%	36.1%	100.0%

7 Estimation Strategy

I use my created metrics of behavioral integration and established measures of administrative integration to separately identify efficiency of the healthcare production function by looking at utilization and outcomes. Behavioral integration increases efficiently if it either decreases utilization while not decreasing quality outcomes, or increases quality outcomes while not increasing utilization.

I use a reduced form approach, examining differences across health referral regions (HRRs) and changes in HRRs over time with the goal of investigating loosely how the healthcare production function changes when doctors integrate.

Attempting to identify the effect on individual physicians or practices is problematic. Conceptually, this analysis is confounded by several selection issues: selection of patients by doctors, selection of doctors by patients, and selection of doctors into groups. Take the example of trying to establish the efficiency of an integrated practice that has achieved a high level of quality.

Patients choose a practice based on their health status, the convenience of the practice like travel and wait times, and the perceived quality of the practice. A sicker patient may be willing to sacrifice some convenience to get quality. If these underlying health differences are not fully observed or controlled for this may downwardly bias any measure of a high-quality practice's effectiveness.

High quality practices may also have the ability to choose patients with higher expected returns. This introduces a similar bias in that if effectiveness is being measured by resource usage and the patient's needs are not fully controlled for the high-quality practice will be observed as using more resources.

Finally, physicians self-select into groups. If high quality physicians choose to only practice with high quality physicians than what we are observing is not an increase in efficiency through integration, but the concentration of the efficient doctors in one practice. There may not be any change in the aggregate level of efficiency.

These selection issues are greatly eased if we instead study the aggregate efficiency of the region. Because healthcare is generally delivered locally, if a practice increases integration we can observe the effect on aggregate health and utilization and infer the impact of that integration.

Figure 7: Identifying the impact of integration by comparing across practices

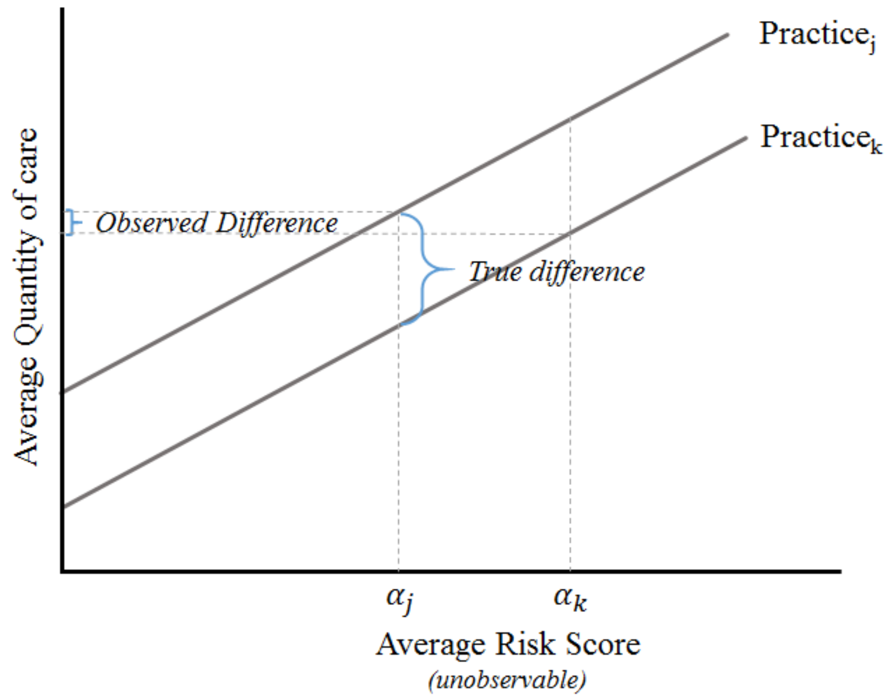
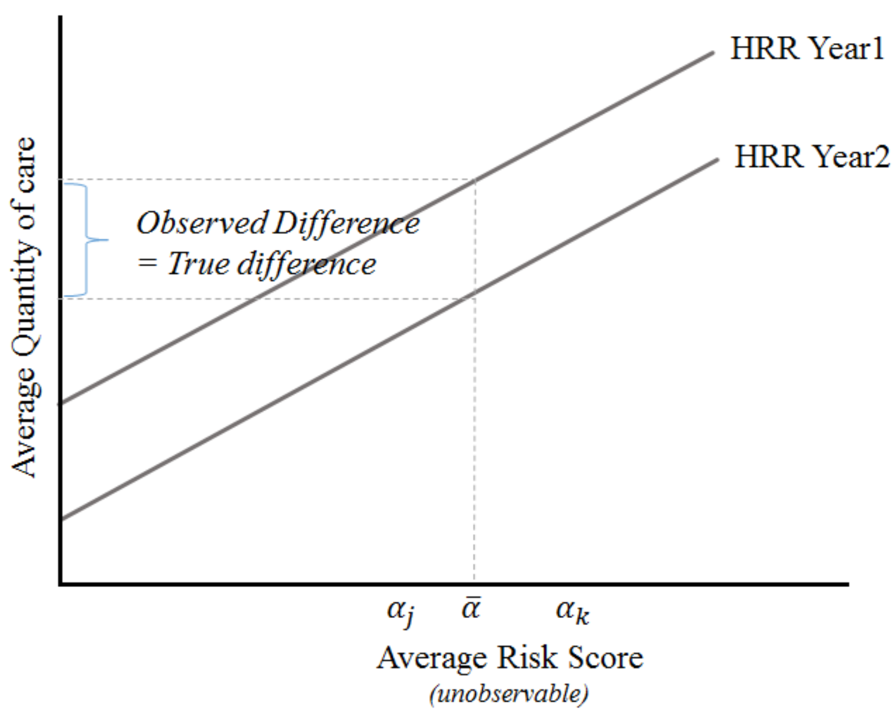


Figure 8: Identifying the impact of integration by comparing across years



The ability to look at behavioral integration at the market level is an advantage of my metric as it is easily aggregated. Most previous studies looking at coordinated care have only been able to look at specific providers or specific groups of providers that are identified as either “integrated” or “not integrated”.

With the exception of fully integrated systems such as Kaiser, care is generally provided by many different doctors in different systems. For example, a 2007 study of Medicare patients found that over a two-year period they saw a median of two PCPs and five specialists, and those physicians worked in an average of four practices (Pham et al. 2007). Furthermore, it has been noted that, among top ranked hospitals, in the last 6 months of life, 34% of patients see more than 10 physicians (Mehrotra et al. 2011).

Running this analysis at the region level also allows me to sidestep the difficulty of assigning patients to practices and disentangling both their usage and outcome levels. These difficulties have been highlighted both by the experience of Medicare Share Savings Program participants and attempts to analyze that program’s effectiveness (see, for example McWilliams 2014).

Furthermore, because my measure of integration is continuous I can capture small changes over time. This gives me the ability to look at changes and include region level fixed effects and control for potentially unobserved covariates.

As described earlier, my metric seems to capture behavioral integration, in that regions noted for coordinating care are high. Is it worth noting the potential sources for these regional differences. The Mayo Clinic has been committed to the team practice of medicine since its founding in the

1860s and Geisinger was founded in the early 20th century to be a Mayo Clinic clone. Its location is somewhat an accident of history as Abigail Geisinger chose to use her late husband's iron mining fortune to found a hospital in Danville, PA because that is where she grew up and lived. A portion of regional differences is caused by the persistence of these type of historical accidents. Part of the persistence of these differences is due to the transfer of a region's medical practice culture to new physicians (Song, Skinner, Bynum, Sutherland, Wennberg, Fisher 2010). This cultural difference can also be negative. In the previously mentioned New Yorker article on McAllen, TX, Gawande notes a certain "entrepreneurial spirit" among physicians there, many of whom were not only doctors, but owned other businesses and properties as well. Competitive forces can also lead to a high integration metric. The Urbana HRR has one of the highest levels of behavioral integration as measured by my metric. This HRR is characterized by the competition between two large systems, Carle and the Christie Clinic. These systems rarely share patients. Madison, WI is similar with the University of Wisconsin Health system rarely sharing patients with the SSM Health Care System.

Various forces can cause a region's practice norms and culture to change. The negative press McAllen, TX received from that article, along with the formation of several accountable care organizations, made McAllen one of the faster integrating areas, according to my metric. Legislative and organizational changes can drive behavioral integration. San Mateo formed a large ACO in 2012 and this change is accompanied by a large shift in the integration metric for that HRR. Finally, competitive forces also can serve as the driver for a shift, as behavioral can also follow administrative integration. Fierce competition in Pennsylvania has led to increasing levels of vertical integration. York, Lancaster and Pittsburgh all are above average both in their level of behavioral integration, and in terms of the changes over the past couple years.

My main empirical strategy is to control for market specific structures, by using fixed effects and other variables which capture market characteristics, and examine changes over time in order to identify the effect of integration on utilization. The necessary identifying assumption is that within-HRR changes in my measure of behavioral integration are uncorrelated with the time-HRR error term, conditional on the other covariates. This assumption would be violated if there is some factor that impacts both average cost of care for a Medicare patient and my metric, conditional on the other covariates such as average group size, share hospital owned or the number of doctors. An example of this could be a health system simultaneously pursuing a set of other changes along with changing referral patters, such as hiring more qualified doctors from other regions[7], changing internal system processes such as check lists or streamlining follow up care. In that case, the increased behavioral integration is only incidental and not the driving force in decreasing costs.

However, it is important to note that the goal of this research is not to argue that referral patterns are the causal mechanism that decreases the costs of care. Rather, referral patterns, and my metric, serve as a proxy for the level of behavioral integration more broadly defined, which could include such things as more streamlined sharing of patient data or careful management of preexisting conditions across providers. Furthermore, I would not be concerned with the choice to increase behavioral integration being driven by a region being high-cost. As long as my metric of behavioral reflects changes in care patterns and as long as this is the channel through which costs are saved, the estimated equation would be showing returns to behavioral integration.

[7] As noted, this is an advantage of aggregating to the region level. Healthcare provider shifting based on skill, or patient shifting based on health status will only bias the results if it is both systematic, that is, correlated with the main explanatory variables, and cross-region.

As a complementary approach, for robustness, I perform the analysis at the smaller HSA level, still using HRR fixed effects to control for other market-level characteristics. For this specification, the necessary identifying assumption is that conditional on the other covariates, such as average group size, share hospital owned, across HSA, within-HRR differences in behavioral integration are uncorrelated with other causes of across HSA, within-HRR differences in the average cost of care for a Medicare patient.

Finally, I also do my analysis without fixed effects for comparison and to allow integration to explain regional differences. I aggregate my integration to the HSA or HRR level, as detailed above and then estimate variations of the following specifications:

$$Utilization_{r,t} = \beta^{\mathrm{u}} Behavioral\ Integration_{r,t} + \gamma^{u} Pct\ Hosp\ Owned_{r,t} + \boldsymbol{X_{r,t}}\boldsymbol{\Psi}^{\mathrm{u}} + \Gamma_r^u + \tau_t^u + \varepsilon_{r,t}^u$$

$$Outcome_{r,t} = \beta^{\mathrm{O}} Behavioral\ Integration_{r,t} + \gamma^{O} Pct\ Hosp\ Owned_{r,t} + \boldsymbol{X_{r,t}}\boldsymbol{\Psi}^{\mathbf{O}} + \Gamma_r^O + \tau_t^O + \varepsilon_{r,t}^O$$

where r denotes region and t denotes HRR region. Utilization is primarily measured by Dartmouth Atlas's price, age, race and gender adjusted measure of Medicare spending. The results are robust to using other measures of spending (details below). My main outcome variable is hospital readmission rate.

The coefficients of interest are β^u and β^O, which capture the impacts of my behavioral integration metric. I include estimates with alternate integration measures in the appendix. Of secondary interest are the coefficients γ^u and γ^O, which show the association of the share of practices owned by a hospital with the outcome variables. I also include year and HRR fixed effects, Γ_r and τ_t

respectively, and an array of market-level characteristics, $\boldsymbol{X_{r,t}}$, consisting of physician practice HHI, number of doctors per enrollee, the share of doctors in a solo practice, average group size and the log of the number of physicians. I run the estimations with and without these market-level controls to see to what extend my metric is capturing something different than market structure. While these variables may not exogenous, the inclusion of them serves as an indicator of the degree to which the level of behavioral integration is a function of these market characteristics. If the estimates on β differ significantly with and without these controls this may indicate potential endogeneity issues.

8 Results

Using the behavioral integration metric which I constructed, detailed above, I estimate the impact of increased behavioral integration on efficiency. First, I look at Dartmouth Atlas's total spending per beneficiary and perform my analysis at the HRR level. This measure has been adjusted for race, age, gender and price. The price adjustment eliminates regional variation driven by differences in Medicare reimbursement rates, therefore this measure can be viewed as a measure of healthcare resource utilization. I also used utilization measures that are unadjusted, standardized using methodology that differs from Dartmouth Atlas, and adjusted for patient health-risk[8]. Next, I run my analysis on the HSA level using HRR fixed effects and identifying through the variation across HSAs within an HRR. For all specifications, standard errors are clustered at the HRR or

[8] For details regarding the risk-adjustment methodology, see the CMS documentation: https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Geographic-Variation/GV_PUF.html

HSA level[9].I also run specifications without HRR fixed effects, allowing the explanatory variables to account for regional differences in health care spending.

I run the specification with and without the following covariates: physician and hospital concentration (HHI) within the HRR (or HSA), average group size, share of doctors in a solo practice, number of doctors per enrollee and the log of the total number of doctors. In the pooled regressions especially, I primarily view both HHI and the share of providers owned by a hospital as controls for otherwise unobserved market dynamics, however, the estimates provide some suggestive evidence and can be used to inform areas in need of future research.

I also run the estimations separately on different spending categories. Using Dartmouth Atlas's categories, spending is separated into the categories of hospital / SNF, physician services, outpatient services, home health care, hospice and equipment.

Finally, I estimate the impact of integration on readmission rates, which serve as a proxy for the quality of care and overall effectiveness. The estimates were little changed when I instead used a measure from the Institute of Medicine's report which adjust for illness using Hierarchical Condition Categories (HCCs) (results not reported).

For ease of interpretation, I have converted the behavioral integration metrics to z-scores[10], therefore the coefficients represent the effect of a one standard deviation change in the relevant behavioral integration metric.

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[9] Specifically, I used SAS's panel with the "HCCME=3 cluster" options for panel data and SAS's proc genmod with HRR as the repeated subject. Furthermore, for the proc genmod I used the finite sample size adjustment to standard errors as described here: http://www.sciencedirect.com/science/article/pii/S0304405X10001923

[10] The z-score is calculated as the number of standard deviations away from the average. Specifically, the integration z-score for region r is define as:

$$z\_score_r = \frac{Integration_r - Avg(Integration)}{SD(Integration)}$$

Utilization

Fixed Effects

The first specifications (Table 7) includes both year and HRR fixed effects. The negative coefficient on behavioral integration implies that there is an association between increased integration and decrease spending at the HRR level. Without the covariates, the unweighted estimated coefficient for the share of in-group referrals is -98.4 (Table 7); meaning a one standard deviation change in integration would decrease spending by nearly 100 dollars per beneficiary. This estimate is significant at the 5% level (standard errors were clustered at the HRR level for all specifications). The estimate using the specialty weighted metric is lower (-63.6) and only significant at the 10% level. To put this level of reduction in context, by one estimate, the Medicare Shared Savings Program saved an average of $67 per beneficiary attributed to an ACO (Williams 2016). Some authors have argued that this estimate is on the high side, and the actual impact is lower (for example, see Chernew, Barbey, McWilliams 2017).

Surprisingly, the estimates using the practice-agnostic behavioral integration measure, based on the tightness of a provider's referral network, are quite similar. The unweighted coefficient for this metric is -81.4 and it is only significant at the 10% level. The weighted coefficient is -62.8 and it is not significant.

These estimates do not change substantially when the covariates are excluded, indicating that the integration metrics are orthogonal to the other controls and capturing something different than the traditional measures of integration.

The estimates on the share of physicians owned by a hospital are positive and the estimates on both physician and hospital HHI are negative. However, with the exception of physician HHI, which is weakly significant for some specifications, none of these estimates are statistically significant. All of the coefficients are similar across the different integration measures and when run without any integration measure. When year dummies are excluded (not reported) the estimates are similar, but the referral network concentration measures of integration because larger (around -110) and significant.

Pooled

Variation across regions is much larger than variation across time. In fact, a regression that only includes year and HRR dummies has an R^2 of 0.991. The year over year HRR level correlation for the level of integration is 0.98. Both integration and utilization rates are slow to change.

If the benefits to integration take time to accumulate then a panel data estimation may underestimate the long-term impact of integration. In the case of the FTC vs St. Luke's, Alain Enthoven, a professor at Stanford's Graduate School of Business and St. Luke's primary efficiencies expert, testified that it would take St. Luke's ten years or more to achieve their desired results from integration[11]. For comparison and in order to allow for this possibility, I also estimate a pooled, cross sectional model.

Table 9 and Table 10 show the results of a regression without HRR fixed effects. Using this approach, the estimated effect are considerably larger: a one standard deviation change in integration decreases per-capita cost by around 600 dollars for three of the behavioral integration metrics. The outlier is the weighted in-group share integration measure as the estimate with this

[11] Plaintiffs' Joint Pre-Trial Memorandum - Federal Trade Commission; ST. LUKE'S HEALTH SYSTEM, LTD. Et al v. FTC https://www.ftc.gov/system/files/documents/cases/130910stlukepretrialmemo.pdf

coefficient is a decrease of only 150 and is not statistically significant. All the other coefficients are significant at the one-percent level.

In these specifications, a one-percent increase in the hospital ownership of physician practices increases cost by around $22 per year/beneficiary. These estimates were not affected by the inclusion of different measures of behavioral integration and all were significant at the 5% level. Interestingly, in this specification another variable shows a consistently significant effect at the 5% level - the share of physicians that are solo practitioners. A one-percent increase in the share of physicians that are solo practitioners increases cost by around $100 per year/beneficiary. No other variables were significant across all specifications.

One possible interpretation of the large difference between the models with and without HRR fixed effects is that the fixed effect model captures the immediate, one-year change impact while the cross-sectional estimates capture the long-term effects. This could be the result of slow to accumulate advantages to integration. However, this also could be the result of uncontrolled for regional differences, or some other factors that correlate with integration. I receive very similar estimates both when I run the model without year fixed effects (not reported) and when I run this estimation on each year independently, allowing both the intercepts and slopes to vary by year (not reported).

HSA Level

As discussed earlier, Health Referral Region are made up of between 1 and 75 Hospital Service Areas (HSAs). As an alternative method of identification, I perform similar regressions at the HSA level using HRR fixed effects. This method is identified through the variation across HSAs within

HRR regions. The estimates were similar when run on individual years (not reported) or run on all three years with year fixed effects. Broadly, the estimates were similar to the ones from the model identified only through the year-over-year changes within HRRs. The estimated impact of a 1-standard deviation increase in behavioral integration varying from -96 to -128 depending on the version of the metric, and the estimated impact of a change in the share of physicians owned by a hospital is again positive, with a one percentage point change increasing cost by between eight and nine dollars per beneficiary per year. In these models, all the estimates for behavioral integration and the share of physicians owned by a hospital are significant at the 1% level.

Robustness – Other Dependent Variables

As a robustness check against the possibility that these results might be either somehow correlated with the construction of the adjusted version of Medicare health care spending, or correlated with the underlying risk profile of the patients I also run the specifications using other versions of total spending as alternate dependent variables. The four different dependent variables I use are a version that does not include the price adjustment (but is still adjusted for age, sex and race), an unadjusted spending measure, a measure that is standardized by CMS and not adjusted for age, sex and race and finally, a measure that is adjusted for patient health-risk. The results are presented in Table 12 and organized into four sub-tables based on the four versions of the behavioral integration metric. Most of the estimates are in-line with the main specifications using the age, sex, race and price adjusted metric. A graph of the estimates follows tables of the regressions (Figure 9).

Decomposing Utilization

In an attempt to better understand the channels through which behavioral and administrative integration impacts utilization I use The Dartmouth Atlas's decomposition of spending into the categories of hospital / skilled nursing facilities (SNF), physician services, outpatient services, home health care, hospice and equipment and regress these on my metrics for behavioral and administrative integration using both the fixed effects and pooled specifications. Across HRRs, Physician and outpatient services negatively correlate, the correlation is -0.63. To account for the possibility that these services are substitutes for each other, I also included as a dependent variable the sum of physician and outpatient services.

With the HRR fixed effects and in-group share as the measure of behavioral integration (Table 13), the effect seems to come primarily from hospital/SNF and physician services. Hospice, home health care and outpatient services are secondary, though in the decomposed regression few coefficients were statistically significant. Using the referral network concentration metric for behavioral integration the effect seems to primarily come from hospital/SNF and outpatient services.

Interestingly, hospital ownership of physician practices decreased physician spending while increasing outpatient and hospital/SNF. This was true regardless of what measure of physician behavioral integration was used. The coefficients on physician utilization and outpatient utilization are both significant at the one-percent level.

In the cross-sectional regressions (Table 14), the estimated coefficients for each component are higher. Three of the seven components consistently show a significant and negative relationship with behavioral integration (hospital/SNF, physician, physician+outpatient, and home health care). While the weighted in-group measure is different, the other three measures have similar coefficients for the physician and hospital/ SNF components of spending. In all three, a standard deviation increase in behavioral spending is estimated to decrease hospital spending by around $300/patient and physician spending $200 patient/yr. The coefficients on home health care may seem high in light of the fact that home health care makes up a small (6%) average portion of spending. However, there is a lot of variability across regions and previous studies have shown integrated care is connected to lower home health care cost, with 2002 US Department of Health and Human Services noting that “primary nurses have greater control over the development of their patients' care plans in low-volume states” (US Department of Health and Human Services, 2002).

With hospital ownership we see the same pattern where physician spending is lower, while hospital/ SNF and outpatient spending are higher. As with the other specifications, the causal implication of the ownership coefficient estimates is questionable. This is especially true for cross sectional estimates. The high coefficient on hospital spending could reflect hospitals with higher volume being financially healthier, and that financial health being a driver in the acquisition of physician practices. While ownership and HHI are primarily included to control for otherwise unobserved market characteristics, they do indicate a clear difference between ownership and behavioral integration as their inclusion does not significantly change the estimate effect of behavioral integration (regression not shown).

Health Outcomes

To establish that this is an increase in efficiency, and not a tradeoff between health and utilization, I next estimate integration’s impact on health outcomes. If integration is increasing efficiency, then it should not cause a decrease in health outcomes. I use hospital readmission rates to proxy for quality.

For each version of behavioral integration, an increase in behavioral integration is predicted to decrease the readmission rate, however, the effect is weakly significant (10%) for the unweighted version of the share in-group measure and statistically insignificant for the other versions of the metric. In contrast, hospital ownership is predicted to increase the readmission rate. While this effect is significant at the 10% level, it is quite small. A one percent change in hospital ownership is predicted to increase the readmission rate by 1.5 basis points (0.015%). No other variables are significantly related to readmission.

As with the utilization regressions, I also run specifications with the HRR fixed effects omitted (Table 16). I estimate that a one standard deviation increase in integration decreases readmissions by between 50 and 100 basis points for three of the behavioral integration measures, all statistically significant at the one-percent level. The exception, again, is the weighted version of the in-group share where the estimated decrease is only 7 basis points, and the coefficient is not statistically significant. With the cross-sectional specification, I estimate that a one-percent increase in hospital ownership increases readmission rates by around 6 basis points.

As with the utilization regression, the results are robust to running the regression on any one year from 2010-2014. These specifications explain a non-trivial portion of readmission rates (R^2 = 0.255-0.425), with the referral network concentration metrics adding the most explanatory power.

These coefficients may at first glance seem small, but readmission rates do not change very much over time. The national readmission rate fell significantly when legislation was passed to tie readmissions to reimbursements, and that significant change was approximately 1% (from around 18.2% to around 17.2%).

9 Discussion and Conclusion

This paper speaks to two competing claims regarding health care integration. The first claim is that integration will lead to an increase in efficiency as the coordination of care leads to a decrease in unnecessary utilization. The second claim is that integration will lead to a decrease in efficiency due to physician agency and the internalization of the monetary benefits of increased utilization.

I differentiate between two different types of integration, behavioral and administrative. Behavioral integration refers to patient and information sharing while administrative integration is related to ownership, or other formal relationship. While these two concepts are related, they are not the same and empirically when looking across geographic areas there is only weak correlation between the two measures. I demonstrate how the first claim, the coordination of care will increase efficiency, relates to behavioral integration, and the second claim, integration will lead to perverse incentives, relates to administrative integration. By developing new metrics that capture behavioral integration I am able to explore the different effects of behavioral and administrative integration on the healthcare system efficiency, as measured by utilization and health outcomes. I find some evidence to support both claims.

My results suggest that behavioral integration both decreases resource utilization and increases health outcomes. This evidence supports the optimistic story that integration leads to efficiency gains, when integration is measured behaviorally as the tightness of the physician patient-sharing network. I estimate that a one standard deviation change in integration would save approximately

$75/patient year, when HRR fixed effects are included, though this increases to $120 when the model is identified using HSAs. In terms of magnitude, these estimates seem to be in same range as Weeks et al (2010) who found savings of $272 per patient/year in large, multi-specialty groups. When fixed effects are not included the estimated effect is $600 per patient per year. This difference could reflect slow to accumulate benefits from integration, or point to potentially uncontrolled for differences other HRR specific variables.

There is also some limited evidence to support the pessimistic story when looking at physician practice ownership by hospitals. While it is possible to question the causal nature of these estimates, as a hospital could target high volume physician practices, but what is clear is that behavioral integration is a distinct from ownership both in conceptual definition and in empirical results. This distinction should be kept in mind both in policy discussions and in future research.

Interestingly, hospital ownership of physician practices decreased physician spending while increasing outpatient and hospital/SNF. This was true regardless of what measure of physician behavioral integration was used. The coefficients on physician utilization and outpatient utilization are both significant at the one-percent level. The focus out outpatient services is complimented by Neprash et al (2015) who note that practices acquired by hospitals increased their prices for outpatient services.

While these metrics as I diagnostic and empirical tool, I would caution policy makers or health system administrators against the use of these metrics as any sort of target or goal. While I believe that these behavioral integration metrics track well with actual behavioral integration metrics, as a target it is fairly easy to game the system and increase these integration metrics without changing the underlying, efficiency producing behaviors such as efficient patient sorting or information sharing.

This study is limited due to the fact that identification is only based on changes over time, or across HSAs. The lack of an exogenous shock weakens the causal case that behavioral integration impacts efficiency, and leaves open the possibility that tight referral networks may simply be one of many things done in tandem to improve efficiency. However, even if my measure of vertical integration is simply capturing an indicator of more efficient providers, it does demonstrate a robust relationship between behavioral integration and efficiency. Furthermore, it providers evidence to support the belief that differences in integration and efficiency do in fact account for a share of regional variation in healthcare utilization.

The findings of this paper are bolstered by anecdotal evidence. As noted earlier, with the implementation of the Affordable Care Act prompting the formation of Accountable Care Organizations, there was a push toward integrated care in McAllen, TX, moving it from a ridiculed outlier to a success story. This change, which was previously only observable in a qualitative way, is captured quantitatively through my behavioral integration metrics.

This paper contributes to conversation about the impacts of physician integration. It emphasizes the two different components of integration, behavioral and administrative, and introduces a new way to measure the behavioral portion. No prior metric cleanly captures behavioral integration using administrative data.

These results contribute to the discussion as a data point in a developing body of evidence about the efficacy of integration. The results are encouraging as they support the conventional wisdom that coordinated care increases efficiency, while lending support to those concerned about unintended consequences and incentives.

10 Tables

Table 7: Total Utilization, Year/HRR FE

Regression		Unweighted	Unweighted	Weighted	Weighted
Avg Pct In-Group		-98.35 **		-63.56 *	
		(41.97)		(35.43)	
Ref Network Concentration			-81.38 *		-62.75
			(44.74)		(42.70)
Pct Hosp Owned	6.26	6.71	6.65	6.40	6.60
	(4.17)	(4.15)	(4.15)	(4.14)	(4.17)
Phy HHI	-0.138 *	-0.091	-0.132 *	-0.110	-0.130
	(0.078)	(0.084)	(0.080)	(0.083)	(0.080)
Hosp HHI	-0.026	-0.032	-0.034	-0.033	-0.032
	(0.024)	(0.024)	(0.026)	(0.025)	(0.025)
Avg Grp Size	-0.349	-0.208	-0.414	-0.196	-0.389
	(0.380)	(0.382)	(0.392)	(0.387)	(0.386)
Pct Solo	-0.360	-2.371	-0.303	-1.270	-0.145
	(4.790)	(4.847)	(4.776)	(4.778)	(4.777)
Docs/Enrl	2.178	2.830	2.587	1.915	2.732
	(4.718)	(4.719)	(4.706)	(4.682)	(4.717)
ln(NumDocs)	-41.47	-70.27	-45.65	-46.87	-47.65
	(87.08)	(87.80)	(86.46)	(86.56)	(86.54)
HRR FE	X	X	X	X	X
Year FE	X	X	X	X	X
Obs (HRR \ Yr)	918	918	918	918	918
R^2	*0.1645*	*0.1733*	*0.1721*	*0.1698*	*0.1687*

Standard errors in parentheses, clustered at the HRR level.
*Significantly different from 0 at the 10% level ** 5% *** 1%

Table 8: Total Utilization, Year/HRR FE – No Other Controls

Regression		Unweighted	Unweighted	Weighted	Weighted
Avg Pct In-Group		-109.61 ***		-79.21 ***	
		(35.30)		(30.18)	
Ref Network Concentration			-66.39		-47.71
			(45.01)		(42.10)
HRR FE	X	X	X	X	X
Year FE	X	X	X	X	X
Obs (HRR \ Yr)	918	918	918	918	918
R^2	*0.1439*	*0.1572*	*0.1492*	*0.1539*	*0.1465*

Standard errors in parentheses, clustered at the HRR level.
*Significantly different from 0 at the 10% level ** 5% *** 1%

Table 9: Total Utilization, Pooled, Year FE

Regression		Unweighted	Unweighted	Weighted	Weighted
Avg Pct In-Group		-646.51 ***		-151.05	
		(98.59)		(97.81)	
Ref Network Concentration			-570.76 ***		-623.98 ***
			(69.38)		(67.54)
Pct Hosp Owned	24.17 **	21.94 **	23.58 ***	24.12 **	21.05 **
	(11.22)	(9.85)	(8.80)	(11.05)	(8.20)
Phy HHI	-0.07	0.43 **	0.02	0.06	0.00
	(0.17)	(0.17)	(0.14)	(0.19)	(0.13)
Hosp HHI	0.01	-0.05	-0.14 **	0.00	-0.16 ***
	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)
Pct Solo	114.81 ***	72.17 ***	103.02 ***	105.44 ***	94.02 ***
	(15.66)	(15.33)	(13.76)	(16.69)	(13.85)
Avg Grp Size	-0.66	-0.33	-0.75	-0.51	-0.64
	(0.65)	(0.76)	(0.68)	(0.67)	(0.59)
Docs/Enrl	-0.19	12.94 *	11.79	0.40	16.07 **
	(7.68)	(7.56)	(7.37)	(7.74)	(7.08)
ln(NumDocs)	337.24 **	283.40 *	-32.08	326.31 **	-95.31
	(153.96)	(147.27)	(155.94)	(154.59)	(155.41)
HRR FE					
Year FE	X	X	X	X	X
Obs (HRR \ Yr)	918	918	918	918	918
R^2	0.256	0.377	0.437	0.263	0.464

Stardard errors in parentheses, clustered at the HRR level.
*Significantly different from 0 at the 10% level ** 5% *** 1%

Table 10: Total Utilization, Pooled, Year FE – No Other Controls

Regression		Unweighted	Unweighted	Weighted	Weighted
Avg Pct In-Group		-637.55 ***		-418.26 ***	
		(69.46)		(79.40)	
Ref Network Concentration			-583.73 ***		-650.54 ***
			(66.50)		(62.88)
HRR FE					
Year FE	X	X	X	X	X
Obs (HRR \ Yr)	918	918	918	918	918
R^2	0.002	0.263	0.222	0.114	0.276

Stardard errors in parentheses, clustered at the HRR level.
*Significantly different from 0 at the 10% level ** 5% *** 1%

Table 11: Total Utilization, Year/HRR FE – HSA level

Regression		Unweighted	Unweighted	Weighted	Weighted
Avg Pct In-Group		-125.803 ***		-120.277 ***	
		(21.640)		(21.355)	
Ref Network Concentration			-96.106 ***		-127.952 ***
			(28.047)		(28.787)
Pct Hosp Owned	9.130 ***	8.171 ***	8.951 ***	7.946 ***	8.941 ***
	(1.339)	(1.344)	(1.340)	(1.349)	(1.336)
Phy HHI	0.006	0.010	0.011	0.009	0.012
	(0.014)	(0.014)	(0.015)	(0.014)	(0.015)
Avg Grp Size	-0.525 **	-0.235	-0.477 *	-0.326	-0.445 *
	(0.260)	(0.235)	(0.252)	(0.239)	(0.251)
Pct Solo	5.105 ***	3.885 ***	5.301 ***	4.028 ***	5.352 ***
	(1.167)	(1.146)	(1.208)	(1.171)	(1.207)
Docs/Enrl	0.825	1.072	0.937	0.910	1.094
	(1.293)	(1.411)	(1.337)	(1.338)	(1.394)
ln(NumDocs)	-78.801 ***	-67.634 ***	-112.940 ***	-55.028 **	-121.472 ***
	(21.156)	(21.664)	(24.315)	(21.727)	(24.034)
HRR FE	X	X	X	X	X
Year FE	X	X	X	X	X
Obs (HRR \ Yr)	918	918	918	918	918
R^2	0.0%	0.0%	0.0%	0.0%	0.0%

Stardard errors in parentheses, clustered at the HSA level.

*Significantly different from 0 at the 10% level ** 5% *** 1%

Table 12: Total Utilization, Year/HRR FE – Alternative Dependent Variables
a. Behavioral Integration Metric: Share in-group

Dependent Variable:	No Price Adjustment	Raw Cost	CMS Standardized	CMS Risk Adjusted
Avg Pct In-Group	-127.366 ***	-150.511 ***	-106.229 ***	-112.938 ***
	(41.750)	(39.201)	(36.805)	(41.851)
Pct Hosp Owned	6.707 *	5.468 *	3.738	6.435
	(3.713)	(3.086)	(2.912)	(4.805)
Phy HHI	-0.138 *	-0.057	-0.083	-0.082
	(0.076)	(0.065)	(0.059)	(0.071)
Hosp HHI	-0.020	-0.026	-0.007	0.006
	(0.032)	(0.031)	(0.031)	(0.039)
Avg Grp Size	0.718 **	0.517 *	0.356	0.812 **
	(0.334)	(0.291)	(0.235)	(0.357)
Pct Solo	3.447	2.499	1.394	6.152
	(4.604)	(4.064)	(3.992)	(5.084)
Docs/Enrl	-4.271	-7.156 *	-7.121 **	-16.189 ***
	(4.001)	(4.037)	(3.403)	(4.422)
ln(NumDocs)	39.457	107.757	91.210	234.436 ***
	(79.310)	(78.686)	(68.236)	(88.120)
HRR FE	X	X	X	X
Year FE	X	X	X	X
Obs (HRR \ Yr)	918	918	918	918
R^2	*0.1933*	*0.0959*	*0.1394*	*0.2411*

Standard errors in parentheses, clustered at the HRR level.
*Significantly different from 0 at the 10% level ** 5% *** 1%

b. Behavioral Integration Metric: Referral Network Concentration

Dependent Variable:	No Price Adjustment	Raw Cost	CMS Standardized	CMS Risk Adjusted
Ref Network Concentration	-101.479 *	-83.700 **	-87.699 ***	-138.329 ***
	(52.698)	(41.851)	(32.385)	(38.523)
Pct Hosp Owned	6.613 *	5.180	3.675	6.588
	(3.781)	(3.152)	(2.877)	(4.803)
Other Controls	X	X	X	X
HRR FE	X	X	X	X
Year FE	X	X	X	X
Obs (HRR \ Yr)	918	918	918	918
R^2	*0.1902*	*0.0782*	*0.1373*	*0.2505*

Standard errors in parentheses, clustered at the HRR level.
*Significantly different from 0 at the 10% level ** 5% *** 1%

The regression coefficients for other controls were similar to the ones shown in table 12a.

c. Behavioral Integration Metric: Share in-group – Specialty Weighted

Dependent Variable:	No Price Adjustment	Raw Cost	CMS Standardized	CMS Risk Adjusted
Avg W Pct In-Group	-82.082 **	-90.812 ***	-61.475 **	-56.874
	(37.670)	(34.282)	(29.997)	(36.774)
Pct Hosp Owned	6.301 *	4.974	3.383	6.039
	(3.742)	(3.131)	(2.929)	(4.853)
Other Controls	X	X	X	X
HRR FE	X	X	X	X
Year FE	X	X	X	X
Obs (HRR \ Yr)	918	918	918	918
R^2	*0.1871*	*0.0823*	*0.1314*	*0.2346*

Standard errors in parentheses, clustered at the HRR level.
*Significantly different from 0 at the 10% level ** 5% *** 1%

The regression coefficients for other controls were similar to the ones shown in table 12a.

d. Behavioral Integration Metric: Referral Network Concentration – Specialty Weighted

Dependent Variable:	No Price Adjustment	Raw Cost	CMS Standardized	CMS Risk Adjusted
W Ref Network Concentratio	-70.438	-57.758	-65.167 **	-101.666 **
	(49.862)	(39.321)	(32.191)	(42.683)
Pct Hosp Owned	6.499 *	5.084	3.599	6.463
	(3.810)	(3.163)	(2.913)	(4.838)
Other Controls	X	X	X	X
HRR FE	X	X	X	X
Year FE	X	X	X	X
Obs (HRR \ Yr)	918	918	918	918
R^2	*0.1832*	*0.0718*	*0.1306*	*0.2406*

Standard errors in parentheses, clustered at the HRR level.

*Significantly different from 0 at the 10% level ** 5% *** 1%

The regression coefficients for other controls were similar to the ones shown in table 12a.

Figure 9: Comparison of Estimates of the Effect of Behavioral Integration on Various Measures of Utilization

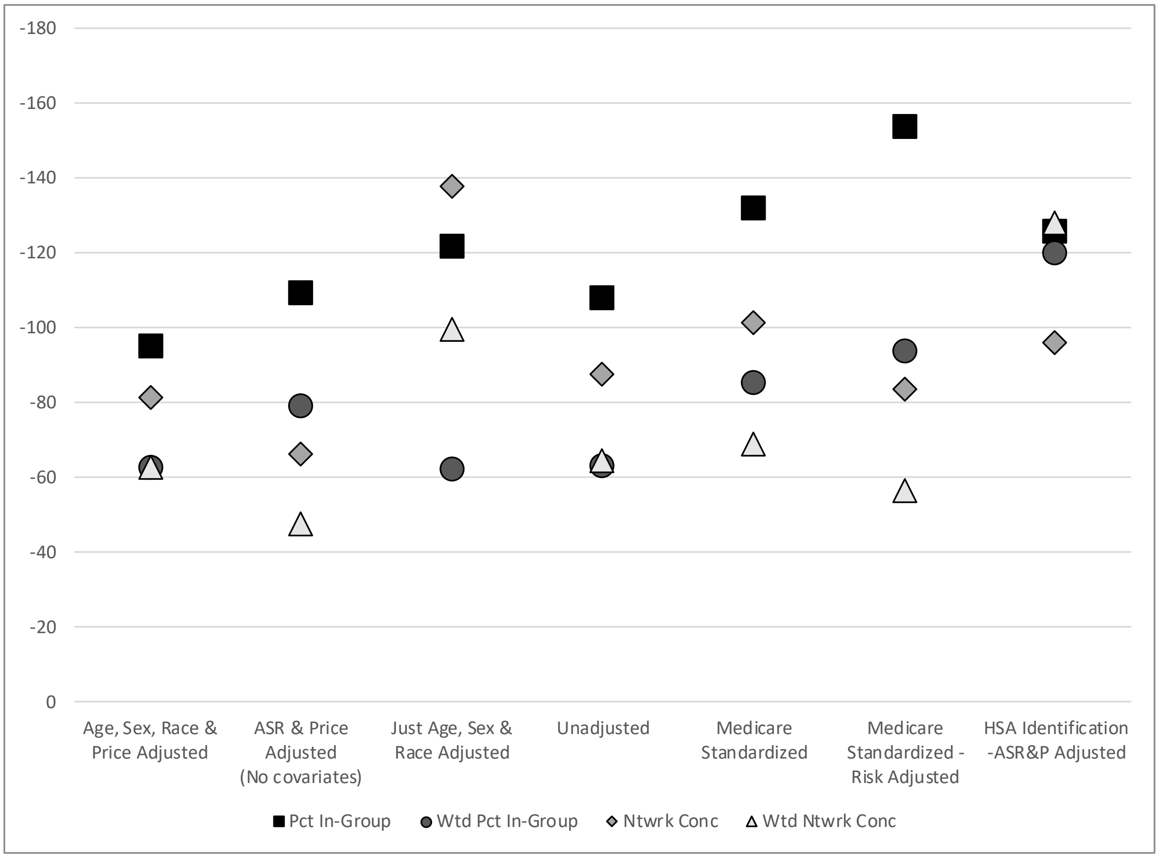

Table 13: Utilization by Type: HRR/Year FE

Behavioral Integration Metric: Share in-group

Regression	**Total**	**Hosp_SNF**	**Physician**	**Outpatient**	**Phy+Out**	**Home**	**Hospice**	**Equipment**
Avg Pct In-Group	-98.355 **	-35.517	-38.426 **	9.682	-28.744	-17.406 **	-14.393 *	-2.679
	(41.966)	(27.111)	(17.901)	(20.008)	(20.240)	(8.084)	(7.618)	(2.311)
Pct Hosp Owned	6.71	2.22	-3.31 **	8.73 ***	5.41 **	-0.95	0.11	0.04
	(4.15)	(2.31)	(1.34)	(2.78)	(2.18)	(1.18)	(0.45)	(0.18)
Phy HHI	-0.091	-0.031	-0.019	-0.025	-0.044	0.001	-0.004	-0.009 **
	(0.084)	(0.059)	(0.032)	(0.042)	(0.055)	(0.015)	(0.016)	(0.004)
Hosp HHI	-0.032	-0.014	-0.015 **	0.005	-0.010	-0.003	-0.003	-0.002
	(0.024)	(0.019)	(0.007)	(0.010)	(0.011)	(0.006)	(0.007)	(0.002)
Avg Grp Size	-0.208	-0.189	0.219 *	-0.406 *	-0.187	0.051	0.042	0.054
	(0.382)	(0.262)	(0.116)	(0.232)	(0.186)	(0.076)	(0.061)	(0.018)
Pct Solo	-2.371	-3.064	-4.943 ***	5.571 ***	0.628	1.215	-0.996	-0.296
	(4.847)	(3.259)	(1.535)	(2.076)	(2.352)	(0.882)	(0.894)	(0.258)
Docs/Enrl	2.830	1.056	1.438	0.871	2.308	-0.856	1.319 **	-0.387
	(4.719)	(3.056)	(1.310)	(1.876)	(1.878)	(0.857)	(0.659)	(0.235)
ln(NumDocs)	-70.27	-24.26	-57.49 **	15.14	-42.34	20.55	-32.63 **	-2.28
	(87.80)	(56.89)	(28.74)	(36.99)	(37.43)	(15.65)	(13.76)	(4.78)
HRR FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Obs (HRR \ Yr)	918	918	918	918	918	918	918	918

Standard errors in parentheses, clustered at the HRR level.
*Significantly different from 0 at the 10% level ** 5% *** 1%

b. Behavioral Integration Metric: Referral Network Concentration

Regression	Total	Hosp_SNF	Physician	Outpatient	Phy+Out	Home	Hospice	Equipment
Ref Ntwrk Conc	-81.377 *	-28.481	-5.109	-39.372 **	-44.481 **	-9.723	6.388	-7.857 ***
	(44.744)	(26.558)	(11.376)	(19.246)	(20.182)	(8.630)	(7.922)	(2.435)
Other Controls	X	X	X	X	X	X	X	X
HRR FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X

c. Behavioral Integration Metric: Share in-group – Specialty Weighted

Regression	Total	Hosp_SNF	Physician	Outpatient	Phy+Out	Home	Hospice	Equipment
Wtd Avg Pct In-Group	-63.555 *	-12.948	-17.447	-8.916	-26.363	-11.579	-11.190 *	-0.044
	(35.427)	(22.864)	(13.264)	(14.801)	(16.866)	(7.596)	(6.292)	(2.355)
Other Controls	X	X	X	X	X	X	X	X
HRR FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X

d. Behavioral Integration Metric: Referral Network Concentration – Specialty Weighted

Regression	Total	Hosp_SNF	Physician	Outpatient	Phy+Out	Home	Hospice	Equipment
Wtd Ref Ntwrk Conc	-62.752	-27.588	-1.476	-38.587 **	-40.063 **	-2.097	12.633	-5.674 **
	(42.702)	(27.886)	(13.910)	(19.209)	(20.266)	(7.797)	(8.889)	(2.580)
Other Controls	X	X	X	X	X	X	X	X
HRR FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X

Table 14: Utilization by Type: Pooled, Year FE

a. Behavioral Integration Metric: Share in-group

Regression	Total		Hosp_SNF		Physician		Outpatient		Phy+Out		Home		Hospice		Equipment	
Avg Pct In-Group	-646.51	***	-309.08	***	-153.81	***	21.26		-132.55	***	-138.84	***	-49.14	***	-13.93	***
	(79.683)		(44.282)		(26.752)		(18.658)		(25.969)		(22.621)		(12.963)		(2.595)	
Pct Hosp Owned	21.94	***	14.42	***	-17.56	***	19.33	***	1.77		5.01	***	0.86		-0.03	
	(7.963)		(5.078)		(2.672)		(2.353)		(2.705)		(1.771)		(1.272)		(0.277)	
Phy HHI	0.43	***	0.18	***	0.09	*	0.06		0.16	***	0.06		0.02		0.01	*
	(0.135)		(0.067)		(0.051)		(0.037)		(0.052)		(0.043)		(0.026)		(0.005)	
Hosp HHI	-0.05		-0.05	*	0.05	***	-0.02	*	0.03	**	-0.02	**	0.00		0.00	
	(0.043)		(0.026)		(0.014)		(0.011)		(0.015)		(0.012)		(0.007)		(0.002)	
Avg Grp Size	-0.33		0.10		-0.09		-0.09		-0.18		-0.12		-0.08		-0.02	
	(0.616)		(0.369)		(0.234)		(0.156)		(0.166)		(0.142)		(0.082)		(0.017)	
Pct Solo	72.17	***	18.07	**	47.09	***	-10.49	***	36.60	***	14.33	***	1.64		-0.14	
	(12.390)		(7.420)		(4.784)		(2.865)		(4.376)		(3.948)		(1.865)		(0.463)	
Docs/Enrl	12.94	**	5.92	*	1.57		-1.46		0.11		4.93	***	1.01		0.12	
	(6.107)		(3.338)		(1.952)		(1.387)		(1.910)		(1.763)		(0.795)		(0.178)	
ln(NumDocs)	283.40	**	23.70		400.23	***	-127.35	***	272.89	***	-5.21		-5.84		-4.16	
	119.03		67.71		40.16		28.50		38.57		31.45		17.36		3.93	
HRR FE	X		X		X		X		X		X		X		X	
Year FE	X		X		X		X		X		X		X		X	
Obs (HRR \ Yr)	918		918		918		918		918		918		918		918	
R^2	0.377		0.221		0.586		0.434		0.430		0.296		0.103		0.404	

Stardard errors in parentheses, clustered at the HRR level.

*Significantly different from 0 at the 10% level ** 5% *** 1%

b. Behavioral Integration Metric: Referral Network Concentration

Regression	Total		Hosp_SNF		Physician		Outpatient		Phy+Out		Home		Hospice		Equipment	
Ref Ntwrk Conc	-570.76	***	-300.09	***	-190.36	***	-1.16		-191.53	***	-62.68	***	-14.03		-3.26	
	(56.079)		(33.641)		(22.565)		(16.059)		(17.795)		(14.966)		(9.637)		(2.487)	
Other Controls	X		X		X		X		X		X		X		X	
HRR FE																
Year FE	X		X		X		X		X		X		X		X	

c. Behavioral Integration Metric: Share in-group – Specialty Weighted

Regression	Total	Hosp_SNF	Physician	Outpatient	Phy+Out	Home	Hospice	Equipment
Wtd Avg Pct In-Group	-151.05 *	-53.05	-46.71 *	23.30	-23.42	-48.86 **	-17.16	-5.25 **
	(79.056)	(46.717)	(24.529)	(20.904)	(24.042)	(20.345)	(11.603)	(2.653)
Other Controls	X	X	X	X	X	X	X	X
HRR FE								
Year FE	X	X	X	X	X	X	X	X

d. Behavioral Integration Metric: Referral Network Concentration – Specialty Weighted

Regression	Total	Hosp_SNF	Physician	Outpatient	Phy+Out	Home	Hospice	Equipment
Wtd Ref Ntwrk Conc	-623.98 ***	-337.99 ***	-215.29 ***	6.44	-208.84 ***	-67.95 ***	-7.91	-1.64
	(54.592)	(31.338)	(22.609)	(16.886)	(18.249)	(14.810)	(9.491)	(2.592)
Other Controls	X	X	X	X	X	X	X	X
HRR FE								
Year FE	X	X	X	X	X	X	X	X

Table 15: Hospital Readmission Rate (basis points): Year/HRR FE

Regression		Unweighted	Unweighted	Weighted	Weighted
Avg Pct In-Group		-27.74 *		-18.07	
		(14.23)		(11.69)	
Ref Network Concentration			-2.59		-3.37
			(12.78)		(12.58)
Pct Hosp Owned	1.50 *	1.63 *	1.51 *	1.54 *	1.52 *
	(0.89)	(0.90)	(0.88)	(0.91)	(0.88)
Phy HHI	0.00	0.01	0.00	0.00	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Hosp HHI	0.00	-0.01	0.00	-0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Pct Solo	-0.63	-1.20	-0.63	-0.89	-0.62
	(1.34)	(1.30)	(1.34)	(1.32)	(1.34)
Avg Grp Size	-0.01	0.03	-0.01	0.03	-0.01
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Docs/Enrl	-1.09	-0.91	-1.08	-1.17	-1.06
	(1.16)	(1.16)	(1.16)	(1.18)	(1.15)
ln(NumDocs)	20.87	12.75	20.74	19.34	20.54
	(23.09)	(23.26)	(23.11)	(23.43)	(23.07)
HRR FE	X	X	X	X	X
Year FE	X	X	X	X	X
Obs (HRR \ Yr)	918	918	918	918	918
R^2	*0.3295*	*0.3354*	*0.3295*	*0.3332*	*0.3296*

Standard errors in parentheses, clustered at the HRR level.
*Significantly different from 0 at the 10% level ** 5% *** 1%

Table 16: Hospital Readmission Rate (basis points), Pooled, Year FE

Regression		Unweighted	Unweighted	Weighted	Weighted
Avg Pct In-Group		-54.45 ***		-7.25	
		(18.83)		(16.59)	
Ref Network Concentration			-86.69 ***		-100.78 ***
			(12.20)		(12.00)
Pct Hosp Owned	6.16 ***	5.97 ***	6.07 ***	6.16 ***	5.65 ***
	(1.99)	(1.92)	(1.77)	(1.98)	(1.67)
Phy HHI	0.00	0.04	0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.04)	(0.02)
Hosp HHI	0.00	-0.01	-0.02	0.00	-0.03 **
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Avg Grp Size	0.00	0.03	-0.01	0.01	0.01
	(0.12)	(0.15)	(0.15)	(0.12)	(0.14)
Docs/Enrl	0.99	2.09	2.81 **	1.02	3.61 ***
	(1.36)	(1.37)	(1.16)	(1.36)	(1.15)
ln(NumDocs)	78.48 ***	73.95 ***	22.39	77.96 ***	8.62
	(24.97)	(25.28)	(24.83)	(25.15)	(23.97)
HRR FE					
Year FE	X	X	X	X	X
Obs (HRR \ Yr)	918	918	918	918	918
R^2	0.223	0.255	0.379	0.224	0.425

Stardard errors in parentheses, clustered at the HRR level.
*Significantly different from 0 at the 10% level ** 5% *** 1%

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Appendix A: The Quantity Impact of an Increase in Integration

In this appendix, I show the expected impact on quantity of an increase in integration. Because an increase in integration can effect two channels – efficiency and the monetary returns to quantity for the provider – the impact is ambiguous.

The Impact of Efficiency on Quantity

That an increase in efficiency (z), ceteris paribus, leads to a decrease in the level of procedures (x*) in this model can be shown mathematically:

$$\max_{x} \Psi \mathrm{s(zx)} + \omega \mathrm{pyx}$$

$$s.t. \quad x \leq \bar{x}$$

If the capacity constraint does not bind the first order conditions can be written as:

$$f(z, x, \psi, p, y) = z\psi s'(zx) + py = 0$$

This implicitly defines x as a function of z, ψ, p and y. We are interested in dx*/dz. Using total differentiation:

$$\frac{\partial f}{\partial z}dz + \frac{\partial f}{\partial x}dx + \frac{\partial f}{\partial \psi}d\psi + \frac{\partial f}{\partial p}dp + \frac{\partial f}{\partial y}dy = 0$$

Because $d\psi = dp = dy = 0$, we can rewrite:

$$\frac{\partial f}{\partial z}dz + \frac{\partial f}{\partial x}dx = 0$$

And

$$\frac{dx}{dz} = -\frac{\partial f/dz}{\partial f/dx}$$

$$= -\frac{\psi s'(zx)}{z^2 \psi s''(zx)} = -\frac{(-)}{(+)^2(-)} < 0$$

The above inequality is true because we know that $z \in (0,1) > 0$, and $s''(zx) < 0$ by assumption. Also, rearranging the FOC, $\psi s'(zx) = -py/z < 0$.

The Net Impact of Integration

If we are interested in the effect when both z and y are changing: Let z and y be interrelated, and assume y is being changed. This means that:

$$dz = \frac{\partial z}{\partial y} dy$$

Therefore, the effect on x can be expressed in the following way:

$$\frac{\partial f}{\partial x} dx + \frac{\partial f}{\partial z} dz + \frac{\partial f}{\partial y} dy = 0$$

$$\frac{\partial f}{\partial x} dx + \frac{\partial f}{\partial z}\frac{\partial z}{\partial y} dy \quad + \frac{\partial f}{\partial y} dy = 0$$

Rearranging:

$$\frac{dx}{dy} = -\left(\frac{\partial f}{\partial z}\frac{\partial z}{\partial y} + \frac{\partial f}{\partial y}\right)/(\partial f/\partial x)$$

Substituting from the functional form assumption on f, and rearranging:

$$\frac{dx}{dy} = -\left(\psi s'(zx)\frac{\partial z}{\partial y} + p\right)/(z^2\psi s''(zx))$$

$$\frac{dx}{dy} = -\left(-\frac{py}{z}\frac{\partial z}{\partial y} + p\right)/(z^2\psi s''(zx))$$

$$\frac{dx}{dy} = -\frac{p}{z^2\psi s''(zx)}\left(1 - \frac{y}{z}\frac{\partial z}{\partial y}\right)$$

$$\frac{dx}{dy} = -\frac{p}{z^2\psi s''(zx)}\left(1 - \frac{\partial z/z}{\partial y/y}\right)$$

The conclusion is that a change in y will increase x if the percent change in z (efficiency) is less than the percent change in y (the revenue share).

Appendix B: Data Sources and Technical Notes

Table 17: Model Variables

Variable	Description	Data Source(s)
Utilization	Age, Race, Sex, Price adjusted Medicare spending and Age, Race, Sex adjusted Medicare spending measures by HSA and HRR Broken out into: hospital / skilled nursing facilities (SNF), physician services, outpatient services, home health care, hospice and equipment	Dartmouth Atlas
	Unadjusted, Medicare Adjusted, Risk-Adjusted Medicare spending measures by HRR	Medicare Geographic Variation Public Use File
Readmission	Hospital readmission rates were aggregated up to the HSA and HRR levels using the Dartmouth Atlas's Hospital to HSA map.	CMS Hospital Compare Dartmouth Atlas
Behavioral Integration	For a description on how these were constructed see Section4 4 Integration Definition	CMS Physician Shared Patient Data CMS Physician Compare Dataset CMS MPUP
Hospital Ownership	Following Neprah et al, physicians were categorized as hospital owned based on their use of the hospital outpatient departments place of service code.[12]	CMS Medicare Provider Utilization and Payment Data (MPUP)
Hospital HHI	Using aggregate hospital billing information from HCRIS, and tying hospitals to HRRs I calculate the hospital HHI for each HRR.	CMS Healthcare Cost Report Information System (HCRIS) Data
Physician HHI	Using aggregate physician billing information from MPUP, and tying physicians to practices through the physician compare identifiers I calculate the physician HHI for each HRR.	CMS Medicare Provider Utilization and Payment Data (MPUP) CMS Physician Compare Dataset
Average Group Size	Using the physician compare practice identifiers I calculate average practice size for each HRR.	CMS Physician Compare Dataset
Share Solo Physician	Using the physician compare practice identifiers I calculate the average number of physicians in a solo practice.	CMS Physician Compare Dataset

[12] For more information, see the technical appendix that accompanies the paper: http://jamanetwork.com/journals/jamainternalmedicine/fullarticle/2463591#supplemental-tab

Table 18: Data Sources

Data Source	Link
Dartmouth Atlas	http://www.dartmouthatlas.org/tools/downloads.aspx
Medicare Geographic Variation Public Use File	https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Geographic-Variation/GV_PUF.html
CMS Physician Shared Patient Data	https://questions.cms.gov/faq.php?id=5005&faqId=7977
CMS Medicare Provider Utilization and Payment Data (MPUP)	https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Provider-Charge-Data/index.html
CMS Hospital Compare	https://data.medicare.gov/data/archives/hospital-compare
CMS Physician Compare Dataset	https://data.medicare.gov/data/physician-compare
CMS National Plan and Provider Enumeration System (NPPES) File	http://download.cms.gov/nppes/NPI_Files.html
CMS Healthcare Cost Report Information System (HCRIS) Data	https://www.cms.gov/Research-Statistics-Data-and-Systems/Downloadable-Public-Use-Files/Cost-Reports/Cost-Reports-by-Fiscal-Year.html

Physician Practice and MCO Negotiation

The impact of time sensitive supply and demand

Abstract

When health care providers and managed care organizations (MCOs) bargain, the main tool providers have is the threat to refuse to be in the MCO's network. In fact, anecdotal evidence indicates that a major mechanism that practices employ to maximize profits in the face of differing insurer reimbursements, limited capacity and stochastic demand is to choose insurers discriminately. Providers do not accept patients from every MCO, however, providers do not exclusively accept the most profitable MCO. In this paper, I apply these institutional facts to a Nash cooperative bargaining framework to develop a bargaining model that explicitly models the provider's disagreement point with the MCOs. In doing this, I am able to solve analytically for the interdependence of prices between MCOs and add to previous bargaining models by making the value of a MCO to a provider more explicit. This model shows the impact of MCO market structure on prices. By introducing provider capacity constraints, I am able to model two important provider-side considerations: the risk capacity will be unused, and the risk that a low paying patient will displace a higher paying patient. Neither of these two effects have been previously captured in the bargaining literature, which typically has featured marginal costs as the limiting factor for providers contracting with MCOs. I also show how predictions in my model match empirical observations and estimates from other

work. I demonstrate a strong negative association between MCOs' market power and negotiated prices, and show that the degree of market level price differences predicted by this model is similar to what has been observed. Finally, recent empirical work has found that that price increases for Medicare are positively associated with private MCOs' prices and that this impact is stronger in areas with more concentrated insurers, and areas in which Medicare patients represent a larger share of the market. My model analytically makes these predictions and can explain the underlying mechanisms.

1 Introduction

Many markets feature stochastic and time sensitive consumer demand along with supplier capacity that is static in the short term and non-storable – use it or lose it. Everyday examples include the market for live performances such as concerts or sporting events, restaurants and airline tickets. A common feature of these types of markets is the use of price as a market clearing mechanisms. The price is allowed to vary with contemporaneous demand. More popular events and restaurants have higher equilibrium prices. Airlines rapidly vary prices to avoid having unsold seats. Without price flexibility the result is typically excess demand (sell outs) or excess capacity (empty seats).

Though rarely applied to this context, the market for physician services also features stochastic and time sensitive consumer demand along with static, non-storable provider capacity. However, the market for physician services has both supply and demand side factors that do not allow a similar demand clearing mechanism. Prices for physician services are quite rigid. Medicare, the largest insurance provider in the United States, sets prices nationally. These prices are non-negotiable, and providers that participate in Medicare are forbidden from balance billing[13]. Similarly, Medicaid prices are generally set by states and are also a take it or leave it proposition. Reimbursement rates between physicians and private insurers are typically set once per year through a complex and opaque process of bilateral negotiations.

[13] "Balance billing" is the practice of billing a patient the difference between the provider's charge and the payment amount from a third-party payer, such as an MCO or Medicare.

Furthermore, there are three factors that make patient demand for medical services particularly unresponsive to price. First, for non-preventative care, there are often no good substitutes available, which means the underlying demand for physician services is generally inelastic with respect to price. The current best estimates of price elasticity for healthcare services are around 0.2 (Manning et al 1987, Newhouse et al. 1993, Zweifel and Manning 2000, Ringel et al 2002). Secondly, a substantial portion of the cost of care is covered by insurance, which means patients face neither the true cost of care or even the price that is transacted between their managed care organization and their healthcare provider. The result is that even if patient demand was more price-elastic, the price effect would be muted. Finally, even if a patient was particularly cost sensitive, prices are often unknown and not easily discoverable prior to service (Rosenthal, Lu and Cram 2013). Therefore, the mechanism through which the market for medical services clears must be more complex than menu prices directly influencing consumer demand.

There is a body of literature on provider market power and MCO-provider bargaining. Studies have shown a wide variation in prices across providers and MCOs (Baker, Bundorf, Royalty and Levin 2014, Ginsburg 2010, Cooper et al 2015). For example, Baker et al (2014) find that for internal medicine, the 10th and 90th percentiles for the Herfindahl-Hirschman Index, HHI, a common measure of market concentration, are respectively 666 and 3,154, and for urology they find 3,316 and 7,215. Research has shown that a factor in this price variation is market power, both for hospitals and physicians (Kleiner, White and Lyons 2015, Dunn and Shapiro 2014).

However, this literature currently does not include the above-mentioned features which are the mechanism through which a provider can leverage market power to receive higher prices.

Empirical work has examined how one payer's price impacts the bargained price for another payer, for example changes in Medicare's prices impacting private prices, see Frakt (2011) for a review of the evidence for hospital cost-shifting, and White (2013) for a more recent study. Most models used in empirical work assume bargaining outcomes that are independent across MCO-provider pairs (Grennan 2013, Lewis & Pflum 2015) and thus price does not explicitly depend on the market structure of the MCOs.

The goal of this paper is to add to the existing literature by examining the previously described features of the market for medical services – stochastic, time sensitive consumer demand and static, non-transferable supplier capacity in the face of rigid price structures and inelastic consumer demand. I will explicitly model how they impact the bargaining relationship between multiple managed care organizations (MCOs) and healthcare providers.

This paper proceeds as follows: In section 2, I give more background and motivation to justify and support the development of my approach. I show how I am building on the relevant literature, and contrast my approach with was has been done previously. I then develop, in section 3, a model of the physician's decision to accept or reject a Managed Care Organization (MCO), given the expected price with and without that MCO. I discuss the MCOs desire to contract with the provider (the demand side), before combining the two into a dynamic bargaining model which incorporates the model of physician behavior. In section 4, I present basic predictions from the model. Finally, in section 5, I present some numerical examples and simulations and compare my results with previous research.

2 Background & Related Literature

An important assumption made in this paper is that in the short and medium-term physician and practice supply is relatively fixed. For practices, the intuition is that the main production inputs of space, equipment, and support staff cannot be easily varied day to day or week to week. For individual physicians, the idea is that their services are labor intensive. Physician labor responds to a price increase with competing income and substitution effects. While this assumption can be relaxed, the main formation of the model assumes that the effects cancel out and there is no aggregate supply response to price.

This assumption is not contradicted by the current literature. In an important early work looking at physician behavior McGuire and Pauly (1991) provide a theoretical model to test whether physicians have a target income or seek to maximize profits. They found that the strength of physicians' income effect controls their behavior (Gruber, Kim, Mayzlin 1999, Yip 1998 Mitchell, Hadley, Gaskin 2000). More recently Kantarevic, Kralj and Weinkauf (2008) used reforms to the physician threshold system in Ontario, Canada to study this empirically. They find that, as expected, both the income effect and substitution effects are present with the expected signs. However, for different services, different effects dominate and there is no predominant aggregate supply effect.

The interplay between a practice and multiple payers, including Medicare, is an important mechanism in the model. A branch of the literature has sought to explain the response of private prices to changes in Medicare prices. Hospital administrators have advocated for "cost-shift theory", that is, lower prices from one insurer will need to be made up somewhere to meet cost, and will then be shifted to other insurers. While economists have generally been skeptical of this theory, there is disagreement (Ginsburg 2003). In a 2011 review of the literature, Frakt finds some evidence that cost shifting may occur, however the effects seem to be mild. In a more recent White (2013) finds the opposite effect – lower Medicare rates in hospitals resulted in lower private rates.

For physicians, Clemens and Gottleib (2017) found consistent positive effects on private payer rates from increases in Medicare payments. These effects are larger both when Medicare makes up a larger share of the market and also when insurers have more relative market power. Ketcham, Nicholson, Unur and Lawrence (2014) similarly finds a positive relationship.

There is large existing literature covering MCO bargaining with providers for inclusion in a network. Town and Vistnes (2001) and Capps, Dranove and Satterthwaite (2003) use a logit demand model to construct a patient's willingness-to-pay for inclusion of a provider based on observed provider and patient characteristics. These papers established the WTP concept as a measure of market power as well as the connection between that measure, profits, and prices. While originally focused on hospitals, these models have recently been applied to physicians as well (Carlson et al 2013, Kleiner, White and Lyons 2015). These papers, however, employ a standard bilateral Nash bargaining model, which does not explicitly include or model the interdependence of prices. The models show the impact of market concentration on the provider side, but cannot speak to the impact on prices stemming from different configurations of MCO market power. Across markets, there is wide variation in the concentration of insurers. According to a 2014 study by the Government Accountability Office, the three largest insurers in Wisconsin's large group insurance market had a combined 39 percent of the total enrollees, while for most other states (37) the three largest insurers had more than 80 percent of the total commercial market.

More recent research has incorporated more sophisticated bargaining models. Ho and Lee (2013) study the price impact of insurer consolidation, focused on two competing forces. Increased insurer competition lowers premiums. Lower premiums reduce the surplus available to split between hospital and insurers, resulting in reduced prices. However, increased insurer competition gives hospitals more leverage to raise prices. They specify a general bargaining model in which price is determined by insurers' premiums and payments to other hospitals, and hospitals' costs and reimbursements from other payers. Lewis and Plum (2014) also develop a hospital, MCO bargaining model. Their innovation is to separately look at bargaining position (value of the hospital or network) and bargaining position (ability to obtain a higher share of the surplus).

I add to these bargaining models by making the value of a MCO to a provider more explicit. By introducing capacity constraints, I am able to model two important provider-side considerations: the risk capacity will be unused, and the risk that a low paying patient will displace a higher paying patient. Neither of these two effects have been previously captured in the bargaining literature, which typically has featured marginal costs as the limiting factor for providers contracting with MCOs. My paper will look at price differences arising from relative differences in MCO size stemming directly from the two effects. The model I put forward will not address any price differences that arise from efficiencies, bargaining ability, asymmetric information, or any pass-through price effects from the consumer-MCO price negotiations.

3 Model of Practice MCO Negotiation

Below I develop a model of practice-MCO bargaining. I explicitly specify the benefit of contracting for both the MCO and the practice, and show how for a given provider the negotiated prices are interdependent for each MCO.

In the first section, I introduce the providers problem by specifying the value to a practice of accepting patients of a particular type (taking prices as given). While this can be generalized to include any patient types that can be observable and discriminated, the focus here is on patients from different MCOs. Every MCO k has a price (p_k) and a propensity (λ_l) – which can be thought of as the probability that a patient from MCO k takes a given time slot, given the provider accepts patients from all MCOs. The probability in practice will depend on the contracting decisions for each of the other providers, which is a major mechanism in the model.

This expected value of including plan type k depends on the prices of other accepted MCOs, their propensities, and propensity that a given time slot is unfilled (λ_0). This gives the value of the MCO to the provider.

Second, I characterize the value of the provider to the MCO by using the option-demand framework, developed by Capps et al (2003), to characterize an MCO's willingness-to-pay for a patient to have the provider in the network as a function of patient's expected utility. For use in bargaining, this is converted from utils to dollars and standardized to WTP per time slot to be comparable to the value of the MCO to the provider.

Third, I use the willingness-to-pay and the provider's expected value in a Nash bargaining framework. The MCO and provider reach a deal to include the provider in the MCO network if there is a price between the lowest price the provider would accept, the expected value of a time slot without the provider, and the highest price the MCO would pay, which is the willingness-to-pay. If they do reach an agreement they choose a price that splits the gains from inclusion by a constant fraction. Unlike previous work, the explicit specification of the provider's value function allows me to solve the system of equations and derive a formula for equilibrium prices that is determined simultaneously, depends on the both the provider and MCO competitive landscape. This approach allows me to speak to the predicted relationship of prices across MCOs.

Finally, I discuss the implications from and dynamics in this bargaining framework demonstrating predictions from the model.

Provider's Selection of MCOs

In markets for restaurants, airline flights and concerts the market clears through direct price increases or decreases, and generally prices are uniform across consumers. In the market for health services, price changes happen through negotiations that generally occur once per year. The main threat that providers have in these negotiations is the threat not to accept an MCO's patients. In the exposition below, I will concentrate on the agent being the physician practice, but a similar framework could characterize other types of providers' negotiations with MCOs.

For new patients especially, the availability of a convenient time slot not too far in the future can be a major determinate of choosing a doctor. Anecdotal evidence indicates that physicians take payer-mix into account when deciding whether to accept patients from a low paying insurer. For new managed care contracts, the Practice Management Resource Group encourages practices to evaluate "How the added patients will impact your payer-mix. Will these patients increase or decrease your expected collections? Will they displace higher paying patients?"[14] Similarly, a popular book "Mastering Patient Flow"[15] discourages closing practices fully to new patients due to the fact that it will decrease the practice's ability to alter its payer mix. The alternative suggestion to alleviate capacity issues is to end participation with insurance companies that pay less.

In the model I develop here, the physician practice, indexed by j, faces K types of patients which it can either choose to accept or not accept – while this can be generalized to include any patient types that can be observable and discriminated, the focus for this exposition will be on patients from different MCOs.

Each slot is then filled with a patient of type k with a probability ($Prob_{k,j}$). Also, with positive probability, the time slot is not filled (denoted by $Prob_{0,j}$). This probability can be thought of as being market or provider specific, and in a manner detailed below, these probabilities will depend on the set of MCOs with which the provider has a contract. This way of characterizing the value of a time slot is applicable to arrangements where the provider is compensated through a fee-for-service system, and less relevant for physicians who are strictly salaried, or are compensated through capacitated arrangements, that is one in which the physician receives a set amount per patient year. I make the simplifying assumption that, conditional on contracting with an MCO, the practice cannot discriminate between patient types through

[14] http://www.medicalpmrg.com/payor-mix-analysis.html (last accessed April 17, 2014)
[15] Woodcock, Elizabeth W. *Mastering Patient Flow* (MGMA, 2009) 3rd edition

other means. Therefore, the practice's problem is to evaluate the payouts from each patient type and choose which MCOs to accept.[16]

The physician wants to choose the mix of MCOs (k) to maximize revenue (= the expected value of the time slot):

$$\max_{K_j} EV_{K_J} = \max_{K_j} \sum_{k \in K_j} Prob_{k,j} p_k$$

Probability of type k:

If $Prob_{k,j}$ is exogenous to the choice of K_j (no capacity constraints), then all plans will be included. We do not observe this because, in practice, being able to accept and schedule a patient is conditional on having a time slot available. Therefore, a patient type with a low expected value (i.e. a low-paying MCO) can take the capacity away from a patient type with a higher expected value (a high-paying MCO). Furthermore, if there were no chance that a slot was not filled (excess capacity) then there would be no reason to accept any plan except for the highest paying. The tradeoff then is balancing the probability that no one takes the slot, with the probability that a patient with a lower paying plan prevents the provider from being able to render services to a patient with a higher paying plan.

This tradeoff can be formalized by denoting the unconditional probability of patient type k (the probability if all types are included) by λ_k. Let λ_0 be the probability that there are no

[16] In the Appendices I include several variations and extensions of the model. I explicitly discuss excess capacity (Appendix A:). I explore an alternative formation of the provider problem using a Poisson distribution of patients (**Error! Reference source not found.**). And finally, I show how the inclusion of variable cost (0) or e xogenous physician work hours (Appendix C:) do not significantly change the model.

patients in that time-period, given that all patients are accepted. I term this average excess capacity.

In the appendix, I discuss provider capacity and specify how providers choose capacity given expectations about patient demand, the expected marginal cost and expected payment for patient (not conditioned patient type). Adjusting this capacity is costly and fixed in the short and medium term. This leads to an optimal average excess capacity, or the propensity that a given time slot is unfilled (λ_0).

With these parameters defined, given a provider accepts the set of plans K_j, the probability of patient type k is:

$$Prob_{k,j} = \frac{\lambda_k}{\lambda_0 + \sum_{\kappa \in j} \lambda_\kappa}$$

Expected Value of a Time Slot

Therefore, the expected value of a time slot can be expressed as follows:

$$EV_{K_J} = \sum_{k \in K_j} \lambda_\kappa p_k \,/\left[\lambda_0 + \sum_{k \in K_j} \lambda_\kappa\right] \tag{1.0}$$

Maximizing this leads to the rule that patients of type δ should be included iff:

$$p_{\delta,j} \geq \left[\sum_{k \in K_j/\delta} \lambda_\kappa p_k\right] / \left[\lambda_0 + \sum_{k \in K_j/\delta} \lambda_\kappa\right] = EV_{K_J}$$

It is notable that the decision to include a particular type of patient does not depend on how many patients there are of that type (propensity λ_δ). All that matters is the comparison between the expected value of the patient compared to the expected value of the set of currently accepted patients. This expected value is influenced by share of slots likely to be unfilled, so the sizes of the *other* MCOs matter. While it is a minor distinction, bargaining power for a large MCO does not necessarily stem from the fact that the MCO is large, but stems from the fact that the other MCOs are not "large enough". The ability to withhold quantity is a useless threat if the provider is already at capacity.

> **Prediction 1:** *A provider (j) will want to contract with a MCO (δ) if the expected value of a time slot without the provider is lower than the price the MCO is offering.*

With the rule under which a provider accepts an MCO established, we can examine some of the other dynamics predicted by the model.

Addition of an MCO, δ:

Using this formulation, the increase in the expected value of a time slot if provider i adds an insurer, given other accepted insurers K and prices, is:

$$V_i(\delta|K_j,P) = \left[\lambda_\delta p_\delta + \sum_{k\in K_j} \lambda_\kappa p_k\right] / \left[\lambda_0 + \lambda_\delta + \sum_{k\in K_j} \lambda_\kappa\right] - \left[\sum_{k\in K_j} \lambda_\kappa p_k\right] / \left[\lambda_0 + \sum_{k\in K_j} \lambda_\kappa\right]$$

$$= \frac{\lambda_\delta}{\lambda_0 + \sum_{k\in K_j} \lambda_\kappa} \left(\lambda_0(p_\delta - 0) + \sum_{k\in K_j} (p_\delta - p_k)\lambda_\kappa\right) / \left(\lambda_0 + \lambda_\delta + \sum_{k\in K_j} \lambda_\kappa\right) \qquad (2.0)$$

This is the weighted price difference between δ and the existing prices, normalized to a time slot, and multiplied by the percent increase in λ that δ brings.

Demand Side: MCO's Willingness-to-Pay for a Provider

To be able to discuss prices further, and to be able to examine bargaining dynamics, I first must specify the underlying demand system from the MCO. I do this by leveraging the option demand framework developed by Capps, Dranove and Satterthwaite (2003), through which an MCO has a willingness-to-pay to include the provider in the network.

In their model, a patient i has ex post (that is, after the revelation of a health diagnosis requiring treatment) expected utility for the services from provider j given by the following form:

$$\begin{aligned} U_{ij} &= \alpha R_j + H_j'\Gamma X_i + \tau_1 T_{ij} + \tau_2 T_{ij} X_i + \tau_3 T_{ij} R_j - \gamma(X_i) P_j(Z_i) + \varepsilon_{ij} \\ &= U\left(H_j, X_i, T_{ij}\right) - \gamma(X_i) P_j(Z_i) + \varepsilon_{ij} \end{aligned}$$

where H_j are the provider characteristics, X_i are the patient characteristic and T_{ij} is the geographical location of the patient in relation to the provider. If the error term is logit, and we assume there are no meaningful out of pocket cost differentials between providers, then a patient's utility of having access to a network G of providers is:

$$V^{IU}\left(G, Y_i, Z_i, T_{ij}\right) = E \max_{g \in G}\left[U\left(H_g, Y_i, Z_i, T_{ij}\right) + \varepsilon_{ig}\right] = ln\left[\sum_{g \in G} \exp U\left(H_g, Y_i, Z_i, T_{ig}\right)\right]$$

And the additional utility derived from the inclusion of provider j is:

$$\Delta V_j^{IU}(G, Y_i, Z_i, \lambda_i) = ln\left(\frac{1}{1 - s_j(H_j, Y_i, Z_i, T_{ij})}\right)$$

This is the willingness to pay, in utils, for patient i to have provider j in network G. The willingness for the MCO to pay to have the provider in the system is calculated by summing this additional utility over all of patients in the MCO. In order to be used for my purposes, and compared to price, this WTP is then normalized as a WTP per visit, and converted to dollars.

The willingness-to-pay is the highest price an MCO would pay to have a provider in the network.

It is important to note that even if we assume that patient preferences do not differ systematically across MCOs – that is preferences only differ through the observed characteristics included in the utility function – the willingness-to-pay measures for a given provider can be different. Two main things drive this difference - the MCO's network and the composition of patients.

Both ΔWTP and λ_0 (average excess capacity) reflect a provider's desirability, but it is important to recognize how they are different in this model. The difference is that in this formation ΔWTP is normalized to a patient time slot, to correspond to price, and therefore does not depend on the size of the population. In contrasts λ_0 depends on the interplay between the number of patients, the number of other practices, and the size of the practice. If the number of patients increased, with no change in characteristics, ΔWTP normalized to a patient time slot would not change but λ_0 would decrease.

Provider-MCO Bargaining

I now apply a bargaining framework between providers (j) and MCOs (ℓ) to the above assumptions. In the standard Nash-bargaining framework, parties choose a price that splits the bargaining surplus, normalized to a per time-period amount, with constant parameter $\alpha \in (0,1)$. The typical assumption is that price solves the following:

$$p_{\ell j} = \underset{p_{\ell j}}{\operatorname{argmax}} \left(\mathrm{WTP}_{\ell \mathrm{j}} - p_{\ell j}\right)^{1-\alpha}\left(p_{\ell j} - d_j\right)^{\alpha}$$

Where d_j is the disagreement point for provider j and α is the "price Nash bargaining parameter." The outcome of the bargain depends non-trivially on the disagreement point and my contribution is to explicitly model this as previously described, $d_j = EV_{K_j/\ell}$. This makes the bargaining process between MCOs and providers explicitly interdependent. This is in contrast to other papers which assume independent bilateral bargaining (Lewis and Pflum 2015).

In the Nash solution, the MCO and the provider split the surplus, and this construction leads to the following set of price equations for each MCO (ℓ) provider (j) pair:

$$
\begin{aligned}
p_{\ell j} &= (1-\alpha)\mathrm{WTP}_{\ell \mathrm{j}} + \alpha EV_{K_j/\ell} \\
&= (1-\alpha)\Delta\mathrm{WTP}_{\ell \mathrm{j}} + \alpha\left[\sum_{k\in K_j/\ell} \lambda_\kappa p_k\right] \Big/ \left[\lambda_0 + \sum_{k\in K_j/\ell} \lambda_\kappa\right]
\end{aligned} \tag{3.0}
$$

The previously defined term, $EV_{K_j/\ell}$, means that prices are interdependent within a provider and thus must be determined simultaneously. Because the $\lambda' s$ are taken as given, for each provider j we have L equations with L unknowns, where L is the total number of MCOs, and thus one can explicitly solve the equilibrium prices.

In the following sections, I show the equilibrium prices for some configurations of insurers, and discuss how these prices are impacted by the underlying parameters: the λs, each MCOs WTP, and administratively set prices.

Monopolist

If insurer δ is a monopolist then $EV_{K_j/\delta}$ is 0, and the equilibrium price equation is:

$$p_\delta = (1-\alpha)\Delta\mathrm{WTP}_{\delta j} + \alpha EV_{K_j/\delta} = (1-\alpha)\,\Delta\mathrm{WTP}_{\delta \mathrm{j}}$$

This is effectively the lowest price possible between insurer δ and provider j.

Two Private MCOs and Medicare

Consider the situation with two private insurers (indexed by 1 and 2), and Medicare (indexed by m). Because they are administratively set, in this model Medicare prices are taken as exogenous. This leads to the following equilibrium prices[17]:

$$p_1^* = \left(1 - \alpha^2 \frac{\lambda_1}{\Lambda - \lambda_2}\frac{\lambda_2}{\Lambda - \lambda_1}\right)^{-1} \left[(1-\alpha)WTP_1 + \alpha \frac{\lambda_m}{\Lambda - \lambda_1} p_m + \alpha \frac{\lambda_2}{\Lambda - \lambda_1}\left((1-\alpha)WTP_2 + \alpha \frac{\lambda_m}{\Lambda - \lambda_2} p_m\right)\right] \tag{4.0}$$

Where for expositional simplicity, I have defined $\Lambda \equiv \lambda_0 + \lambda_1 + \lambda_2 + \lambda_m$

This equation characterizes the prices as a function of the underlying parameters. Price is related to the provider competitive landscape through the willingness to pay measure, and the insurer competitive landscape through the number of insurers and their relative sizes. As a note, the case without Medicare is equation 4.0 with $\lambda_m = 0$.

[17] Details in Appendix E:.

$p_1^* =$		Equilibrium price is:
1	$\left(1 - \alpha^2 \frac{\lambda_1}{\Lambda - \lambda_2} \frac{\lambda_2}{\Lambda - \lambda_1}\right)^{-1}$	Market concentration premium (MCP)
2	$[(1-\alpha)WTP_1$	Own MCO's willingness-to-pay
3	$+\alpha \frac{\lambda_m}{\Lambda - \lambda_1} p_m$	First order impact of Medicare price
4	$+\alpha \frac{\lambda_2}{\Lambda - \lambda_1}$	Other MCO price impact rate
5	$((1-\alpha)WTP_2$	Other MCO's willingness-to-pay
6	$+\alpha \frac{\lambda_m}{\Lambda - \lambda_2} p_m)$	Second order Medicare price

To explain this equilibrium price, I have separated it into six parts in the above table. The first part is the term $\left(1 - \alpha^2 \frac{\lambda_1}{\Lambda-\lambda_2} \frac{\lambda_2}{\Lambda-\lambda_1}\right)^{-1}$ which I call the market concentration premium (MCP). It is always equal to or greater than 1. It captures a provider's ability to extra a higher price by playing the MCOs off each other. If the prices were independently negotiated, then MCP would be 1. It is highest when the MCOs are the same size and for a given λ_0 and λ_m.[18]

The second term is the MCO's willingness-to-pay, multiplied by the WTP bargaining coefficient $(1-\alpha)$. WTP is the value that MCOs puts on having access to the provider and can change through changes in the underlying characteristics of MCOs population or network.

[18] In the more general case, with more than 2 insurers the MCP is 1/det(A), where A is the matrix defined in the technical appendix.

Due to the MCP, an increase in MCO 1's WTP for provider j increases the price between provider j and MCO by more than the bargaining parameter $(1-\alpha)$. Intuitively, one can envision the following process leading to larger increase:

1. Looking at equation 3.0, when MCO 1's WTP increases there is an immediate impact of an increase in p_1 as they split the now larger surplus and the provider's share is $(1-\alpha)$.
2. However, this impacts the bargained prices between the provider and other MCOs. Having secured this higher price, the provider's threat point (the expected value without the other MCOs) has increased. Therefore, the provider can now go to other MCOs and demand a higher price.
3. Once the provider has received the higher prices from the other providers they can return to MCO 1, and the process continues.

The third part is the first order impact of the Medicare price. The first term of this is the bargaining parameter α, and the second term, $\frac{\lambda_m}{\Lambda-\lambda_1}$, is Medicare's expected share of time slots if provider j did not accept MCO 1 patients. This is multiplied by the Medicare price, so this term is the contribution of Medicare to the expected value of the provider without MCO 1.

In a similar manner, the fourth term is the expected share of time slots for MCO 2 without MCO 1 multiplied by the bargaining parameter α, $\alpha\frac{\lambda_2}{\Lambda-\lambda_1}$. This term captures the degree to which a price change for MCO 2 impacts the price for MCO 1. However, because the price for MCO 2 is not exogenous, the term is not just p_2.

The fifth and sixth reflect the impact of MCO 2's price on MCO 1's price. The fifth term is the WTP bargaining coefficient $(1-\alpha)$ multiplied by MCO 2's WTP. The sixth term is the same as the third, however, it is multiplied by the price propagation factor, $\alpha \frac{\lambda_2}{\Lambda-\lambda_1}$. This is the second order impact of Medicare, that is the impact on MCO 1's price that happens through Medicare prices impacting MCO 2's price.

4 Comparative Statics

These equilibrium prices lead to the following comparative statics and predictions. The equation that I present are only for the case with two private MCO and Medicare, but the predictions should hold more generally:

> **Prediction 2:** *The share of increase in MCO k's demand (WTP) captured by provider j will be greater than the bargaining parameter $(1-\alpha)$, and will depends on the market shares of all MCOs and the propensity for provider j to have an unfilled time slot (λ_0).*

$$\frac{\partial p_1^*}{\partial WTP_1} = \left(1 - \alpha^2 \frac{\lambda_1}{\Lambda - \lambda_2} \frac{\lambda_2}{\Lambda - \lambda_1}\right)^{-1} (1-\alpha) \geq (1-\alpha) \tag{5}$$

This prediction flows directly from equation (5) and the fact that this derivative is greater than the base bargaining parameter of $1-\alpha$. This is a result of modeling the interdependence of prices. An increase in WTP for MCO 1 will have a first-order increase on MCO 1's price, however, this increase in MCO 1's price will have a second-order impact on MCO 2's price, and this chance in MCO 2's price will have a third-order impact on MCO 1's price, etc. The increase in price above $1-\alpha$ is result of that process being infinitely repeated, and is the equilibrium price. This leads to the next prediction from the model:

Prediction 3: *There is a positive relationship between MCO i's demand for provider j and other MCO's contracted price with that provider.*

$$\frac{\partial p_1^*}{\partial WTP_2} = \left(1 - \alpha^2 \frac{\lambda_1}{\Lambda - \lambda_2} \frac{\lambda_2}{\Lambda - \lambda_1}\right)^{-1} \alpha \frac{\lambda_2}{\Lambda - \lambda_1}(1 - \alpha) > 0 \tag{6}$$

The second-order effect, described above, is shown in equation (6). An increase in demand by MCO 1 for provider j increases the equilibrium between provider j and other MCOs.

Prediction 4: *There will be positive relationship between Medicare prices and private prices.*

$$\frac{\partial p_1^*}{\partial p_m} = \left(1 - \alpha^2 \frac{\lambda_1}{\Lambda - \lambda_2} \frac{\lambda_2}{\Lambda - \lambda_1}\right)^{-1} \left[\alpha \frac{\lambda_m}{\Lambda - \lambda_1} + \alpha \frac{\lambda_m}{\Lambda - \lambda_2} \alpha \frac{\lambda_2}{\Lambda - \lambda_1}\right] > 0 \tag{7}$$

The equilibrium bargained price depends strongly on the disagreement point, which is modeled as $EV_{K_{j/\ell}} = \left[\sum_{k \in K_{j/\ell}} \lambda_\kappa p_k\right] / \left[\lambda_0 + \sum_{k \in K_{j/\ell}} \lambda_\kappa\right]$ (from equation (1)). The magnitude of the impact is the product of the market concentration premium, and the sum of what can be thought of as the first-order impact of the change in Medicare's price ($\lambda_m/(\Lambda - \lambda_1)$) and the second-order impact on MCO 1 ($\alpha \frac{\lambda_2}{\Lambda - \lambda_1}$) of the impact of the change in the Medicare price on MCO 2's price ($\alpha \frac{\lambda_m}{\Lambda - \lambda_2}$).

In short, the price provider j can command from MCO 1 has increased with the increase in Medicare's reimbursement because the providers expected value without MCO 1 has increased. The increase in the Medicare price has increased the disagreement point, and therefore surplus that the MCO and the provider are bargaining has decreased.

Prediction 5: *Even with identical underlying demand (WTP), larger insurers will pay a lower price.*

$$p_1^*/p_2^* = \left[1 + \alpha\left(\frac{\lambda_2}{\lambda_0 + \lambda_2}\right)\right] / \left[1 + \alpha\left(\frac{\lambda_1}{\lambda_0 + \lambda_1}\right)\right] \tag{8}$$

$$\frac{\partial}{\partial \lambda_j}\frac{\lambda_j}{\lambda_0 + \lambda_j} = \frac{\lambda_0}{\left(\lambda_0 + \lambda_j\right)^2} > 0 \tag{9}$$

For predictions 5 and 6, I am ignoring Medicare and fixing WTP for MCO 1 equal to WTP for MCO 2. The size premium is the price discount, compared to other MCOs, that a larger MCO can achieve from its relative size. This ratio is less than 1 if $\lambda_1 + \lambda_2(1+\alpha) < \lambda_2 + \lambda_1(1+\alpha) \Rightarrow \alpha\lambda_2 < \alpha\lambda_1$, which means that if insurer 1 is larger then insurer 1 will pay less. The mechanism for this effect is the expected value to the provider without insurer 1 is smaller than the expected value without insurer 2.

Prediction 6: *The differences in prices between large and small MCOs will be more pronounced among markets or providers with more excess capacity.*

$$\frac{\partial}{\partial \lambda_0}\left(\frac{\partial}{\partial \lambda_j}\frac{\lambda_j}{\lambda_0 + \lambda_j}\right) = \frac{\lambda_j - \lambda_0}{\left(\lambda_0 + \lambda_j\right)^3} > 0 \quad \text{if } \lambda_j > \lambda_0 \tag{10}$$

With an increase in λ_0, the size premium increases ($\frac{\partial}{\partial \lambda_0} p_1^*/p_2^* > 0$). This happens because with a higher level of excess capacity the disagreement point for the provider, which is MCO's threat to not contract, is lower. While this is true for both MCOs, the effect is larger for the bigger MCO.

5 Examples

In this final section of the paper, I compute some expected prices, as a share of the difference between willingness-to-pay and cost, for several configurations of MCOs. I also show how prices and expected values change with the parameters.

Many of my predicted effects match empirical observations in the literature. I should a strong association between MCOs HHI and prices, and the magnitude is compatible with the Dunn and Shapiro estimates (2012).

I predict market level price differences that are similar to what Baker, Bundorf, Royalty, and Levin observe (2014). My model also matches the findings in Clemens and Gottleib (2017) that Medicare's influence will be strongest in areas with concentrated insurers, and larger when Medicare makes up a larger share of the market.

Georgia vs Alabama

In order to illustrate the predicted differences in price as a function of market dynamics, I use data on the insurance markets for Alabama and Georgia. These numbers come from data on covered lives from the Medical Loss Ratio reports, so I'm simplifying by ignoring Medicare, Medicaid and self-insured plans. I also assume that the willingness-to-pay is identical across the insurer-providers pairs and the propensity that a given time slot is unfilled (λ_0) is 0.2.

What is shown in the table below is the market shares of the top five insurers for Alabama and George, and the corresponding implied prices (as a multiple of WTP).

	Alabama		**Georgia**	
	Market Share	**Price**	**Market Share**	**Price**
1	74%	0.6950	33%	0.7940
2	10%	0.7778	28%	0.7984
3	8%	0.7792	15%	0.8101
4	5%	0.7819	14%	0.8104
5	3%	0.7849	10%	0.8115
Wtd Avg		0.7162		0.8018

The predicted prices for each MCO leads to the following three observations.

First, the price ratio of the 5th largest to the largest is 1.02 in Georgia and 1.13 in Alabama. Second, the insurer with 10% market share in George has a 4.5% higher price than the insurer with the 10% market share in Alabama. This is a function of the dominant player being able to command a lower price, which results in a lower threat point for the rest of the insurers. Finally, the weighted average price is significantly (11%) lower in Alabama than in Georgia. The magnitude of this predicted difference is very much in line with the findings Baker, Bundorf, Royalty, and Levin (2014) who found the price difference in office visits between high HHI and low HHI regions to be between 8% and 16%.

In Georgia, the top insurer is Humana, and the fifth largest is Aetna. I can also estimate the impact of the merger had it been approved. I must note, however, that this analysis does not take into consideration any pass-through effects from their ability to raise prices on the plan consumers who purchase the plans, or any strategic responses on by providers.

Current	**With Merger**

	Market Share	Price	Market Share	Price	Price Change
1	33%	0.7940	43%	0.7776	-2.0%
2	28%	0.7984	28%	0.7926	-0.7%
3	15%	0.8101	15%	0.8041	-0.6%
4	14%	0.8104	14%	0.8049	-0.6%
5	10%	0.8115			-4.4%
Wtd Avg		0.8018		0.7896	-1.5%

By merging with Humana, Aetna could cut their reimbursement prices by 4.4% and Humana can cut theirs by 2.0%. Overall, prices drop by 1.5%, with the other insurers dropping reimbursements by more than 0.5%.

Impact of an increase in WTP

This model predicts how a change in how one MCO values a provider will change the price for both that MCO (prediction 3) and other MCOs (prediction 4). To illustrate with a numerical example, I set the bargaining parameter, α, at 0.5, the Medicare propensity, λ_m, 0.25, both the MCOs propensities, λ_1 and λ_2, 0.3, and the propensity of a time slot to be unfilled, λ_0, 0.15. With these levels, below are the corresponding partial effects of an increase in WTP for MCO 1:

$$\frac{\partial p_1}{\partial \Delta WTP_{1j}} = 0.5240 * d\Delta WTP_{1j}$$

$$\frac{\partial p_2}{\partial \Delta WTP_{1j}} = 0.1129 * d\Delta WTP_{1j}$$

A model that used the same base Nash-bargaining parameters, but which ignored the interdependence of prices would predict an increase in price of $0.5 * d\Delta WTP_{1j}$ for MCO 1 and 0 for MCO 2. My model predicts a slightly larger increase in prices for MCO 1, approximately 5% (0.524/0.5-1) higher than the static model. But my model also predicts that there will be a considerable change in the prices for MCO 2. In fact, the provider is able to raise the price for MCO 2 by about 20% of the increase for MCO 1 (0.1129/.05240).

Impact of an increase in Medicare Reimbursements

The model also predicts a strong positive relationship between Medicare prices and private prices (prediction 4). Using the same parameters above, the impact of an increase in the Medicare price on MCO 1's price is:

$$\frac{\partial p_1}{\partial p_m} = 0.2273 * dp_m$$

While this is a significant effect, the increase is much less than 1, and much smaller than observed by Clemens and Goettlieb (2017). However, the positive predicted effect is incompatible with the theory of hospital cost-shifting (Frakt 2011).

Impact of MCO Size Differences

My model also can speak directly to the relationship between the relative size of the MCO and the relative prices each MCO will pay (prediction 5).

The MCO-provider negotiated prices have been modeled as a function of the characteristics and needs of the MCO's customers, and the other providers already in the MCO network (substitutability). However, the resulting willingness-to-pay, once normalized to patient-visit, does not factor in the bargaining power of the MCO that stems for the relative importance of that MCO to the particular provider. To see how this plays out numerically I have calculated a couple of scenarios in which I have set average excess capacity (λ_0, in the first column), and the size parameters for MCO 1 and MCO 2 ($\boldsymbol{\lambda_1}$ and $\boldsymbol{\lambda_2}$ in columns 3 and 4 respectively). From those three parameters, I calculate the prices. I am setting WTP1=WTP2=0.

λ_0	λ_1	λ_2	Price1	Price2	Size Premium
0.2	0.65	0.25	0.71	0.77	8.2%
0.05	0.65	0.25	0.88	0.91	3.4%
0.1	0.65	0.25	0.80	0.85	5.6%
0.1	0.75	0.15	0.75	0.83	10.9%
0.1	0.85	0.05	0.63	0.78	24.1%
0.1	0.55	0.35	0.83	0.85	2.5%

The exact size premium depends non-trivially on the values of the parameters. However, the size premium is consistent and for large differences in size, considerable.

Impact of Average Excess Capacity (λ_0)

It is important to recognize how willingness-to-pay (WTP) and λ_0 (average excess capacity) differ in this model, as both reflect aspects of a provider's desirability. In my model, WTP is normalized to a patient time slot, to correspond to price, and therefore it does not depend on the size of the population. Instead, it depends on patient and provider characteristics such as location, health status, etc). In contrasts, average excess capacity (λ_0) depends on the interplay between the overall number of patients, the number of other practices, the propensity for a patient to choose the practice and the size of the practice. An increase in the total number of patients, without a corresponding increase in physicians, will not increase the patient normalized willingness-to-pay, but it will decrease λ_0 (average excess capacity). An increase in a practice's capacity again, would not increase the patient normalized willingness-to-pay, but this will increase λ_0.

Below I provide a numeric example of how a change in λ_0 results in higher prices, even while ignoring any impacts from the increase in willingness-to-pay. Using the model of prices with two insurers (no Medicare), the following table contains the corresponding equilibrium prices for two different configurations of market share, and two different values for λ_0, 0.2 (meaning that the underlying probability that a slot will be taken is 80%) and 0.1. WTP_1 and WTP_2 both are fixed at 1:

	$\lambda_0 = 0.2$		$\lambda_0 = 0.1$	
	λ	**Price**	**Price**	**% Price Increase**
1	0.40	0.7500	0.846	12.8%
2	0.40	0.7500	0.846	
	λ	**Price**	**Price**	**% Price Increase**
1	0.64	0.6676	0.7693	15.2%
2	0.16	0.7543	0.8377	11.1%
Wtd Avg		0.6849	0.7830	14.3%

In both cases, with the MCOs have equal market share and where one is larger, there is a significant increase in price from the decrease in λ_0. The increase is smaller in the equal shares case, a 12.8% increase. With different shares, the larger MCO is forced to increase their reimbursement more than the smaller – 15.2% vs 11.1%. The weighted average price increase is 14.3%. These price increases do not stem from a higher willingness-to-pay for a timeslot, but are the result of providers being able to be firmer in their negotiations as there is a smaller probability that they will not find patients, given they are not accepting patients from an MCO.

Finally, the following charts provide a visualization of the price dynamics with two insurers. I show the price for each MCO (the lines) and the expected value of a time slot (the areas). I show these three values along one of three dimensions: the relative size of the insurers, average excess capacity (λ_0) and the ratio of the insurers' willingness-to-pay. Lastly, I compare Herfindahl-Hirschman Index (HHI) and price resulting from my model.

Varying the high-paying share

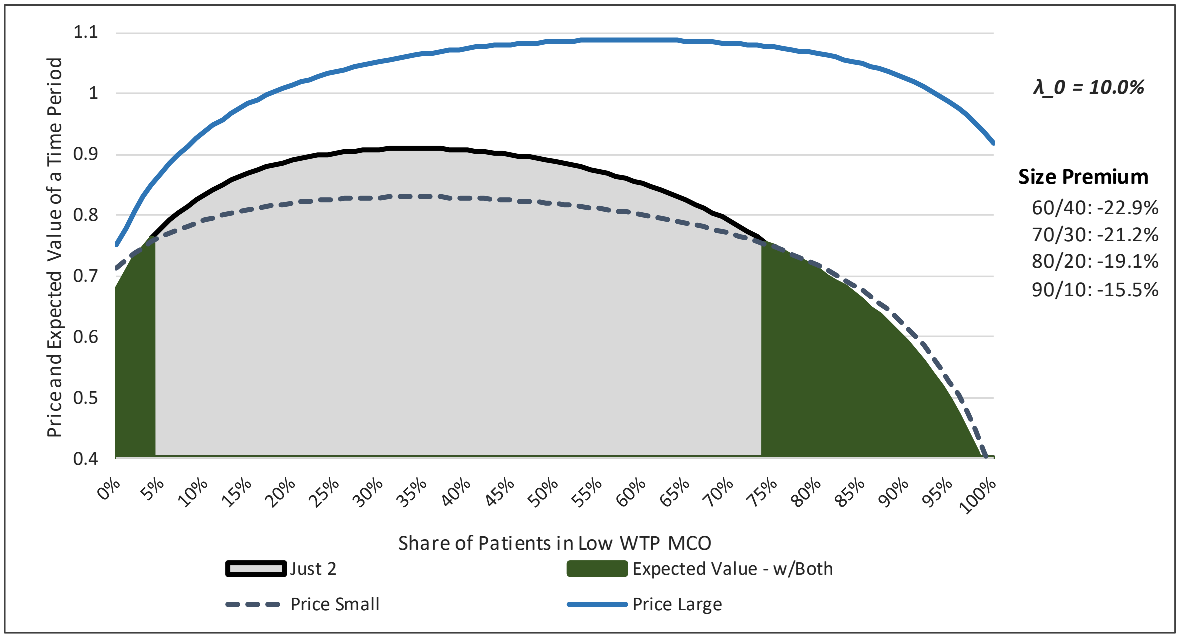


Figure 10: Price and Expected Value by Share of Patients in Low WTP MCO

In Figure 10, the two insurers have a different WTP, meaning the provider is more valuable to one MCO than to the other. This could stem from the provider's skill set matching up better with the needs of one MCO's population, or it could result from convenience and distance. The WTP is set to 1 for the insurer that values the provider less and the WTP is 2 for the other insurer. The average excess capacity, λ_0, is held constant at 10%. What varies on the x-axis is the share of patients that are in the high paying MCO. The main insight from this graphic is that at the two extremes the provider accepts both patients, but in the middle the provider only accepts the higher-paying patient type. The intuition is that if the high paying share is "high enough" (in this example 25%) than the risk of a low paying patient crowding out a low paying patient is not worth the risk of having an empty slot. On the other end, as the MCO that is willing to pay more has a higher share, it is able to use that market power to drive down their price. Eventually, the price is low enough that the cost of a low-paying patient crowding out a high-paying one is small.

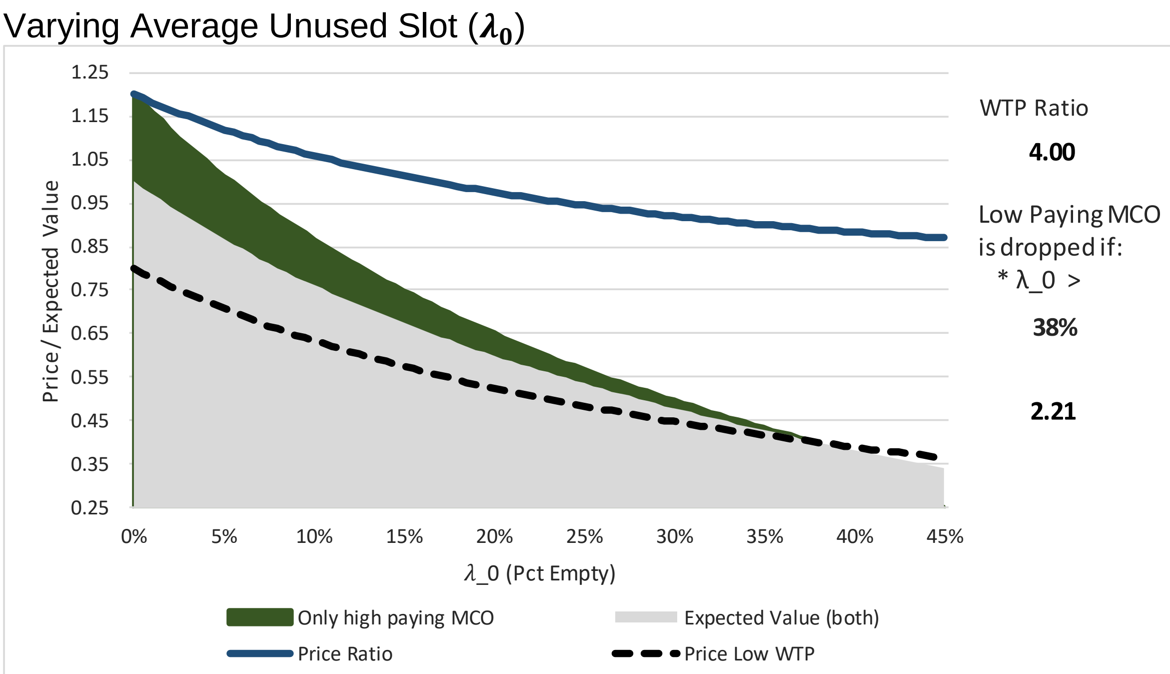


Figure 11: Price and Expected Value by Average Excess Capacity

In Figure 11, both the size of the MCO patient population and the MCO's WTP are held constant at 2 and 1. What varies is λ_0. For low value of λ_0, the provider should only accept patients from the high-paying MCO, which is the grey portion of Figure 11.

The intuition is straightforward. As λ_0 falls, there is a smaller probability that there will be unused capacity if the provider drops the low paying MCO.

Varying the ratio of the MCOs' willingness-to-pay

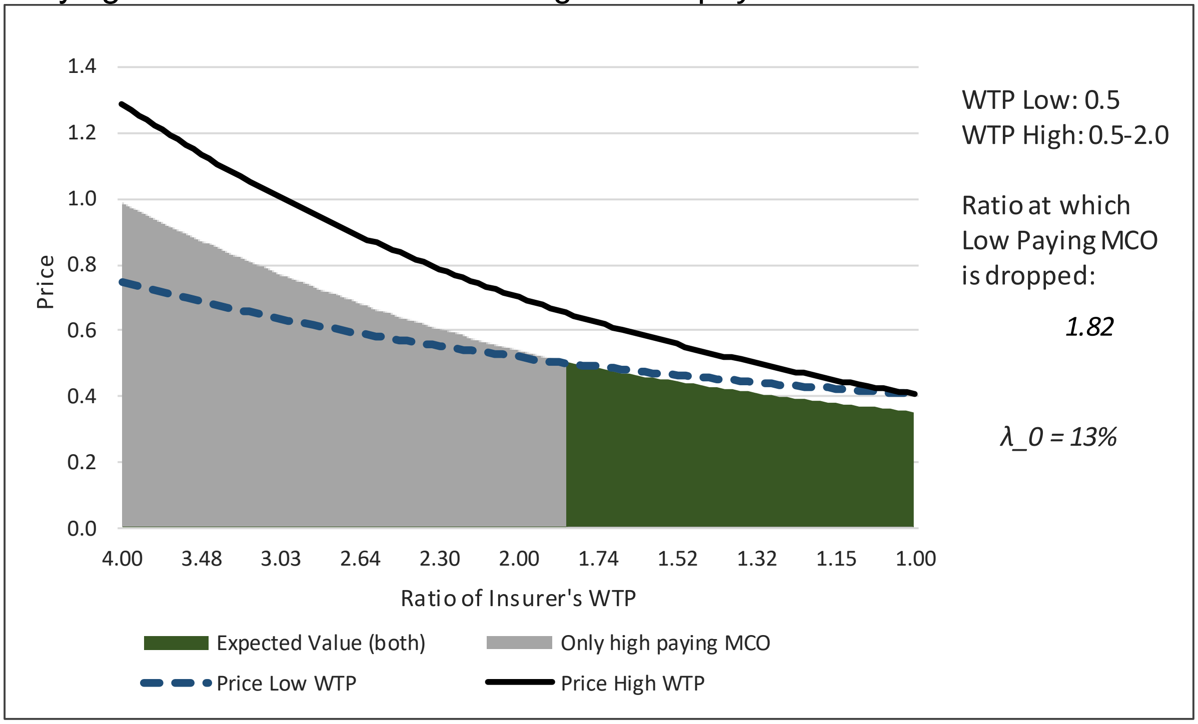


Figure 12: Price and Expected Value by Ratio of MCOs' WTP

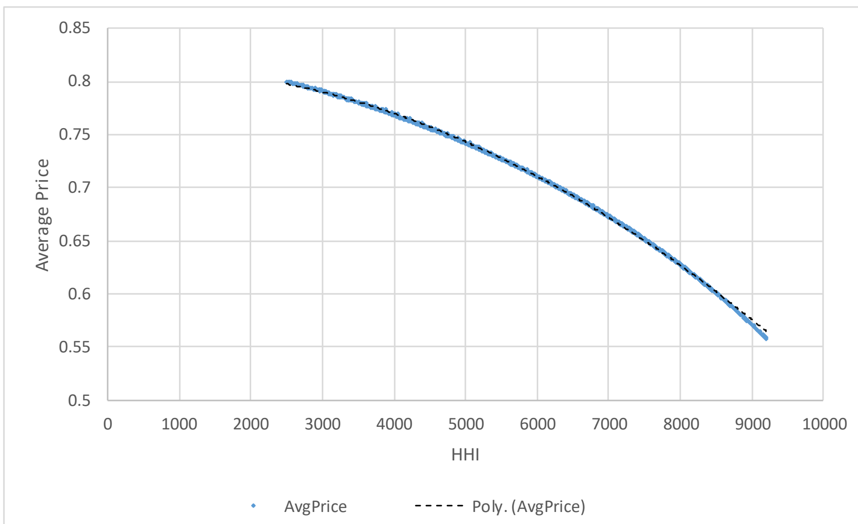
In the above graphic, the WTP ratios are varied in such a way as to keep the average WTP constant at 1. The patient populations of both MCOs are held constant and equal. The expected value to the provider decreases as the WTP ratio heads to one. The provider should accept patients from both MCOs unless the WTP ratio is higher than 1.82.

Herfandahl-Herman Index and Average Price

The Herfandahl-Herman Index (HHI) is a standard measure of industry concentration that is often used in industrial organization literature and used by government agencies tasked with enforcing antitrust law. The assumption is that more concentrated markets (higher HHI) on the producer side (in this case the providers) will result in higher prices and more concentrated markets on the purchaser side (in the case, the MCOs) will result in lower prices. By using my model, I can calculate simulate different arrangements of market structure and calculate the corresponding average negotiated price (as a share of willingness-to-pay). I do this for a set off 2,500 various market shares with four MCOs, holding λ_0 constant. As shown in the graph below, there is a striking relationship between HHI and average price resulting from above model. The fitted quadratic equation is given by:

$$price \ = \ 0.8134 + \ 0.015 \, HHI - 0.3101 \, HHI^2$$

where HHI has been divided by 10,000 in the equation above for readability. In the figure below the fitted line is in black and the generated HHI, average price pairs are plotted in blue.



6 Conclusion

In this paper, I propose a structural bargaining model that is most readily applicable to MCO-healthcare provider bargaining. The main innovation of this model is to model the disagreement point explicitly for a provider not reaching an agreement with an MCO. In the model, the disagreement point is a function of the negotiated prices between other MCOs and the provider, as well as overall demand-side factors which play into willingness-to-pay and average excess capacity. In this way, the prices for each MCO are explicitly interdependent within providers. I am able to model this disagreement point by exploiting the fact that two large factors in provider-MCO bargaining are providers have a limited ability to service patients, and patient demand is time sensitive and variable.

Using this model, I demonstrate the conditions under which a provider will want to contract with a MCO and I analytically solves for how relative provider size and provider concentration impact the negotiated prices, and how price-interdependence leads to cross-price effects within a provider between MCOs. The magnitude and direction of the model's predicted effects are validated by comparing predictions of model to previously observed statistics or estimated relationships, such as the average price difference between regions, the positive impact of an increase in Medicare prices on private MCO prices (including when that impact will be strongest). My model matches some previous findings, while providing a potential explanation for underlying causal mechanisms.

While this model is limited by the fact that I do not explicitly model concentration on the provider side, and do not take into consideration the impact of MCO concentration prices on premiums, it adds to our understanding of MCO bargaining, as the mechanisms of limited capacity and time-sensitive demand have not previously been incorporated into a structural MCO-provider bargaining framework. While this work is most easily applied to MCO-provider negotiation, this model could potentially be adapted to apply more closely to other industries as many markets face time sensitive demand and non-storable supply.

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Appendix A: Capacity

In this appendix, I derive the average excess capacity (λ_0). Excess capacity is a profit maximizing strategy for firms when there are fixed cost associate with building that capacity and uncertainty about how many consumers will arrive in a given period of time.

First, let the firm (physician) have a belief about the expected value of a given unit of capacity (EV_c) which is expected net price (expected price minus expected variable cost). Second, denote capacity by S (size) and let the cost for every unit of capacity be fixed at c_S. Finally, let the number of customers (patients) in a given time-period be approximated by a Poisson distribution with mean and variance x.

The firm then chooses capacity S to maximize the following profit function:

$$\Pi = -c_S S + EV_p \sum_{i=0}^{S} i \frac{e^x x^i}{i!} + EV_p \left(\sum_{i=S+1}^{\infty} S \frac{e^x x^i}{i!} \right)$$

And the change in expected profit from an extra unit of capacity is:

$$\frac{\Delta\Pi}{\Delta C} = -c_S + EV_p \left[S \left(\frac{e^x x^S}{S!} - \frac{e^x x^{S+1}}{(S+1)!} \right) + \sum_{i=S+2}^{\infty} \frac{e^x x^i}{i!} \right]$$

Therefore, the rule to maximize profit is to add a unit of capacity if (subject to positive overall profit):

$$c_S < EV_p \left[S \left(\frac{e^x x^S}{S!} - \frac{e^x x^{S+1}}{(S+1)!} \right) + \sum_{i=S+2}^{\infty} \frac{e^x x^i}{i!} \right]$$

This provides the optimal level of capacity as a non-linear function of the unconditional average number of patients in a time-period (x) and the ratio between the cost of an extra unit of capacity and the expected value of a patient and also allows the average excess capacity (λ_0) to be calculated.

$$S^* = S\left(x, \frac{c_s}{EV_p}\right)$$

$$\lambda_0\left(x, \frac{c_s}{EV_p}\right) = \frac{1}{S^*}\sum_{i=0}^{S^*}(S^* - i)\frac{e^x x^i}{i!}$$

Optimal capacity is increasing in the unconditional mean (x) and decreasing in the cost/expected value ratio (holding constant EV higher cost of capacity will lead to less capacity). Lambda_0 is decreasing both in the unconditional mean and capacity, and increasing in the capacity cost to expected value ratio. To give an example, with a fixed cost-to-expected value ratio of 10%, a provider facing a patient Poisson distribution with a mean of 20 will have a capacity of 30 and an average excess capacity of 33.4% percent, while a provider facing a patient demand distribution with a mean of 455 will have a capacity of 500 and an average excess capacity of only 9.4% percent.

An important note on the definitions of a time-periods and capacity. For a restaurant, capacity can be thought of tables, for hospitals beds and for physicians, appointment slots. The time-period is the relevant period for which a consumer’s demand remains active. For a patient, the time-period should be thought of as a period in which once a patient realizes their health state, they can be flexible. Therefore, it will differ by type of service, and type of patient. The relevant time-period for a cardiac intensive care unit may have a time-period of 30 minutes, while the correct time-period for primary care office may be several weeks.

Appendix B: Provider Problem Including Variable Costs

If variable costs are included then the expected value of a time slot is:

$$EV_{K_J} = \frac{\sum_{k \in K_j} \lambda_\kappa (p_k - c_j)}{\lambda_0 + \sum_{k \in K_j} \lambda_\kappa} = \frac{\sum_{k \in K_j} \lambda_\kappa p_k}{\lambda_0 + \sum_{k \in K_j} \lambda_\kappa} - c_j \frac{\sum_{k \in K_j} \lambda_\kappa}{\lambda_0 + \sum_{k \in K_j} \lambda_\kappa}$$

And the change in expected value of time slot from including patients of type δ is:

$$\left(\frac{\lambda_\delta (p_k - c_j) + \sum_{k \in K_j} \lambda_\kappa (p_k - c_j)}{\lambda_\delta + \lambda_0 + \sum_{k \in K_j} \lambda_\kappa}\right) - \left(\frac{\sum_{k \in K_j} \lambda_\kappa (p_k - c_j)}{\lambda_0 + \sum_{k \in K_j} \lambda_\kappa}\right)$$

This equation is very similar to equation used in the paper. Furthermore, the inclusion rule is very similar, it only now includes costs explicitly. This changes the amount of total surplus that the MCO and provider negotiate over, and therefore can change the predictions about the price. The underlying fact that provider's threat point is the expected value without the MCO, however, remains mostly unchanged.

Appendix C: Time & Leisure in the Physician's Problem

In what follows, I allow the hours worked for the physician to depend on the expected return to working.

$$u_j(c,q) = \log\left(\sum_{k=1}^{K} p_k q_k\right) - \alpha_j \log\left(X - \sum_{k=1}^{K} q_k\right)$$

$$q = \sum_{k=1}^{K} q_k$$

$$\max_{K_j,q} E\left[u_j\left(q, K_j\right)\right] = \max_{K_j,q}\left(-\alpha_j \log(X-q) + \sum_{k\in K_j} q_k * p_k * Prob_k\right)$$

Note that price should be thought of not as the list of transacted price for that patient, but full net expected payment taking into considerations the cost of working with that type of patient or insurance company.

For simplicity let $q_k = 1, \forall k$

FOC q:

$$\frac{\partial EU}{\partial q} = \frac{\alpha_j}{X-q} + \sum_{k\in K_j} p_k * Prob_k = 0$$

$$q^* = X - \frac{\alpha_j}{\sum_{k\in K_j} p_k * Prob_k}$$

Then using this to calculate the expected utility of accepting the set of patients K_j:

$$E\left[u_j\left(q * |K_j\right)\right] = \alpha_j \log\left(X - (X - \frac{\alpha_j}{\sum_{k\in K_j} p_k * Prob_k})\right) + (X - \frac{\alpha_j}{\sum_{k\in K_j} p_k * Prob_k}) \sum_{k\in K_j} p_k * Prob_k$$

$$= \alpha_j \log\left(\frac{\alpha_j}{\sum_{k\in K_j} p_k * Prob_k}\right) + X\sum_{k\in K_j} p_k * Prob_k - \alpha_j$$

$$= X\sum_{k\in K_j} p_k * Prob_k - \alpha_j\left[1 - \log(\alpha_j) + \log\left(\sum_{k\in K_j} p_k * Prob_k\right)\right]$$

Partial Derivatives for Physician Problem

For the following derivatives prices are held constant.

Hours Worked, wrt p_l:

$$q^* = X - \alpha_j \frac{\lambda_0 + \sum_{k\in K_j}\lambda_\kappa}{\sum_{k\in K_j}\lambda_\kappa p_k} = X - \alpha_j \frac{\lambda_0 + \sum_{k\in K_j}\lambda_\kappa}{\lambda_l p_l + \sum_{k\in K_{j/l}}\lambda_\kappa p_k}$$

$$\frac{\partial q^*}{\partial p_l} = -\alpha_j \frac{\lambda_0 + \sum_{k\in K_j}\lambda_\kappa}{\left(\sum_{k\in K_j}\lambda_\kappa p_k\right)^2} = -\frac{\alpha_j}{\sum_{k\in K_j}\lambda_\kappa p_k}\left(\frac{1}{EV(K_j)}\right) < 0$$

Hours Worked, wrt λ_l:

Note that an increase in λ_l can be interpreted as an increase in demand by patients of type l.

$$q^* = X - \alpha_j \frac{\lambda_0 + \sum_{k\in K_j}\lambda_\kappa}{\sum_{k\in K_j}\lambda_\kappa p_k} = X - \alpha_j \frac{\lambda_l}{\lambda_l p_l + \sum_{k\in K_{j/l}}\lambda_\kappa p_k} - \alpha_j \frac{\lambda_0 + \sum_{k\in K_{j/l}}\lambda_\kappa}{\lambda_l p_l + \sum_{k\in K_{j/l}}\lambda_\kappa p_k}$$

$$\frac{\partial q^*}{\partial \lambda_l} = -\alpha_j\left[\frac{\sum_{k\in K_{j/l}}\lambda_\kappa p_k}{\left(\sum_{k\in K_j}\lambda_\kappa p_k\right)^2} - \frac{p_l\left(\sum_{k\in K_{j/l}}\lambda_\kappa\right)}{\left(\sum_{k\in K_j}\lambda_\kappa p_k\right)^2}\right]$$

$$= -\alpha_j\left[\frac{\sum_{k\in K_j}\lambda_\kappa (p_k - p_l)}{\left(\sum_{k\in K_j}\lambda_\kappa p_k\right)^2}\right]$$

$$= -\alpha_j\left[\frac{\sum_{k\in K_j}\lambda_\kappa p_k}{\left(\sum_{k\in K_j}\lambda_\kappa p_k\right)^2} - \frac{\sum_{k\in K_j}\lambda_\kappa p_l}{\left(\sum_{k\in K_j}\lambda_\kappa p_k\right)^2}\right]$$

$$= -\frac{\alpha_j}{\sum_{k\in K_j}\lambda_\kappa p_k}\left[1 - p_l\frac{\sum_{k\in K_j}\lambda_\kappa}{\sum_{k\in K_j}\lambda_\kappa p_k}\right]$$

$$= -\frac{\alpha_j}{\sum_{k\in K_j}\lambda_\kappa p_k}\left[1 - p_l * 1/EV\left(K_j\right)\right]$$

$$= \frac{\alpha_j}{\sum_{k\in K_j}\lambda_\kappa p_k}\left[\frac{p_l}{EV_{K_j}} - 1\right]$$

So, if p_l is higher than the expected value of the set then hours worked increases. Else, it decreases.

Since all included p_l's must be higher than the expected value (assuming ability to discriminate on types), then for all l, work increase with the number of patients.

$$\frac{\partial q^*}{\partial \lambda_l} > 0$$

If we're talking about λ_0, than p is 0 so because a_j is greater than 0 the derivative is negative (less work). So in this simple model, doctors work more in respect to positive demand shocks, and less in response to negative demand shocks (as expected). The substitution effect dominates the income effect.

Patients Seen (wrt $\boldsymbol{\lambda_l}$):

Patients seen =

$$q^*(1 - prob_0) = q^*\left(1 - \frac{\lambda_0}{\lambda_0 + \sum_{\kappa\in j}\lambda_\kappa}\right) = q^*\left(\frac{\sum_{\kappa\in j}\lambda_\kappa}{\lambda_0 + \sum_{\kappa\in j}\lambda_\kappa}\right)$$

q* rises (number of slots), and patients per slot (fill rate) rises drops as well, so patients seen rises.

Expected Value (wrt λ_l):

$$\frac{\partial EV_{K_J}}{\partial \lambda_l} = \frac{p_l\left[\lambda_0 + \sum_{k\in K_j/l}\lambda_\kappa\right]}{\left[\lambda_0 + \sum_{k\in K_j}\lambda_\kappa\right]^2} - \frac{\left[\lambda_0 + \sum_{k\in K_j/l}\lambda_\kappa p_k\right]}{\left[\lambda_0 + \sum_{k\in K_j}\lambda_\kappa\right]^2}$$

$$= \frac{\lambda_0 p_l + \sum_{k\in K_j/l}\lambda_\kappa p_l - \lambda_0 - \sum_{k\in K_j/l}\lambda_\kappa p_k}{\left[\lambda_0 + \sum_{k\in K_j}\lambda_\kappa\right]^2}$$

$$= \frac{\sum_{k\in K_j}\lambda_\kappa\,(p_l - p_k)}{\left[\lambda_0 + \sum_{k\in K_j}\lambda_\kappa\right]^2} + \frac{\lambda_0(p_l - 1)}{\left[\lambda_0 + \sum_{k\in K_j}\lambda_\kappa\right]^2}$$

$$= \frac{1}{\sum_{k\in K_j}\lambda_\kappa}\left[\frac{\left(\lambda_0 + \sum_{k\in K_j}\lambda_\kappa\right)p_l}{\lambda_0 + \sum_{k\in K_j}\lambda_\kappa} - \frac{\left(\lambda_0 + \sum_{k\in K_j}\lambda_\kappa\right)p_k}{\lambda_0 + \sum_{k\in K_j}\lambda_\kappa}\right]$$

$$= \frac{1}{\sum_{k\in K_j}\lambda_\kappa}\left[p_l\frac{\lambda_0 + \sum_{k\in K_j}\lambda_\kappa}{\lambda_0 + \sum_{k\in K_j}\lambda_\kappa} - \frac{\sum_{k\in K_j}\lambda_\kappa\,p_k}{\lambda_0 + \sum_{k\in K_j}\lambda_\kappa}\right]$$

$$= \frac{p_l - EV_{K_J}}{\sum_{k\in K_j}\lambda_\kappa} > 0$$

Not surprisingly, an increase in demand increases the expected value of a time slot. The magnitude of the increase depends on the difference between the price of that type and the expected value.

Note: this does not take into account large changes in demand that potentially could impact which patient types are included. This happens if the increase pushes the expected value higher than the price for the lower patient types.

Expected value wrt p_l:

$$\frac{\partial EV_{K_J}}{\partial p_l} = \frac{\lambda_\kappa}{\lambda_0 + \sum_{k\in K_j}\lambda_\kappa} = Prob_{k,j} > 0$$

Note: this does not take into account large changes in price that potentially could impact which patient types are included. This happens if the increase pushes the expected value higher than the price for the lower patient types.

Appendix D: Two private insurers

In this appendix, I work out the solutions for two private insurers (indexed with 1 and 2). The conditions from a bargaining equilibrium are generally:

$$p_{1j} = (1-\alpha)\Delta\mathrm{WTP}_{1\mathrm{j}} + \alpha\left[\sum_{k\in K_j/1} \lambda_\kappa p_k\right] / \left[\lambda_0 + \sum_{k\in K_j/1} \lambda_\kappa\right]$$

In the two-MCO case, this yields the following system of two equations in two unknowns:

$$p_{1j} = (1-\alpha)\Delta\mathrm{WTP}_{1\mathrm{j}} + \alpha\lambda_2/(\lambda_0+\lambda_2)p_{2j}$$

$$p_{2j} = (1-\alpha)\Delta\mathrm{WTP}_{2\mathrm{j}} + \alpha\lambda_1/(\lambda_0+\lambda_1)p_{1j}$$

Which can be rewritten in the following matrix form:

$$A\begin{bmatrix} p_0 \\ p_1 \\ p_2 \end{bmatrix} = \begin{bmatrix} 0 \\ (1-\alpha)\, WTP_1 \\ (1-\alpha)\, WTP_2 \end{bmatrix}$$

Where:

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & -\alpha\left(\dfrac{\lambda_2}{\lambda_0+\lambda_2}\right) \\ 0 & -\alpha\left(\dfrac{\lambda_1}{\lambda_0+\lambda_1}\right) & 1 \end{bmatrix}$$

In this formulation, it is assumed that the provider contracts with all insurers.

A^{-1}

$$= \frac{1}{1-\alpha\left(\frac{\lambda_1}{\lambda_0+\lambda_1}\right)\alpha\left(\frac{\lambda_2}{\lambda_0+\lambda_2}\right)}\begin{bmatrix} 1-\alpha\left(\frac{\lambda_1}{\lambda_0+\lambda_1}\right)\alpha\left(\frac{\lambda_2}{\lambda_0+\lambda_2}\right) & 0 & 0 \\ 0 & 1 & \alpha\left(\frac{\lambda_2}{\lambda_0+\lambda_2}\right) \\ 0 & \alpha\left(\frac{\lambda_1}{\lambda_0+\lambda_1}\right) & 1 \end{bmatrix}$$

This leads to the following equilibrium prices:

$$p_0 = 0$$

$$p_1^* = \frac{1}{1-\alpha\left(\frac{\lambda_1}{\lambda_0+\lambda_1}\right)\alpha\left(\frac{\lambda_2}{\lambda_0+\lambda_2}\right)}\left[(1-\alpha)\,WTP_1 + \alpha\left(\frac{\lambda_2}{\lambda_0+\lambda_2}\right)(1-\alpha)\,WTP_2\right]$$

$$p_2^* = \frac{1}{1-\alpha\left(\frac{\lambda_2}{\lambda_0+\lambda_2}\right)\alpha\left(\frac{\lambda_1}{\lambda_0+\lambda_1}\right)}\left[(1-\alpha)\,WTP_2 + \alpha\left(\frac{\lambda_1}{\lambda_0+\lambda_1}\right)(1-\alpha)\,WTP_1\right]$$

$$p_1^* = (1-\alpha)\left[1-\alpha^2\frac{\lambda_1\lambda_2}{(\lambda_0+\lambda_1)\,(\lambda_0+\lambda_2)}\right]^{-1}\left[WTP_1 + \alpha\left(\frac{\lambda_2}{\lambda_0+\lambda_2}\right)WTP_2\right]$$

$$p_2^* = (1-\alpha)\left[1-\alpha^2\frac{\lambda_1\lambda_2}{(\lambda_0+\lambda_2)\,(\lambda_0+\lambda_1)}\right]^{-1}\left[WTP_2 + \alpha\left(\frac{\lambda_1}{\lambda_0+\lambda_1}\right)WTP_1\right]$$

The relationship between prices and size

The equilibrium price ratio is:

$$\left[WTP_1 + \alpha\left(\frac{\lambda_2}{\lambda_0+\lambda_2}\right)WTP_2\right] / \left[WTP_2 + \alpha\left(\frac{\lambda_1}{\lambda_0+\lambda_1}\right)WTP_1\right]$$

If two insurers have the same WTP then the ratio of prices is:

$$p_1^*/p_2^* = \left[1+\alpha\left(\frac{\lambda_2}{\lambda_0+\lambda_2}\right)\right] / \left[1+\alpha\left(\frac{\lambda_1}{\lambda_0+\lambda_1}\right)\right]$$

$$p_1^*/p_2^* = \left(\frac{\lambda_0+\lambda_2+\alpha\lambda_2}{\lambda_0+\lambda_2}\right) / \left(\frac{\lambda_0+\lambda_1+\alpha\lambda_1}{\lambda_0+\lambda_1}\right)$$

$$\frac{\partial}{\partial\lambda_j}\frac{\lambda_{\mathrm{j}}}{\lambda_0+\lambda_{\mathrm{j}}}=\frac{\lambda_0}{\left(\lambda_0+\lambda_{\mathrm{j}}\right)^2}>0$$

Which means that if insurer 1 is larger, the denominator will be larger than the numerator and the ratio will be less than 1, meaning insurer 1 will pay less. The mechanism is that the expected value to the provider without insurer 1 is smaller than the expected value without insurer 2.

Appendix E: Two MCOs and Medicare

In a manner similar to Appendix D, I work out the solutions for two private insurers (indexed with 1 and 2) and an exogenously set public payor (indexed with m). The conditions from a bargaining equilibrium are generally:

$$p_{ij}=(1-\alpha)\Delta\mathrm{WTP}_{\mathrm{ij}}+\alpha\left[\sum_{k\in K_j/\mathrm{i}}\lambda_\kappa p_k\right]/\left[\lambda_0+\sum_{k\in K_j/\mathrm{i}}\lambda_\kappa\right]$$

$$p_{1j}=(1-\alpha)\Delta WTP_{1j}+\alpha\frac{\lambda_2}{\lambda_0+\lambda_2+\lambda_m}p_{2j}+\alpha\frac{\lambda_m}{\lambda_0+\lambda_2+\lambda_m}p_m$$

$$p_{2j}=(1-\alpha)\Delta\mathrm{WTP}_{2\mathrm{j}}+\alpha\frac{\lambda_1}{\lambda_0+\lambda_1+\lambda_m}p_{1j}+\alpha\frac{\lambda_m}{\lambda_0+\lambda_1+\lambda_m}p_m$$

$$p_m=\overline{p_m}$$

Consider the situation with two private insurers (indexed with 1 and 2). This leads to the following matrix formation of the simultaneous equations:

$$A \begin{bmatrix} p_1 \\ p_2 \\ p_m \end{bmatrix} = \begin{bmatrix} (1-\alpha)\,WTP_1 \\ (1-\alpha)\,WTP_2 \\ \overline{p_m} \end{bmatrix}$$

Where:

$$A = \begin{bmatrix} 1 & -\alpha \dfrac{\lambda_2}{\lambda_0 + \lambda_2 + \lambda_m} & -\alpha \dfrac{\lambda_m}{\lambda_0 + \lambda_2 + \lambda_m} \\ -\alpha \dfrac{\lambda_1}{\lambda_0 + \lambda_1 + \lambda_m} & 1 & -\alpha \dfrac{\lambda_m}{\lambda_0 + \lambda_1 + \lambda_m} \\ 0 & 0 & 1 \end{bmatrix}$$

In this formulation, it is assumed that the provider contracts with all insurers.

$$A^{-1} = \frac{1}{\det(A)} \begin{bmatrix} 1 & -1 & 0 \\ \alpha \frac{\lambda_2}{\lambda_0 + \lambda_2 + \lambda_m} & 1 & 0 \\ \alpha \frac{\lambda_m}{\lambda_0 + \lambda_2 + \lambda_m} + \alpha^2 \frac{\lambda_2}{\lambda_0 + \lambda_2 + \lambda_m} \frac{\lambda_m}{\lambda_0 + \lambda_1 + \lambda_m} & \alpha \frac{\lambda_m}{\lambda_0 + \lambda_1 + \lambda_m} + \alpha^2 \frac{\lambda_1}{\lambda_0 + \lambda_1 + \lambda_m} \frac{\lambda_m}{\lambda_0 + \lambda_2 + \lambda_m} & 1 - \alpha^2 \frac{\lambda_1}{\lambda_0 + \lambda_1 + \lambda_m} \frac{\lambda_2}{\lambda_0 + \lambda_2 + \lambda_m} \end{bmatrix}$$

$$\det(A) = 1 + \alpha \frac{\lambda_2}{\lambda_0 + \lambda_2 + \lambda_m}$$

This leads to the following equilibrium prices:

$$p_1^* = \left(1 - \alpha^2 \frac{\lambda_1}{\Lambda - \lambda_2} \frac{\lambda_2}{\Lambda - \lambda_1}\right)^{-1} \left[(1-\alpha)WTP_1 + \alpha \frac{\lambda_m}{\Lambda - \lambda_1} p_m + \alpha \frac{\lambda_2}{\Lambda - \lambda_1} \left((1-\alpha)WTP_2 + \alpha \frac{\lambda_m}{\Lambda - \lambda_2} p_m\right)\right]$$

$$p_2^* = \left(1 - \alpha^2 \frac{\lambda_2}{\Lambda - \lambda_1} \frac{\lambda_1}{\Lambda - \lambda_2}\right)^{-1} \left[(1-\alpha)WTP_1 + \alpha \frac{\lambda_m}{\Lambda - \lambda_2} p_m + \alpha \frac{\lambda_1}{\Lambda - \lambda_2} \left((1-\alpha)WTP_1 + \alpha \frac{\lambda_m}{\Lambda - \lambda_1} p_m\right)\right]$$

For Quality or Quantity?

The Impact of ACO Formation on Physician Referrals

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Abstract

This paper examines how primary care providers (PCPs) change their referral patterns to specialists after they join a Medicare Shared Savings Program Accountable Care Organization (ACO). We find that primary-care providers respond differently to ACO formation depending on the degree to which the providers have a pre-existing relationship with specialists in the ACO. Relatively speaking, the smaller the previous PCP-specialist relationship, the bigger the response. We also find that primary-care providers without a pre-existing relationship with ACO specialists make up a large share of the ACOs PCPs and referrals. PCPs that sent a large share of referrals to specialists that join an ACO in the years prior to ACO formation decrease the number of patient they refer to those specialists.

[19] Contact: DL679@cornell.edu. I am grateful to my graduate committee (Sean Nicholson, Samuel Kleiner and George Hay) for their direction and support. All errors are my own. This research was supported by the grant from Cornell University's Institute for the Social Sciences

1 Introduction

Substantial efforts have been underway in recent years to adopt payment models that tie provider reimbursement to the quality or value of care provided (Burwell, 2015). Notably, Congress created the Medicare Shared Savings Program (MSSP) as part of the Affordable Care Act (ACA). The program, administered by the Center for Medicare and Medicaid Services (CMS), allows collections of physicians, hospitals and other health providers to voluntarily create accountable care organizations (ACOs). The organizations collectively take responsibility for a large patient population, and can receive payments that are tied to the quality and cost of the care that they deliver.

The hope for ACOs in the Medicare Shared Savings Program is that by promoting integration and providing quality-based incentives, ACOs will improve cooperating and reducing waste, therefore increasing the efficiency with which healthcare is delivered. While recent research has indicated that the program has achieved cost savings and improved quality (CMS, 2015b), a potential concern with the ACO program is that collaborative agreements across ACO providers could enable the exercise of market power among participants, which could lead to an increase in the price of medical care, or other anti-competitive behaviors.

Given the competing forces inherent with the creation of these organizations, ACO formation poses a unique challenge for antitrust enforcement. The Department of Justice (DOJ) and the Federal Trade Commission (FTC) have recognized these challenges. While they have provided some limited waivers for ACOs, and have outlined requirements for ACOs to avoid antitrust scrutiny, they have noted that providers that join a Medicare ACO have the potential to engage in anticompetitive practices (FTC and DOJ, 2011). While preliminary analysis has shown that few providers meet the criteria for increased scrutiny on their own, little research has analyzed provider behavior following the decision to participate in an ACO (Kleiner et al., 2016).

Because Medicare prices are not negotiated, but rather are set administratively, there is no explicit price-based opportunity for Medicare ACOs to engage in anticompetitive conduct. However, Jay Levine, Co-Chair of Antitrust Practice Group, Porter Wright Morris & Arthur, bluntly stated an “ACO is nothing more than a collaboration of competing providers” (Cheung-Larivee 2012) and ACOs can still run afoul of antitrust laws by self-referring, steering, gainsharing or creating tying contracts. Dominant ACOs could tie sales of their services to a private payer’s purchase of other services from providers that do not participate in the ACO. This “tying contract” would require a purchaser to contract with all physician groups under common ownership, even if only one, of many physician specialty groups under the same ownership, participates in the ACO. Large ACOs could also require exclusivity, to discourage providers from contracting with payers outside the ACO, and could restrict the dissemination of information on the cost and performance of the ACO (Feinstein, 2014). For example, a dominant ACO with large market share could control referrals and potentially prevent non-Medicare payers from steering patients to specific providers. Such an entity could also tie sales of their services to a private payer’s purchase of other services from providers that do not participate in the ACO. Finally, and most relevant to this paper, an ACO with a large market share could control referrals and potentially prevent payers from steering patients to specific providers. This could allow participating practices to grow their market share by guaranteeing referrals while maintaining independence, a concern that regulators have specifically expressed.

By combining physician referral data with information on physician ACO affiliation, we analyze the degree to which ACO affiliation impacts physician referral patterns in terms of the referrals to providers overall, in the ACO network and out of the ACO network. This project builds on previous work examining the impact of hospital ownership on physician referrals, physician responses to incentives and firm behavior under cooperation agreements short of mergers. The extent to which ACO participation affects physician referral patterns is of significant economic and policy interest given the unique arrangement under which ACOs operate and the increasing share of providers that participate in ACO programs.

This paper proceeds as follows: In section two, we provide the relevant background on ACOs and the previous literature about provider behavior. In section three, we introduce our data sources and describe relevant statistics. In section four, we explain our empirical strategy. Section five contains our results which are summarized in section six. In section seven, we conclude.

2 Background

The goal of the Medicare Shared Savings Program is to reduce unnecessary spending and waste while improving patient outcomes. ACOs represent an attempt to change provider incentives with the goal of ensuring that healthcare provided to Medicare beneficiaries is both high-quality and cost-effective. Their creation is part of a larger shift in the medical payment methodology away from fee-for-service, and towards a method of payment that rewards high-value care.

Groups of providers that choose form an ACO to jointly take responsibility for a set of Medicare beneficiaries. Beneficiaries are retroactively attributed to the ACO if a primary care doctor, defined as a physician with the specialty General Practice, Family Practice, Internal Medicine or Geriatric Medicine, within the ACO provides the beneficiary a plurality of their primary care, as measured by Medicare allowed amounts. Only traditional, fee-for-service Medicare beneficiaries can be attributed to an ACO.

If an ACO is able to provide care to these patients at a lower cost than expected CMS may pay the ACO a portion of the cost savings. The expected cost is calculated using past cost for the ACO and risk-adjustments for the patients. Recently, CMS adjusted this methodology to also factor in regional averages to the expected cost calculation. An ACO can also be liable for a portion of cost overruns if they elect to participate in the two-sided, savings and losses, option. In practice, 99% of MSSP ACOs are in the one-sided option. The appeal of the two-sided, shared savings and losses model is that if there are savings, the portion that goes to the ACO is higher: 60% rather than the 50% in the savings-only version.

However, even if an ACO generates savings it may not be eligible for the shared savings payouts. First, the ACO must meet a standard of care as measured by 30 quality metrics. Then, the ACOs generated savings must meet or exceed the minimum savings rate (MSR), which is between 2% and 4% depending on the size of the MCO. In 2015, of 392 Medicare ACOs 202 produced savings but only 119 generated enough savings to receive bonus payments from CMS; 189 generated losses.

The shared savings program was set up with the hope that the potential for financial rewards would align physician incentives with the goals of efficiency and effectiveness. While there is a substantial literature that has examined the extent to which physician behavior responds to financial incentives, the predicted physician response is unclear for ACO arrangements. Ho and Pakes (2014) show that physicians with capitated compensation arrangements are more likely to refer patients to lower-priced hospitals,[20] while Baker et al. (2014) demonstrate that physician practices acquired by hospitals are more likely to refer patients to the hospital that owns their practice. Physician responses to such incentives have also been documented for practices whose income is tied to prescription drug profitability (Iizuka, 2012), and physicians who own imaging equipment (Baker, 2010). However, Rebitzer and Votruba (2011) note that because ACOs do not require participants to limit themselves to a single ACO, ACO formation may be less likely to elicit a large behavioral response. Rebitzer and Votruba (2011) furthermore suggest that ACOs are likely to be most effective in settings where care is already integrated, suggesting that ACOs may do little to change care referral patterns across providers.

Shared savings payouts are only one part of the complex set of incentives and tradeoffs facing physicians as they join, or consider joining an ACO. Primary-care doctors both have a strong role in controlling cost, and appear to get most of the shared savings payouts (Evans 2015), therefore, the shared saving incentive seems most relevant to them. However, Frandsen and Rebitzer (2013a) argue that that the performance incentives in ACOs are "under-powered" and thus too weak to elicit meaningful changes in provider behavior. To achieve the savings, providers must lower the amount of care and the corresponding reimbursements. ACO participation has increased substantially in recent years, with some specialties reporting that as many as 30% of providers have joined these organizations (Medscape, 2015). It is doubtful that the potential for shared savings alone would be sufficient to induce such large a share of providers to form ACOs.

There are many other factors that providers must when deciding whether to participate in an ACO. For example, in a list of reasons physicians should join ACOs, put together by a healthcare thought

[20] A capitated arrangement is one in which a medical provider is given a set fee per patient, regardless of the treatment required.

leader, the focus was on the potential economic benefits, such as extending the referral network and increasing access to both specialists and beneficiaries (Govette 2015). While patient health and cost reductions were mentioned, the author did not view those as the primary justifications for joining an ACO.

Furthermore, ACO startup costs can be very high. Estimates of the startup costs for an ACO range from $2 million to $26 million ($2 million CMS commissioned Physician Group Practice Demonstration project[21], $4 million National Association of ACOs[22], $11.6 to $26.1 million American Hospital Association[23]). A large portion of these costs are infrastructure investments that are necessary to fully meet the ACO reporting requirements and helpful to successfully achieve the efficiency goals, such as electronic health record systems (EHR), referral management software, or additional non-physician care management staff. These investments can be used to increase practice efficiency and improve the patient experience for a provider's entire patient population, thereby increasing patient satisfaction and retention for lucrative private patients as well. Not being able to implement these technologies could put a practice at a competitive disadvantage (Westgate 2013). Joining an ACO can provide access to capital, either from larger providers in the ACO, especially hospitals (Colla 2016), or from a CMS incentive program[24].

It could be that ACOs are behaving like firms. One role of firms is to manage the allocation of capital and labor within the firm to make use of comparative advantages and therefore increase overall efficiency. Physician group practices perform a similar role in efficiently matching patients

[21] http://www.fiercehealthcare.com/healthcare/will-acos-show-financial-returns

[22] http://www.beckershospitalreview.com/accountable-care-organizations/acos-need-4m-of-startup-capital-survey-finds.html

[23] http://www.aha.org/presscenter/pressrel/2011/110513-pr-aco.shtml

[24] https://www.cms.gov/Newsroom/MediaReleaseDatabase/Press-releases/2014-Press-releases-items/2014-10-15-3.html

with specialists (Epstein, Ketcham and Nicholson 2010), and some researchers have found an association between large, multispecialty practices and higher quality care at a lower cost (Weeks et al 2010, Tollen 2008). A hope of policy makers is that ACOs can provide efficiency benefits that are similar to large, multi-specialty firms without the corresponding anti-competitive concerns. While the savings have been small, preliminary results on the ACO program have been mostly positive, indicating that ACOs may be successfully controlling costs (Nyweide 2015).

The access to capital and electronic medical record systems that could come with joining an ACO are appealing incentives for smaller practices, especially primary care providers. The hope of increased efficiency through better management of records, patients and referrals could be a large factor in the decision, particularly if it is financed by a larger provider or hospital in the ACO.

There does not seem to be prima facie reasons for a hospital to incur this cost, while simultaneously pursuing a reduction of the quantity of care and the corresponding reimbursements. A potential counterbalancing incentive could be the ability to secure quantity through the tightening of referral networks. Rick Weil, a partner at Oliver Wyman and a member of the global consulting firm's Health and Life Sciences Practices notes that there is “a huge incentive to keep the referrals within the ACO” and urges practices to consider participating in an ACO soon to avoid a decline in referral volume (Westgate 2013). While PCPs may also want to increase their referral network and options, this desire to secure referrals is especially true for specialists (Dupree 2014).

In this paper, we investigate the impact of ACO formation on the referral relationship between PCPs and specialists. We are seeking to add to our understanding about the potential incentives for ACO formation and the behavior of physicians once they have formed an ACO.

3 Data

Our data on physician referrals is provided by the Center for Medicare and Medicaid Services (CMS). Medicare refers to this as “patient referral” data and following them and other literature, we do as well; however, it is more precisely “shared patient” data as this dataset captures any patient sharing relationship between providers of health services within a given time frame (either 30, 60, 90 or 180 days) whether or not there existed a formal referral. This dataset is publicly available and is constructed using the National Claims History (NCH) database which includes most Medicare claim types: Inpatient, Outpatient, Home Health Agency (HHA), Skilled Nursing Facilities (SNF), Carrier claims and Durable Medical Equipment Regional Carrier (DMERC) claims. It has information on referrals from 2009 through part of 2015, which allows us to observe changing referral patterns over time.

At the year level, we observe the referring physician (that is, the physician the patient saw first), the receiving physician, the number of shared connections (patient-visits) and the count of unique shared patients. Due to privacy constraints, this data set omits physician pairs that share fewer than 10 patients.

We use the Accountable Care Organization Provider Level File from CMS to identify providers in ACOs. The dataset includes a list of every Shared Savings Program Accountable Care Organization, the date the ACO began operating, the county primarily served, and all associated participating practices’ taxpayer identification numbers (TINs). This file does not include Pioneer, Next Generation or Comprehensive ESRD Care ACOs and these types of ACOs are not included in our analysis. We confirmed the quality of the ACO data by checking our list against SK&A’s list of the top ACOs[25]. We found that our data showed a similar number of locations and physicians

[25] SK&A Market Insight Report “Top 30 Accountable Care Organizations” http://www.skainfo.com/reports/top-accountable-care-organizations Last accessed 6/15/2017

for these six Medicare ACOs: Health Connect Partners, Advocate Physician Partners, Indiana University Health ACO, Arizona Care Network, Iowa Health Accountable Care and Mercy ACO. Our data include ACOs that started in four different waves: April 2012, July 2012, January 2013 and January 2014. For analysis in which we separate out the ACOs by start year, we treat both the 2012 ACOs cohorts as one group and do not perform any corrections to account for the fact that relatively speaking, some of the 2012 cohorts started up to six months later in the year. Table 19 shows characteristics of the ACOs by start date.

A similar number of ACOs started in each year, with 111, 103 and 119 starting in 2012, 2013 and 2014 respectively. ACOs that joined in 2014 on average consist of fewer firms, defined by a tax identifier (24 vs 34) and fewer overall primary care providers (69 vs 93) and specialists than ACOs formed in 2012 and 2013. The number of primary care providers (PCPs) per firm (conditional on having at least one) was similar across all cohorts (3), and for firms that did not join an ACO.

The official start date is the date after which CMS begins to track and score the ACO for shared savings purposes. However, the membership of the Medicare Accountable Care Organizations is finalized early on during the previous year and the providers could have been planning to form the ACO for even longer. Therefore, for our analysis, we view the year that the ACO membership is finalized as year 0 and the first year of the ACO as year 1. We will refer to the year prior to the announcement as the prior year, so the "prior year" for an ACO that officially started in January 2013 is 2011.

Accountable Care Organizations are defined as a collection of providers that bill under a set of taxpayer identifiers numbers (TINs). In order to be associated with the ACO, Medicare billings must be associated with one of the TINs. While physicians can bill under multiple tax identifiers, in our data (2013) only 7% of the physicians bill using a TIN not associated with their ACO.

Over our analysis timeframe we hold constant the NPIs in an ACO, that is if Doctor A1 is in firm B1 which is part of ACO C1 in 2012, but Doctor A1 was not in firm B1 in 2010 (and ACO C1 did not exist) we still would be interested in how his behavior changes. Likewise, if Doctor A2 was in firm B2 in 2010, but not in B2 in 2012 and B2 joined ACO2 in 2012 we would NOT be interested in how Doctor A2's behavior changed. This allows us to avoid results driven by changes in the composition of practices, and in particular, practices growing larger. While the relationship between practice composition and ACO formation may be an interesting research area, it is out of the scope of this work.

To associate physicians with practices, and thus ACOs, we use CMS's Medicare Data on Physician Practice and Specialty (MDPPAS). This MDPPAS file also includes information on physician and practice billings as well as physician specialty. In addition to associating physicians with Accountable Care Organizations, this data set allows the grouping of providers from the Medicare relational data into practices using their Taxpayer Identification Number (TIN). This will allow us to observe behavior at the practice level.

Although a firm can include PCPs and specialist, we exclude from analysis the PCP-firm pairs where the PCP is part of the firm as we are trying to examine the impact of a new relationship, the formation of the ACO, rather than examine changes to pre-existing relationships. As the PCP and specialists were already in the same firm, we would not expect to see a substantial changes to referral patterns resulting from the formation of an ACO. This data also extends from 2009 to 2014, allowing us to observe relationships and behavior before and after ACO formation.

Because we are interested in how the formation of ACOs impacts physicians actively directing patients, we concentrate on the referrals from primary care providers (PCPs) to a set of specialists as we believe that these types of relationships are most likely to reflect that type of behavior. We categorize physicians with the specialties Family Practice, Internal Medicine and General Practice as PCPs. We analyze referrals to the following seven specialties: cardiology, gastroenterology, general surgery, nephrology, ophthalmology, orthopedic surgery, and pulmonary disease. We chose this set because we believe these specialties are the ones most likely to reflect an active, directed referral from a PCP. We also believe that in most markets there are options for these types of specialists both in and out of the ACOs. We omit physician extenders, emergency medicine and more specialized types such as neurosurgery.

Because CMS assigns patients to ACOs based on their primary care provider, ACOs must contain PCPs. More than 99% of ACOs have a Family Practice doctor, and the same share of ACOs have a physician with the Internal Medicine specialty. A much smaller share (53%) have a General Practitioner. A high percentage (86%) of ACOs included at least one of these seven specialties, and more than a fourth contain them all. This aligns with another study that found 16% of ACOs were composed entirely of primary care physicians (Schulz 2015).

ACOs without any of our seven specialties of interests were not included, as in those ACOs, there are no PCP-specialist relationships to analyze. Table 20 shows characteristics of the Medicare Accountable Care Organizations by start year, for only those ACOs that included at least one specialist.

Table 21 shows the characteristics of our sample of ACOs by specialty. The most numerous specialty is cardiology with 3,631. Cardiology is also the most likely of the seven selected specialties to be found in an ACO with 70% of ACOs including at least one cardiologist. The lowest share of ACOs contain an ophthalmologist (40%). On average, an ACO has four of these seven specialties, with a fifth of them having all seven.

For firms with at least one primary care provider, 31.7% of those firms included providers with other specialties. A similar share of firms with primary care providers that joined ACOs were multispecialty (30.2%). For firms with at least one specialist of interest, 35.3% of those firms included providers with other specialties. A much higher share of specialty firms joining ACOs were multispecialty (52.2%).

4 Empirical Strategy

To analyze how referral patterns are impacted by the formation of accountable care organizations, we use an event study approach. With data from both before and after the formation of accountable care organizations, we can estimate the conditional means for each of our metrics of interest by year, relative to year the ACO membership was finalized. We term the year that the ACO was set year zero, and the first year the ACO is scored on performance is year 1. With this approach, the changes in referrals over time are not constrained to be linear, and the change in referrals with the ACO after formation is, likewise, not constrained by a functional form. We also look at the referral behavior for providers that do not join an ACO, but at some point in our analysis period referred to a specialists in an ACO.

If we believe that, absent the ACO formation, changes to ACO PCPs referrals patterns would be similar to changes to non-ACO referrals patterns we could isolate the causal impact of ACO formation by observing the differing changes between these two groups. However, we know that the formation of ACOs is an endogenous choice made simultaneously by the PCPs and the specialists. We can check the trends in referrals patterns prior to the ACO formation to see how likely it is that the referrals patterns would have remained similar between ACO PCPs and non-ACO PCPs without the formation of the ACO. If there are significant differences in the pre-period trends, then it is likely that even without the formation of the ACO, the referral patterns compared across the two groups would have differed.

If that is the case, we can still examine referrals within ACO PCPs and look for a marked change at the point of ACO formation. While non-ACO PCPs may not serve as a sufficient control group, substantial changes in referral patterns in the pre vs post period for ACO PCPs may indicate the impact of ACO formation. We would need to assume that contemporaneous shocks at the point of the ACO forming were not the driver of referral pattern changes, however, because the ACOs formed in three different years, this is less of a concern.

As part of our analysis strategy, we will also investigate whether providers with plausibly different reasons to join an ACO, identified through their pre-ACO formation referral share, have different patterns of change across the year coefficients in the periods leading up to the formation of the ACO compared to the periods after ACO formation. Below we formally specify the equations we will empirically estimate.

In our first set of regressions, we estimate the number of referrals in a year that a PCP in an ACO refers to specialty providers in the ACO. Our unit of observation is a primary care provider, year:

$$AR_{it} = \gamma_i + \sum_{s \in S} \alpha_s^A M_{it}^s + \varepsilon_{it} \qquad (1)$$

where the dependent variable, ACO Referrals, is indexed by PCP_i and $year_t$. We include PCP fixed effects (γ_i) report the results with and without this control. The variable M_{it}^s is an indicator that is one if the ACO formed s years after time t, that is if an ACO formed in 2012, an observation in time 2012 would be 1 only for s=0 and an observation in time 2014 would be 1 only for s=2.

The coefficients of interests are the α_s coefficients ($s \in \{-4,3\}$), and in particular, we are interested in how these coefficients change as s moves from -1 (pre-period) to +1 (post-period).

We are interested to see if ACO PCPs are increasing referrals to ACO specialists. This could be impacting efficiency as well. If we believe that there is overuse in the healthcare system, some of that may consist of unnecessary specialist visits. A decline in total referrals could indicate PCPs proactively reducing wasteful overuse. However, if there are efficiency gains from specialization across the ACO, an increase in referrals may reflect the exploitation of these efficiencies.

Next, we estimate the effect that ACO formation has on the number of referrals from a PCP in an ACO to non-ACO specialist providers:

$$NR_{it} = \gamma_i + \sum_{s \in S} \alpha_s^O \, M_{it}^s + \varepsilon_{it} \qquad (2)$$

In this specification, the dependent variable is Other Referrals. The meaning of the other coefficients and variables are unchanged from specification (1).

We examine the total number of referrals, to see how these changes are impacting the net number of referrals. If ACO PCPs are trying to reduce utilization, they may reduce the number of total referrals to specialists:

$$TR_{it} = \gamma_i + \sum_{s \in S} \alpha_s^O \, M_{it}^s + \varepsilon_{it} \tag{3}$$

We also look at the patients sent from the PCP to specialists in the affordable care organization as a share of the total patients sent by the PCP, which enables us to observe the net combination of changes in the ACO PCPs referrals of patients to ACO providers, patients to non-ACO providers and total patients, and gives us a general idea of how ACO specialists have changed in relative importance to the PCPs. Formally, we examine the share of patients from PCP i that are referred to specialist in PCP_i's ACO. This is given by S_{it}:

$$S_{it} = \sum_{j \in J} R_{ijt} \Big/ \sum_{\forall j} R_{ijt} = \sum_{j \in J} R_{ijt} \Big/ \left(\sum_{j \in J} R_{ijt} + \sum_{j \notin J} R_{ijt} \right)$$

Where J is the set of specialist providers in the same accountable care organization as PCP_i. The regression equation to be estimated is therefore:

$$S_{it} = \gamma_i + \sum_{s \in S} \alpha_s^S \, M_{it}^s + \varepsilon_{it} \tag{4}$$

Finally, to examine whether changes in referrals are driven by the specialists being in any ACO, or the specialists being in the same ACO as the PCP we estimate the number and share of referrals sent from PCPs in ACOs to specialists in other ACOs:

$$OR_{it} = \gamma_i + \sum_{s \in S} \alpha_s^O \, M_{it}^s + \varepsilon_{it} \tag{5}$$

We also estimate equations 1-4 for primary care providers that refer to a specialists in an ACO, however, in equation (4) we are estimating the share to any ACO specialists, as the non-ACO PCPs do not belong to any particular ACO.

By Pre-Period Referral Share

As discussed, providers join ACOs to achieve different goals, such as the shared savings payouts, the investment incentives provided by CMS for upgrading technologies like electronic health records (EHR), or increased access to provider networks and patient retention and acquisition. We would expect different responses to joining an ACO, in terms of referral patterns, based on the different goals. A factor in those goals could be the position of the provider in the network of ACO providers prior to the formation of the ACO and one indicator of this position is the level of relationship with the other providers in the ACO in the years prior to forming the ACO. Providers who already have a strong, established relationship would be less likely to join together for the goal of increasing their provider network. Instead, those types of providers would most likely be pursuing the shared savings payouts or attempting to secure capital for infrastructure investments. On the other hand, it is more likely that groups of providers who do not have much of a pre-existing relationship are joining together to establish a provider referral network and secure access to patients. The potential for this type of tacit patient-sharing agreement is higher in formal ACOs due to the inherent, pre-existing sharing of patient information, the alignment of incentives, and the potential joint investments that come along with formal ACO formation

To allow for the potential that heterogeneous ACO formation goals correspond with the level of the pre-existing relationship, we estimate equations one through five separately for subgroups of PCPs. We categorize PCPs into five groups based on the pre-existing relationship between the PCPs and the ACO specialists, measured by the share of the PCP referrals that are to specialist in the ACO in the years prior to the formation of the ACO. The first three groups, Groups 1-3 respectively, are terciles. The highest tercile, Group 3, sent more than 67% of their referrals to ACO specialists. The middle tercile, Group 2, sent between 29% and 67% of their referrals to ACO specialists. Finally, the lowest tercile, Group 1, sent more than 0%, but fewer than 29% of their referrals to ACO specialists in the years prior to the formation of the ACO.

The fourth group consists of PCPs who had no referrals to specialists in ACOs in the prior periods. We term these PCPs "Group 0". Finally, there are PCPs who during the prior years did not send any referrals to our specialists of interest, either ACO or non-ACO. We label these PCPs as the null group, as it is impossible to calculate a prior period referral share.

Examining this group, it seems that many of the physicians are just starting their practices. The median age for a physician in this group is 34 vs 49 for physicians in the other group. We also looked at our billing data (MDPPAS) to see if whether they were not billing Medicare, or just not referring patients. The average first in the billing data year for the null group is 2011 and the average for the other PCPs is 2009.1 (our data only goes back to 2009). The two facts support the hypothesis that most of these physicians are either new doctors or new to Medicare. Most ACOs have providers representing more than one type. In fact, 68% of providers are in an ACO with all five and the average provider is in a group with 4.38.

For PCPs not in ACOs, we categorize them using the same share cutoffs explained above. The cutoffs were chosen to make the groups equal for ACO PCPs, so unlike with the ACO PCPS, the non-ACO PCPs do not have an equal number of providers in Groups 1-3.

5 Results

We estimate, using OLS, the event study coefficients from equations (1) through (5). The results for ACO PCPs can be found in

Table 25 through Table 30 and results for non-ACO PCPs can be found in Tables 31-34. Standard errors are clustered at the PCP level for all specifications.

When looking at ACO PCPs referrals in the aggregate, we observe a constantly increasing number of referrals to ACO specialists with an average increase of 21 referrals in the three years leading up to ACO formation (table 7), and a slightly faster increase of 42 the four years after. However, referrals to non-ACO specialists change dramatically after the formation of the ACO. In the pre-period, there is a very slight, insignificant drop of 3 referrals, from 205 to 203. After the formation of the ACO, ACO PCPs decrease their referrals to non-ACO specialists, by 50, a drop of 25% (table 8). The share of referrals to ACO specialists increases in the pre-period from 27% to 34% and increases in the post period to 47% (table 10).

Overall, non-ACO PCPs changed their referrals very little in the years leading up to ACO formation increasing referrals to non-ACO specialists by 3% and to ACO specialists by 2% (table 13). After the formation of the ACOs, non-ACO PCPs decreased referrals to non-ACO and ACO specialists by a similar absolute amount, 7 and 6, respectively; however, as a share of the prior year baseline this represents a small 3% drop for non-ACO specialists (table 13), but a large, 21% drop to ACO specialists. Consequently, while the share of referrals to ACO specialists had be stable at around 10% prior to the formation of the ACO, after formation dropped to 9% (table 16).

At the aggregate level, we see smooth increases in referrals from ACO PCPs to ACO specialists, in terms of both number of referrals and share of total referrals. However, this aggregation masks significant changes that occur at the point of formation for sub-populations of providers, which become evident when we separately analyze the PCPs based on their pre-existing relationship with the specialists in the ACO. We create these analysis groups for both PCPs in ACOs, and PCPs not in ACOs using the same criteria based on the share of referrals to ACO specialists in the pre-period. In what follows, we discuss the results for each group, contrasting the trends prior to ACO formation with the trend after ACO formation.

First, we discuss primary care providers that sent more than 67% of their referrals to ACO specialists in the period prior to ACO formation. We refer to these PCPs as Group 3. PCPs that joined ACOs and PCPs that did not both sent a similar share of their referrals the year before ACO formation, 83% and 87% respectively, however, their prior trend differed.

PCPs that joined the ACO averaged nearly 205 referrals per year the year before they joined, and had increased referrals by more nearly 50 over the four years before. The level for PCPs that did not join an ACO was significantly lower, 154 referrals per year, and leading up to the formation of ACOs, their rate of increase was smaller as well, adding only 5 referrals per year over the same period.

After the ACO formed, both sets of providers decreased referrals to ACO specialists and overall. For PCPs in ACOs, the decrease in referrals to ACO specialist was from 170 to 150, but the overall decrease was large, 205 to167, driven by a 50% decrease in referrals to non-ACO specialists. In net, for these providers the share of referrals increased to 92%. In contrasts, non-ACO PCPs doubled their referrals to non ACO specialists, 35 to 70, over this time-period while significantly decreasing referrals to ACO specialists - from 120 referrals to 64, a decrease of nearly 50%. Three years after the formation of the ACO, PCPs who had been sending 83% of their referrals to specialists in the ACO only sent 54%. It is not clear from our data the exact cause of this large drop in the share. It could be that non-ACO PCPs feel a competitive threat from the formation of the ACO and are consequently trying to find their own set of partners. Alternatively, there could be a capacity issue where the ACO specialists cannot treat the both increased number of patients from ACO PCPs and the non-ACO PCPs' patients.

For PCPs in Group 2, providers that sent between 29% and 67% of their referrals to specialists in ACOs, those that join ACOs sent slightly more overall referrals (386 vs 367) in the year prior to the formation of the ACO than those that did not.

In this group, ACO PCPs were sending an increasingly large share of their patients to specialists in ACOs leading up to those PCPs joining their ACOs. In the three years leading up to ACO formation, their share, on average, increased by 13.7%. This was primarily driven by an increase in referrals to ACO specialists, 22%, but they did decrease referrals to non-ACO specialists as well, but only by 8% (from 212 to 196). In contrast, in the prior periods, PCPs in Group 2 that did not join the ACO only barely changed their share of referrals to specialists in ACOs.

Surprisingly, after the ACO is formed PCPs in the ACO cease to increase the number of referrals to ACO specialists. However, they dramatically decrease the referrals to non-ACO specialists, and the net effect is that the share continues to climb at nearly the same rate it was climbing in the pre-period, rising from 52% to 66% three years after ACO formation. Referrals to specialists in ACOs which the PCP does not participate in do not grow. Instead, they fall more significantly than referrals to non-ACOs.

For PCPs not affiliated with an ACO, there is a very large drop in referrals to specialists affiliated with ACOs. On average, these types of referrals decline from 163 to 105, a drop of 35%. While non-ACO PCPs decrease the number of referrals overall, the decline to non-ACO specialists is a much less pronounced 5%. Consequently, the share of referrals to non-ACO specialists increases in the post-period to 64%, from a base of 55%.

We categorize primary care providers that sent more than 0% but less than 29% of their referrals in the periods prior to ACO formation to specialists that would eventually join an ACO as Group 1. These providers sent, on average, more referrals than the other providers with ACO PCPs sending 520 and non-ACO PCPs averaging 547 in the period prior to ACO formation. In the period leading up to ACO formation both ACO PCPs increased their overall referrals by 24 and non-ACO PCPs increased their referrals by 3.

In the periods prior to the formation of the ACO, ACO PCPs increased the number of referrals to ACO specialists by 21. However, most of this increase occurred in the year just prior to the ACO formation.

In the three years leading up to ACO formation, non-ACO PCPs slightly decreased the number of referrals to ACO specialists, dropping from an average of 44 per year to an average of 41 per year, and slightly increased referrals to non-ACO PCPs, from 501 to 506. This meant that the share of referrals going to a specialist in an ACO dropped from 9.5% to 8.6%.

After the formation of the ACO, PCPs in ACOs increased their referrals to specialists in ACOs by 20, a marked 25% increase off the prior year baseline, and decreased referrals to non-ACO specialists by an even larger share, 35%, and much larger absolute amount, 160 referrals per year. Notably, referrals to specialists in ACOs which the PCP does not participate decrease slightly more than referrals to non-ACOs, falling 40%. For these PCPs, in the pre-period referrals to other ACOs made up a significant portion of total referrals, 10%.

Surprisingly, non-ACO PCPs also significantly decrease referrals to non-ACO specialists, dropping from 506 to 416, a drop of 17%. However, as a percentage this is much smaller than the drop to ACO specialists, which is 23%. Consequently, for non-ACO PCPs, the share of referrals to ACO specialists falls from 8.8% to 7.7%. The overall drop in referrals for both ACO and non-ACO PCPs is large and similar in magnitude, 25% and 27% respectively.

A significant share of PCPs that refer to ACO specialist in our dataset do not refer to any ACO specialists of interest prior to the formation of the ACOs. We refer to these PCPs as Group 0. For PCPs in the ACO, that share is 31% and for PCPs out of the ACO the share is 47%. In the pre-period, ACO and non-ACO PCPs had a similar number of total referrals to non-ACO specialists, 230 and 210, though non-ACO PCPs were growing at a slightly faster rate adding an average of 9 referrals over the pre-period compared to 4 for ACO PCPs.

After the ACOs form, non-ACO PCPs only add four referrals to ACO specialists while reducing referrals to non-ACO PCPs by 10, while ACO PCPs added 32 referrals to ACO specialists and decrease referrals to non-ACO specialist by 72. Three years after ACO formation, non-ACO PCPs refer 1.4% of their referrals to ACO specialists while ACO PCPs are referring 17.6%. Like Group 1, in the year prior to ACO formation, Group 0 also sends a sizable share of their referrals to ACOs they do not join, nearly 13%. After formation, this share drops to 10%. As seen with the other groups, relatively speaking, this is a larger drop than the drop of referrals to non-ACO specialists.

Finally, some primary care providers in our dataset did not refer to any of our specialists of interest during the pre-period. Providers of this type make up 16% of PCPs that join an ACO, and 14% of non-ACO PCPs that at some point refer to an ACO specialist. While these PCPs had no recorded referrals in the pre-period, in the last period of our data on average they sent more referrals than every group except Group 1, with 233 and 280 referrals for ACO and non-ACO PCPs respectively.

In the year that the ACO is formed, ACO PCPs send 48% of their referrals to ACO specialists while non-ACO PCPs only send 8.8%. Three years after formation, ACO PCPs have increased that share to 60%, while non-ACO PCPs decrease their share to 8.6%. For ACO PCPs, on average they send 7.3% of referrals to ACOs they do not join in the year their ACO is formed, but only 4.2% three years after joining.

For a more easily consumed comparison, I graph the coefficients in tables 25 through 34 in figures 14-19. Each figure includes graphed coefficients for each of the five subgroups as well as an overall, and represents referrals from either PCPs in ACOs or non-ACOs PPOs to one of the following sets of specialists, as detailed below: ACO, Non-ACO, Other ACO, Any. Either share or levels

- Figure 14: The share of referrals to specialist in an ACO: PCPs that join an ACO vs PCPs not in an ACO
- Figure 15: The number of referrals from a PCP in an ACO: to specialists that join an ACO vs specialists that do not
- Figure 16: The number of referrals from a PCP **not** in an ACO: to specialists that join an ACO vs specialists that do not
- Figure 17: The number of referrals to specialist **not** in an ACO: PCPs that join an ACO vs PCPs not in an ACO
- Figure 18: Total number of referrals to specialist: PCPs that join an ACO vs PCPs not in an ACO

Focusing on figures 14 and 15, we can make the following four observations: first, when we look for a response for PCPs joining an ACO (figure 14 and figure 15), overall, PCPs that join an ACO seem to have been increasing the number of referrals to ACO specialists prior to the formation of the ACO. However, it looks like after the formation of the ACO they decrease referrals to non-ACO specialists. In the three years before ACO formation the average share of referrals sent to specialists in an ACO goes from 30% to 34%. In the three years after, the average share increases to 47%. For non-ACO PCPs, the changes are much smaller. In the three years before ACO formation the average of referrals increases from 9.9% to 10.2%. In the three years after, the average share of referrals from non-ACO PCPs to specialists in an ACO decreases to 9.1%.

Second, there appears to be a large response at the some of the extremes. ACO PCPs who had not previously sent any referrals to the ACO significantly increase referrals (from 0% to 17.5%). Non-ACO PCPs, who previously had sent a high share of their referrals to ACO specialists significantly decrease referrals (82.5% to 54.0%).

Third, there is some response in the middle. ACO PCPs who had previously sent a low share, slightly increase referrals to ACO specialists (16% to 29%) and significantly decrease the number of referrals to non-ACO specialists. Non-ACO PCPs, who had previously sent a medium share of referrals to specialists in the ACO decrease referrals to ACO specialists (from 45% to 36%).

Fourth, there is little response at the other extremes. For PCPs who were already sending a significant share of their referrals to specialists in the ACO, they do not continue to increase the raw number of referrals, though a declining number of referrals to non-ACO specialists result in an increasing average referral share – from 87.3% to 92.1%. For PCPs that did not join the ACO, and previously sent no referrals to an ACO, the share of referrals sent barely changes going from 0 to 1.7%.

There are big differences in the referral patterns among primary care providers who previously did not record any Medicare referrals, the null group in figures 15. Those that join an ACO send a significant (>50%) share of their referrals to specialists in the ACO while those that do not join an ACO, send a much smaller share (9-10%).

Looking at figure 20, it appears that changes are not driven by something special about PCPs that join ACOs and specialists that join ACOs, as there is no impact on referrals of PCPs in ACOs to specialists in *other* ACOs. In fact, as a share of prior year referrals, the drop in referrals to other ACOs is slightly larger than the drop in referrals to non-ACO providers (7/22 = 32%, vs 49/202=24%).

Figure 18 shows that there is an overall drop in referrals in each of the groups. This is likely an artifact of the way we are constructing our analysis dataset. We fix the set of physicians that we are going to analyze in "year 0" – when the ACO is announced. As time progresses there is a natural rate of professional attrition, due to physicians retiring or passing away. We see an attrition rate of around 5% in our data, where attrition means we stop observing a physician. While we do not know the cause of this, or if they will reappear. While their figure includes physicians relocating, SK&A estimates that the move rate for primary care physicians is above 10%[26].

This leads to one more comparison, the predicted levels from the regression coefficients compared with a fixed 5% attrition rate (figure 19). I calculate referrals as a share of year 0 referrals, and subtract this from what would be expected with a compounding 5% attrition rate (95%, 90.3%, 85.7% and 81.5%).

Overall, both PCPs in ACOs and non-ACO PCPs that refer to ACOs have a decline that not very different from a 5% attrition rate. However, looking at referrals to specialists in ACOs there is a stark difference is true for all the groups, 1-3 (this metric is not applicable for ACOs in group 0 or

[26] SK&A, "Healthcare Provider Move Rates - Physician Specialties, Hospital and Pharmacy Staff Titles". Market Insights Report. October 2016. Accessed from http://www.skainfo.com/reports/provider-move-rates

the null group). The shift towards ACOs is most pronounced group 3 – the group with a small prior relationship. And the shift away from the ACO is most pronounced in group 1 – the group with the largest prior relationship.

6 Summary

When analyzing the referral patterns from ACO PCPs to ACO specialists, we observe a substantial pre-period increase. This illustrates that the formation of the ACO is an endogenous choice. We also notice that the response to ACO formation differs substantially based on the PCP pre-period relationship with the specialists. For PCPs with similar average referral rates to ACO specialist in the pre-period, those that have been increasing their share are more likely to be the ones that form the ACO. Interestingly, for ACO PCPs that had previously been referring to ACO specialists, they stop increasing the number of referrals to ACO specialists after joining the ACO. However, the aggregate number of referrals to ACO specialists increases at a similar rate which is driven by ACO PCPs that had not previously referred to an ACO specialist, and ACO PCPs that had previously not referred to any specialists. For all groups of ACO PCPs with referrals to non-ACO specialists, ACO formation is associated with a significant drop in referrals to non-ACO specialists, and a net overall drop in referrals. There was no pre-trend in the level of non-ACO referrals.

In net, the share of referrals from ACO PCPs to ACO specialists grows both in the pre-period and in the post period. However, the source of the change in share is different. In the pre-period, it is driven mainly by an increase in referrals from groups 1-3. In the post-period, the overall increase in share is driven both by the decrease in number of referrals to non-ACO specialists, and the increase from PCPs that had not previously referred to ACO specialists. Non-ACO PCPs also lowered their overall number of referrals. While they dropped referrals to ACO and non-ACO specialists, the drop was much more pronounced for ACO specialists.

7 Conclusion

Payment methods other than fee-for-service are becoming increasingly prevalent. While there is an increasing number of large, multi-specialty practices, other, less integrated associations between primary care provider and specialists, such as accountable care organizations, are increasingly common as well. Primary care providers have unique and mixed motivations for joining affordable care organizations. Each provider enters that arrangement with a different prior relationship with the other ACO, and responds differently to the formation of the ACO. We show that there is a heterogenous response to joining an ACO, and the level of the pre-existing relationship determines the type of response a PCP will have. Overall, PCPs joining an ACO decrease the number of referrals to specialists, by decreasing the number of referrals to specialists outside the ACO while still increasing referrals to specialists inside the ACO. However, PCPs without a prior relationship with ACO specialists significantly increase both the referrals to ACO specialists and total referrals.

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Tables and Figures

Table 19: All ACOs by Start Date

Start Date	ACOs	PCPs	Firms	PCP/Firm	Firm/ACO
Apr, 2012	26	1,826	890	2.05	34.23
Jul, 2012	85	9,430	2,749	3.43	32.34
Jan, 2013	103	10,962	3,654	3.00	35.48
Jan, 2014	119	9,520	2,876	3.31	24.17
All ACOs	**333**	**31,738**	**10,169**	**3.12**	**30.54**

Table 20: ACO's with a Specialists by Start Date

Start Date	ACOs	Specialists	Firms	PCP/Firm	Firm/ACO
Apr, 2012	22	834	331	2.52	15.05
Jul, 2012	77	4,275	1,079	3.96	14.01
Jan, 2013	89	5,433	1,301	4.18	14.62
Jan, 2014	98	3,479	785	4.43	8.01
All ACOs	**286**	**14,021**	**3,496**	**4.01**	**12.22**

Table 21: Physician Counts by Specialty

	Cardiology	Gastroenterology	General Surgery	Nephrology	Ophthalmology	Orthopedic Surgery	Pulmonary Disease
Number of Specialists	3,631	1,788	2,577	1,165	1,283	2,098	1,479
Number of Firms	991	598	855	371	457	584	514
Number of ACOs	233	202	211	156	132	172	199
Share of ACOs	70.0%	60.7%	63.4%	46.8%	39.6%	51.7%	59.8%
Specialists / ACO	15.58	8.85	12.21	7.47	9.72	12.20	7.43
Specialists / Firm	3.66	2.99	3.01	3.14	2.81	3.59	2.88

Table 22: Physicians by Quartile Summary Statistics

	Group 3 High ACO Share	**Group 2** Medium ACO Share	**Group 1** Low ACO Share	**Group 0** No ACO Refs	**Group Null** No Refs
Number of PCPs	5,050	5,048	5,049	8,914	3,962
Avg Beneficiaries / Year	299.4	401.5	445.5	307.8	201.9
Avg Allowed Amount	$77,343	$123,582	$159,682	$110,310	$49,558
Avg Number of Referrals (sent)	230.466	399.741	509.474	229.745	80.422
Avg Number of Referrals to ACO (sent)	190.619	203.483	81.195	9.697	41.707

Groups defined by the average share of referrals to ACO providers in the years prior to ACO formation:
Group 3 >67% | 67%> Group 2 > 29% | 29% > Group 1 > 0% | Group 0 =0% | Group Null – No referrals to Specialists in the pre-period

Table 23: Primary Care Providers Summary Statistics

	In ACO	Non ACOs
Number of PCPs	31,738	133,357
Number of Firms	10,169	48,311
Number of Referrals (sent)	24.4 M	181.8 M
Multispecialty Firms (%)	28.4%	17.1%
Average Firm Size (Firm)	13.10	9.15
Average Firm Size (Provider)	430.75	540.82
Average Patients Seen	280.16	268.50
Average Allowed Amount	$87,731	$85,619
Average Allowed Amount per Patient	$313.14	$318.87
Average Referrals	769.77	1363.58
Average Number of Specialists Referred to	26.08	45.39
Average Number of Firms Referred to	9.45	17.21

Table 24: Specialists Summary Statistics

	In ACO	Non ACOs
Number of Specialists	14,021	448,746
Number of Firms	3,496	126,889
Number of Referrals (received)	3.8 M	193.4 M
Multispecialty Firms (%)	52.2%	34.1%
Average Firm Size (Firm)	37.81	12.59
Average Firm Size (Provider)	492.33	609.11
Average Patients Seen	555.01	518.58
Average Allowed Amount	$181,518	$197,105
Average Allowed Amount per Patient	$327.05	$380.09
Average Referrals	270.73	430.95
Average Number of PCPs Received From	9.17	14.36
Average Number of Firms Referred From	4.17	7.18

Table 25: Referrals from ACO PCPs to Specialists in the ACO: By Years Since ACO Formation and Pre-formation Referral Group

Dependent Variable: Referrals to ACO Specialists from ACO PCPs

	Overall	**Group 3** High ACO Share	**Group 2** Medium ACO Share	**Group 1** Low ACO Share	**Group 0** No ACO Refs	**Group Null** No Refs
4 yrs prior	-18.90 ***	-51.09 ***	-40.39 ***	-21.11 ***		
	(0.966)	(3.897)	(3.749)	(1.86)		
3 yrs prior	-16.84 ***	-34.46 ***	-37.58 ***	-17.59 ***		
	(0.693)	(2.449)	(2.554)	(1.321)		
2 yrs prior	-8.35 ***	-18.58 ***	-18.57 ***	-10.77 ***		
	(0.388)	(1.496)	(1.426)	(0.787)		
1 yr prior						
ACO Formed	9.42 ***	6.45 ***	6.39 ***	12.96 ***	6.53 ***	17.60 ***
	(0.459)	(1.54)	(1.39)	(1.058)	(0.426)	(1.02)
1 yr post	18.69 ***	1.15	-0.25	16.43 ***	17.54 ***	62.35 ***
	(0.693)	(1.832)	(1.763)	(1.331)	(0.859)	(2.326)
2 yrs post	31.61 ***	-6.14 ***	2.34	22.68 ***	29.06 ***	110.10 ***
	(1.035)	(2.279)	(2.343)	(1.908)	(1.4)	(3.458)
3 yrs post	34.78 ***	-19.59 ***	-5.93 *	18.37 ***	32.86 ***	130.20 ***
	(1.494)	(3.426)	(3.355)	(2.483)	(1.977)	(4.586)
Prior Yr Mean	74.91 ***	168.70 ***	189.70 ***	71.97 ***	0.00	0.00
	(0.365)	(1.081)	(1.037)	(0.687)	(0.374)	(1.067)
PCP FE	Y	Y	Y	Y	Y	Y
Number of PCPs	28,857	5,064	5,061	5,062	9,005	4,665
Observations	173,142	30,384	30,366	30,372	54,030	27,990

Notes:

Standard errors in parentheses. Clustered at the physician level.

*Significantly different from 0 at the 10% level ** 5% *** 1%

Groups defined by the average share of referrals to ACO providers in the years prior to ACO formation:

Group 3 >67% | 67%> Group 2 > 29% | 29% > Group 1 > 0% | Group 0 =0% | Group Null – No referrals to Specialists in the pre-period

Table 26: Referrals from ACO PCPs to Specialists NOT in the ACO: By Years Since ACO Formation and Pre-formation Referral Group

Dependent Variable: Referrals to on-ACO Specialists from ACO PCPs

	Overall	Group 3 High ACO Share	Group 2 Medium ACO Share	Group 1 Low ACO Share	Group 0 No ACO Refs	Group Null No Refs
4 yrs prior	2.19	5.49 ***	16.16 ***	-2.83	-4.26	
	(2.288)	(1.525)	(4.592)	(7.981)	(4.006)	
3 yrs prior	1.65	2.74 ***	2.21	13.91 **	-4.62	
	(1.446)	(0.871)	(3.047)	(5.441)	(2.833)	
2 yrs prior	2.87 ***	2.05 ***	1.51	16.49 ***	-2.06	
	(0.832)	(0.557)	(1.641)	(3.149)	(1.723)	
1 yr prior						
ACO Formed	-7.98 ***	-0.42	-12.04 ***	-32.81 ***	-12.48 ***	23.84 ***
	(0.834)	(0.672)	(1.625)	(2.653)	(1.826)	(1.296)
1 yr post	-20.15 ***	-5.99 ***	-34.48 ***	-75.29 ***	-36.11 ***	70.61 ***
	(1.198)	(0.863)	(2.233)	(3.526)	(2.433)	(2.912)
2 yrs post	-31.54 ***	-12.21 ***	-55.23 ***	-118.30 ***	-55.52 ***	93.96 ***
	(1.555)	(0.942)	(2.534)	(5.12)	(3.143)	(3.426)
3 yrs post	-44.57 ***	-17.92 ***	-73.29 ***	-160.00 ***	-72.95 ***	103.40 ***
	(2.218)	(1.234)	(4.082)	(6.989)	(4.302)	(4.276)
Prior Yr Mean	191.20 ***	36.30 ***	196.40 ***	447.80 ***	229.10 ***	0.00
	(0.676)	(0.443)	(1.238)	(2.198)	(1.426)	(1.148)
PCP FE	Y	Y	Y	Y	Y	Y
Number of PCPs	28,857	5,064	5,061	5,062	9,005	4,665
Observations	173,142	30,384	30,366	30,372	54,030	27,990

Notes:

Standard errors in parentheses. Clustered at the physician level.

*Significantly different from 0 at the 10% level ** 5% *** 1%

Groups defined by the average share of referrals to ACO providers in the years prior to ACO formation:

Group 3 >67% | 67%> Group 2 > 29% | 29% > Group 1 > 0% | Group 0 =0% | Group Null – No referrals to Specialists in the pre-period

Table 27: Total Referrals from ACO PCPs to Specialists: By Years Since ACO Formation and Pre-formation Referral Group

Dependent Variable: Total Referrals from ACO PCPs

	Overall	Group 3 High ACO Share	Group 2 Medium ACO Share	Group 1 Low ACO Share	Group 0 No ACO Refs	Group Null No Refs
4 yrs prior	-16.71 ***	-45.60 ***	-24.24 ***	-23.94 ***	-4.24	
	(2.656)	(4.927)	(7.215)	(8.57)	(4.055)	
3 yrs prior	-15.19 ***	-31.72 ***	-35.37 ***	-3.68	-5.64 **	
	(1.746)	(3.029)	(4.969)	(5.892)	(2.864)	
2 yrs prior	-5.48 ***	-16.53 ***	-17.05 ***	5.72 *	-2.06	
	(0.987)	(1.878)	(2.676)	(3.392)	(1.723)	
1 yr prior						
ACO Formed	1.44	6.03 ***	-5.65 **	-19.85 ***	-5.95 ***	41.43 ***
	(1.043)	(2.009)	(2.694)	(3.05)	(1.886)	(1.895)
1 yr post	-1.46	-4.84 **	-34.74 ***	-58.86 ***	-18.56 ***	133.00 ***
	(1.521)	(2.387)	(3.469)	(4.05)	(2.55)	(4.34)
2 yrs post	0.07	-18.35 ***	-52.89 ***	-95.61 ***	-26.45 ***	204.10 ***
	(2.08)	(2.864)	(4.223)	(5.832)	(3.4)	(5.77)
3 yrs post	-9.79 ***	-37.51 ***	-79.22 ***	-141.60 ***	-40.09 ***	233.50 ***
	(2.964)	(4.18)	(6.212)	(7.984)	(4.664)	(7.201)
Prior Yr Mean	266.10 ***	205.00 ***	386.10 ***	519.70 ***	229.10 ***	0.00
	(0.838)	(1.385)	(1.991)	(2.446)	(1.452)	(1.852)
PCP FE	Y	Y	Y	Y	Y	Y
Number of PCPs	28,857	5,064	5,061	5,062	9,005	4,665
Observations	173,142	30,384	30,366	30,372	54,030	27,990

Notes:

Standard errors in parentheses. Clustered at the physician level.

*Significantly different from 0 at the 10% level ** 5% *** 1%

Groups defined by the average share of referrals to ACO providers in the years prior to ACO formation:

Group 3 >67% | 67%> Group 2 > 29% | 29% > Group 1 > 0% | Group 0 =0% | Group Null – No referrals to Specialists in the pre-period

Table 28: Referrals from ACO PCPs to Specialists in OTHER ACOs: By Years Since ACO Formation and Pre-formation Referral Group

Dependent Variable: Total Referrals to other ACOs from ACO PCPs

	Overall	**Group 3** High ACO Share	**Group 2** Medium ACO Share	**Group 1** Low ACO Share	**Group 0** No ACO Refs	**Group Null** No Refs
4 yrs prior	0.17	-0.59	-1.29	1.53	-0.06	
	(0.563)	(0.453)	(1.282)	(1.905)	(0.984)	
3 yrs prior	-0.17	-0.04	-0.20	1.44	-1.36 *	
	(0.361)	(0.244)	(0.664)	(1.356)	(0.736)	
2 yrs prior	-0.02	0.27 *	-0.50	2.08 ***	-1.11 **	
	(0.211)	(0.162)	(0.339)	(0.766)	(0.473)	
1 yr prior						
ACO Formed	-0.65 ***	0.18	0.30	-3.36 ***	-1.88 ***	2.77 ***
	(0.223)	(0.175)	(0.373)	(0.715)	(0.512)	(0.32)
1 yr post	-1.87 ***	-0.71 ***	-0.53	-7.24 ***	-5.10 ***	7.53 ***
	(0.342)	(0.207)	(0.916)	(0.976)	(0.699)	(0.664)
2 yrs post	-4.03 ***	-1.40 ***	-3.36 ***	-13.64 ***	-8.75 ***	9.49 ***
	(0.401)	(0.216)	(0.446)	(1.396)	(0.938)	(0.752)
3 yrs post	-6.28 ***	-2.34 ***	-6.68 ***	-19.59 ***	-11.02 ***	9.76 ***
	(0.509)	(0.291)	(0.82)	(1.469)	(1.223)	(0.941)
Prior Yr Mean	20.76 ***	3.82 ***	16.39 ***	51.35 ***	26.15 ***	0.00
	(0.173)	(0.108)	(0.277)	(0.574)	(0.393)	(0.25)
PCP FE	Y	Y	Y	Y	Y	Y
Number of PCPs	28,857	5,064	5,061	5,062	9,005	4,665
Observations	173,142	30,384	30,366	30,372	54,030	27,990

Notes:

Standard errors in parentheses. Clustered at the physician level.

*Significantly different from 0 at the 10% level ** 5% *** 1%

Groups defined by the average share of referrals to ACO providers in the years prior to ACO formation:

Group 3 >67% | 67%> Group 2 > 29% | 29% > Group 1 > 0% | Group 0 =0% | Group Null – No referrals to Specialists in the pre-period

Table 29: Referrals from ACO PCPs to ACO Specialists as a Share of Total Referrals: By Years Since ACO Formation and Pre-formation Referral Group

Dependent Variable: Share of Total Referrals to ACO specialists, from ACO PCPs

	Overall	**Group 3** High ACO Share	**Group 2** Medium ACO Share	**Group 1** Low ACO Share	**Group 0** No ACO Refs	**Group Null** No Refs
4 yrs prior	-7.0% ***	-13.3% ***	-13.7% ***	-6.8% ***		
	(0.00274)	(0.00857)	(0.00843)	(0.00512)		
3 yrs prior	-4.5% ***	-6.8% ***	-8.3% ***	-5.3% ***		
	(0.00171)	(0.00413)	(0.0048)	(0.00356)		
2 yrs prior	-2.4% ***	-3.0% ***	-4.2% ***	-3.6% ***		
	(0.00118)	(0.00278)	(0.00331)	(0.00247)		
1 yr prior						
ACO Formed	3.0% ***	-0.8% ***	2.9% ***	3.7% ***	4.8% ***	
	(0.00118)	(0.00244)	(0.00266)	(0.00233)	(0.00194)	
1 yr post	6.3% ***	1.0% ***	6.3% ***	6.4% ***	9.4% ***	3.5% ***
	(0.00148)	(0.00278)	(0.00313)	(0.00284)	(0.00285)	(0.00669)
2 yrs post	9.6% ***	2.4% ***	9.6% ***	10.1% ***	13.9% ***	7.2% ***
	(0.00189)	(0.00308)	(0.00371)	(0.00384)	(0.00407)	(0.00833)
3 yrs post	13.2% ***	4.6% ***	14.5% ***	12.7% ***	17.6% ***	11.0% ***
	(0.00282)	(0.00459)	(0.0056)	(0.00565)	(0.00616)	(0.0106)
Prior Yr Mean	34.2% ***	87.4% ***	52.1% ***	16.4% ***	0.0%	47.9% ***
	(0.000876)	(0.00172)	(0.00204)	(0.00172)		(0.00608)
PCP FE	Y	Y	Y	Y	Y	Y
Number of PCPs	28,857	5,064	5,061	5,062	9,005	4,665
Observations	134,789	25,639	28,378	28,973	42,988	8,811

Notes:

Standard errors in parentheses. Clustered at the physician level.

*Significantly different from 0 at the 10% level ** 5% *** 1%

Groups defined by the average share of referrals to ACO providers in the years prior to ACO formation:

Group 3 >67% | 67%> Group 2 > 29% | 29% > Group 1 > 0% | Group 0 =0% | Group Null – No referrals to Specialists in the pre-period

Table 30: Referrals from ACO PCPs to Specialists in OTHER ACOs as a Share of Total Referrals: By Years Since ACO Formation and Pre-formation Referral Group

Dependent Variable: Share of Total Referrals to Other ACOs, from ACO PCPs

	Overall	Group 3 High ACO Share	Group 2 Medium ACO Share	Group 1 Low ACO Share	Group 0 No ACO Refs	Group Null No Refs
4 yrs prior	0.6% ***	1.3% ***	1.3% ***	0.8% **	-0.3%	
	(0.00181)	(0.00319)	(0.00365)	(0.00319)	(0.00356)	
3 yrs prior	0.3% ***	0.4% ***	0.8% ***	0.5% **	-0.2%	
	(0.00107)	(0.0013)	(0.00193)	(0.00213)	(0.00234)	
2 yrs prior	0.0%	0.2% *	0.1%	0.3% **	-0.4% **	
	(0.00075)	(0.000929)	(0.00123)	(0.00143)	(0.00171)	
1 yr prior						
ACO Formed	-0.2% ***	0.3% ***	0.0%	-0.1%	-0.8% ***	
	(0.000761)	(0.000914)	(0.00108)	(0.00132)	(0.00182)	
1 yr post	-0.8% ***	-0.1%	-0.3% **	-0.6% ***	-1.9% ***	-1.0% **
	(0.000883)	(0.000915)	(0.00118)	(0.00158)	(0.0022)	(0.00406)
2 yrs post	-1.4% ***	-0.3% ***	-0.6% ***	-1.4% ***	-2.8% ***	-1.9% ***
	(0.00103)	(0.000914)	(0.00127)	(0.00195)	(0.00273)	(0.00487)
3 yrs post	-1.9% ***	-0.3% *	-1.1% ***	-2.1% ***	-2.9% ***	-3.1% ***
	(0.00159)	(0.00174)	(0.00197)	(0.00298)	(0.0041)	(0.00649)
Prior Yr Mean	7.9% ***	1.2% ***	4.4% ***	10.2% ***	12.9% ***	7.3% ***
	(0.000542)	(0.000599)	(0.000793)	(0.000953)	(0.00126)	(0.00364)
PCP FE	Y	Y	Y	Y	Y	Y
Number of PCPs	28,857	5,064	5,061	5,062	9,005	4,665
Observations	134,789	25,639	28,378	28,973	42,988	8,811

Notes:

Standard errors in parentheses. Clustered at the physician level.

*Significantly different from 0 at the 10% level ** 5% *** 1%

Groups defined by the average share of referrals to ACO providers in the years prior to ACO formation:

Group 3 >67% | 67%> Group 2 > 29% | 29% > Group 1 > 0% | Group 0 =0% | Group Null – No referrals to Specialists in the pre-period

Table 31: Referrals from non-ACO PCPs to ACOs Specialists: By Years Since ACO Formation and Pre-formation Referral Group

Dependent Variable: Referrals to ACO Specialists from Non-ACO PCPs

	Overall	Group 3 High ACO Share	Group 2 Medium ACO Share	Group 1 Low ACO Share	Group 0 No ACO Refs	Group Null No Refs
4 yrs prior	0.58 **	-0.59	2.79	2.85 ***		
	(0.227)	(2.519)	(1.904)	(0.413)		
3 yrs prior	0.53 ***	-0.05	4.18 ***	1.54 ***		
	(0.15)	(1.779)	(1.275)	(0.261)		
2 yrs prior	0.19 **	-1.95 *	1.32 *	0.51 ***		
	(0.0844)	(1.017)	(0.705)	(0.148)		
1 yr prior						
ACO Formed	-1.29 ***	-6.90 ***	-11.30 ***	-1.59 ***	0.44 ***	2.25 ***
	(0.0838)	(1.077)	(0.683)	(0.134)	(0.021)	(0.11)
1 yr post	-3.19 ***	-23.44 ***	-28.56 ***	-4.31 ***	1.25 ***	9.03 ***
	(0.154)	(1.914)	(1.213)	(0.24)	(0.0523)	(0.33)
2 yrs post	-4.79 ***	-38.53 ***	-42.78 ***	-7.09 ***	2.08 ***	15.28 ***
	(0.221)	(2.721)	(1.694)	(0.345)	(0.0878)	(0.556)
3 yrs post	-6.37 ***	-56.16 ***	-58.06 ***	-9.78 ***	2.96 ***	24.82 ***
	(0.29)	(3.446)	(2.12)	(0.443)	(0.132)	(0.907)
Prior Yr Mean	30.98 ***	120.40 ***	163.30 ***	41.07 ***	0.00	0.00
	(0.072)	(0.899)	(0.558)	(0.112)	(0.0261)	(0.167)
PCP FE	Y	Y	Y	Y	Y	Y
Number of PCPs	361,642	12,883	29,567	98,946	169,859	50,387
Observations	2,169,852	77,298	177,402	593,676	1,019,154	302,322

Notes:

Standard errors in parentheses. Clustered at the physician level.

*Significantly different from 0 at the 10% level ** 5% *** 1%

Groups defined by the average share of referrals to ACO providers in the years prior to ACO formation:

Group 3 >67% | 67%> Group 2 > 29% | 29% > Group 1 > 0% | Group 0 =0% | Group Null – No referrals to Specialists in the pre-period

Table 32: Referrals from non-ACO PCPs to non-ACO Specialists: By Years Since ACO Formation and Pre-formation Referral Group

Dependent Variable: Referrals to Specialists not in an ACO from Non-ACO PCPs

	Overall	**Group 3** High ACO Share	**Group 2** Medium ACO Share	**Group 1** Low ACO Share	**Group 0** No ACO Refs	**Group Null** No Refs
4 yrs prior	-9.02 ***	-3.74 ***	4.51 *	-5.68 **	-8.88 ***	
	(0.95)	(1.121)	(2.511)	(2.606)	(0.963)	
3 yrs prior	-5.72 ***	-2.68 ***	3.24 **	-2.05	-7.05 ***	
	(0.615)	(0.728)	(1.652)	(1.691)	(0.643)	
2 yrs prior	-3.41 ***	-0.60	1.64 *	-4.08 ***	-4.77 ***	
	(0.347)	(0.398)	(0.905)	(0.955)	(0.361)	
1 yr prior						
ACO Formed	-0.48	5.81 ***	-1.97 **	-13.91 ***	3.34 ***	22.45 ***
	(0.333)	(0.646)	(0.901)	(0.807)	(0.425)	(0.453)
1 yr post	-3.37 ***	15.60 ***	-4.88 ***	-41.14 ***	0.05	95.74 ***
	(0.626)	(1.395)	(1.652)	(1.453)	(0.799)	(1.367)
2 yrs post	-5.93 ***	24.13 ***	-7.87 ***	-65.30 ***	-3.39 ***	158.70 ***
	(0.927)	(2.185)	(2.374)	(2.103)	(1.201)	(2.251)
3 yrs post	-7.70 ***	33.69 ***	-10.96 ***	-90.28 ***	-9.79 ***	255.40 ***
	(1.229)	(3.053)	(3.12)	(2.719)	(1.538)	(3.67)
Prior Yr Mean	273.90 ***	34.41 ***	204.30 ***	506.80 ***	210.80 ***	0.00
	(0.293)	(0.642)	(0.706)	(0.698)	(0.36)	(0.68)
PCP FE	Y	Y	Y	Y	Y	Y
Number of PCPs	361,642	12,883	29,567	98,946	169,859	50,387
Observations	2,169,852	77,298	177,402	593,676	1,019,154	302,322

Notes:

Standard errors in parentheses. Clustered at the physician level.

*Significantly different from 0 at the 10% level ** 5% *** 1%

Groups defined by the average share of referrals to ACO providers in the years prior to ACO formation:

Group 3 >67% | 67%> Group 2 > 29% | 29% > Group 1 > 0% | Group 0 =0% | Group Null – No referrals to Specialists in the pre-period

Table 33: Total Referrals from non-ACO PCPs to Specialists: By Years Since ACO Formation and Pre-formation Referral Group

	Overall	Group 3 High ACO Share	Group 2 Medium ACO Share	Group 1 Low ACO Share	Group 0 No ACO Refs	Group Null No Refs
4 yrs prior	-8.45 ***	-4.33	7.30 *	-2.83	-9.32 ***	
	(1.052)	(3.276)	(3.991)	(2.839)	(0.966)	
3 yrs prior	-5.19 ***	-2.73	7.42 ***	-0.51	-7.27 ***	
	(0.677)	(2.254)	(2.634)	(1.824)	(0.645)	
2 yrs prior	-3.22 ***	-2.54 **	2.96 **	-3.57 ***	-4.77 ***	
	(0.382)	(1.257)	(1.445)	(1.03)	(0.361)	
1 yr prior						
ACO Formed	-1.77 ***	-1.08	-13.27 ***	-15.50 ***	3.77 ***	24.70 ***
	(0.363)	(1.395)	(1.397)	(0.863)	(0.432)	(0.484)
1 yr post	-6.56 ***	-7.84 ***	-33.44 ***	-45.45 ***	1.31	104.80 ***
	(0.682)	(2.587)	(2.518)	(1.553)	(0.818)	(1.45)
2 yrs post	-10.72 ***	-14.39 ***	-50.64 ***	-72.39 ***	-1.31	174.00 ***
	(1.006)	(3.78)	(3.538)	(2.245)	(1.235)	(2.391)
3 yrs post	-14.07 ***	-22.47 ***	-69.02 ***	-100.10 ***	-6.82 ***	280.20 ***
	(1.329)	(4.892)	(4.517)	(2.894)	(1.583)	(3.904)
Prior Yr Mean	304.90 ***	154.80 ***	367.60 ***	547.90 ***	210.80 ***	0.00
	(0.319)	(1.179)	(1.097)	(0.749)	(0.369)	(0.722)
PCP FE	Y	Y	Y	Y	Y	Y
Number of PCPs	361,642	12,883	29,567	98,946	169,859	50,387
Observations	2,169,852	77,298	177,402	593,676	1,019,154	302,322

Notes:

Standard errors in parentheses. Clustered at the physician level.

*Significantly different from 0 at the 10% level ** 5% *** 1%

Groups defined by the average share of referrals to ACO providers in the years prior to ACO formation:

Group 3 >67% | 67%> Group 2 > 29% | 29% > Group 1 > 0% | Group 0 =0% | Group Null – No referrals to Specialists in the pre-period

Table 34: Referrals from non-ACO PCPs to ACO Specialists as a Share of Total Referrals: By Years Since ACO Formation and Pre-formation Referral Group

Dependent Variable: Referrals to ACO Specialists as a share of Total Referrals from Non-ACO PCPs

	Overall	**Group 3** High ACO Share	**Group 2** Medium ACO Share	**Group 1** Low ACO Share	**Group 0** No ACO Refs	**Group Null** No Refs
4 yrs prior	0.3% ***	2.3% ***	0.1%	0.9% ***	-0.1%	
	(0.05%)	(0.60%)	(0.33%)	(0.08%)	(0.01%)	
3 yrs prior	0.3% ***	2.7% ***	0.6% ***	0.4% ***	-0.1%	
	(0.03%)	(0.39%)	(0.22%)	(0.05%)	(0.01%)	
2 yrs prior	0.1% ***	1.2% ***	0.4% ***	0.1% ***	0.0%	
	(0.02%)	(0.23%)	(0.12%)	(0.03%)	(0.00%)	
1 yr prior						
ACO Formed	-0.3% ***	-5.5% ***	-1.8% ***	-0.1% ***	0.3% ***	0.0%
	(0.02%)	(0.25%)	(0.12%)	(0.03%)	(0.01%)	(0.00%)
1 yr post	-0.6% ***	-13.5% ***	-4.3% ***	-0.2% ***	0.7% ***	-0.2%
	(0.03%)	(0.45%)	(0.19%)	(0.05%)	(0.02%)	(0.17%)
2 yrs post	-0.9% ***	-21.0% ***	-6.1% ***	-0.6% ***	1.1% ***	-0.3%
	(0.04%)	(0.67%)	(0.27%)	(0.07%)	(0.03%)	(0.32%)
3 yrs post	-1.2% ***	-28.5% ***	-8.2% ***	-0.8% ***	1.4% ***	-0.2%
	(0.06%)	(0.92%)	(0.35%)	(0.08%)	(0.04%)	(0.48%)
Prior Yr Mean	10.2% ***	82.5% ***	44.9% ***	8.6% ***	0.0% **	8.8% ***
	(0.02%)	(0.20%)	(0.09%)	(0.02%)	(0.01%)	(0.26%)
PCP FE	Y	Y	Y	Y	Y	Y
Number of PCPs	361,642	12,883	29,567	98,946	169,859	50,387
Observations	1,665,970	52,853	151,550	544,577	818,611	98,379

Notes:

Standard errors in parentheses. Clustered at the physician level.

*Significantly different from 0 at the 10% level ** 5% *** 1%

Groups defined by the average share of referrals to ACO providers in the years prior to ACO formation:

Group 3 >67% | 67%> Group 2 > 29% | 29% > Group 1 > 0% | Group 0 =0% | Group Null – No referrals to Specialists in the pre-period

Figures

Figure 13: Analysis Combinations

		to Specialists			
		Non-ACO	In ACO	In Other ACOs	Total
from PCPs	Non-ACO	A	C		G
	In ACO	B	D	F	H

The above table shows the different combinations of referring PCP, receiving specialists that are analyzed. The colors of the cells are what is used in the figures below.

Figure 14: Share of Referrals sent to the PCPs ACO, vs share sent to another ACO: By Pre-formation Referral

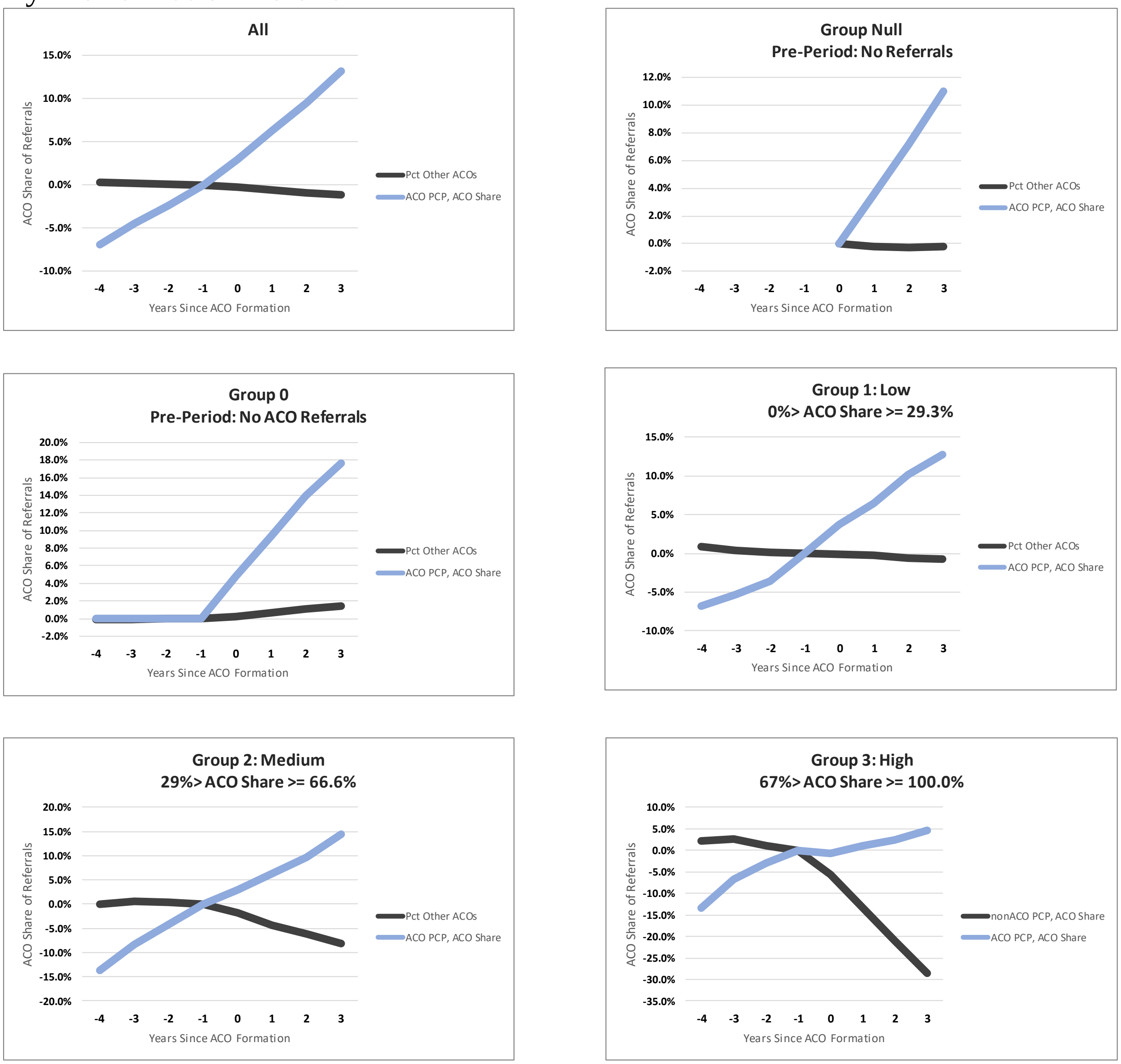
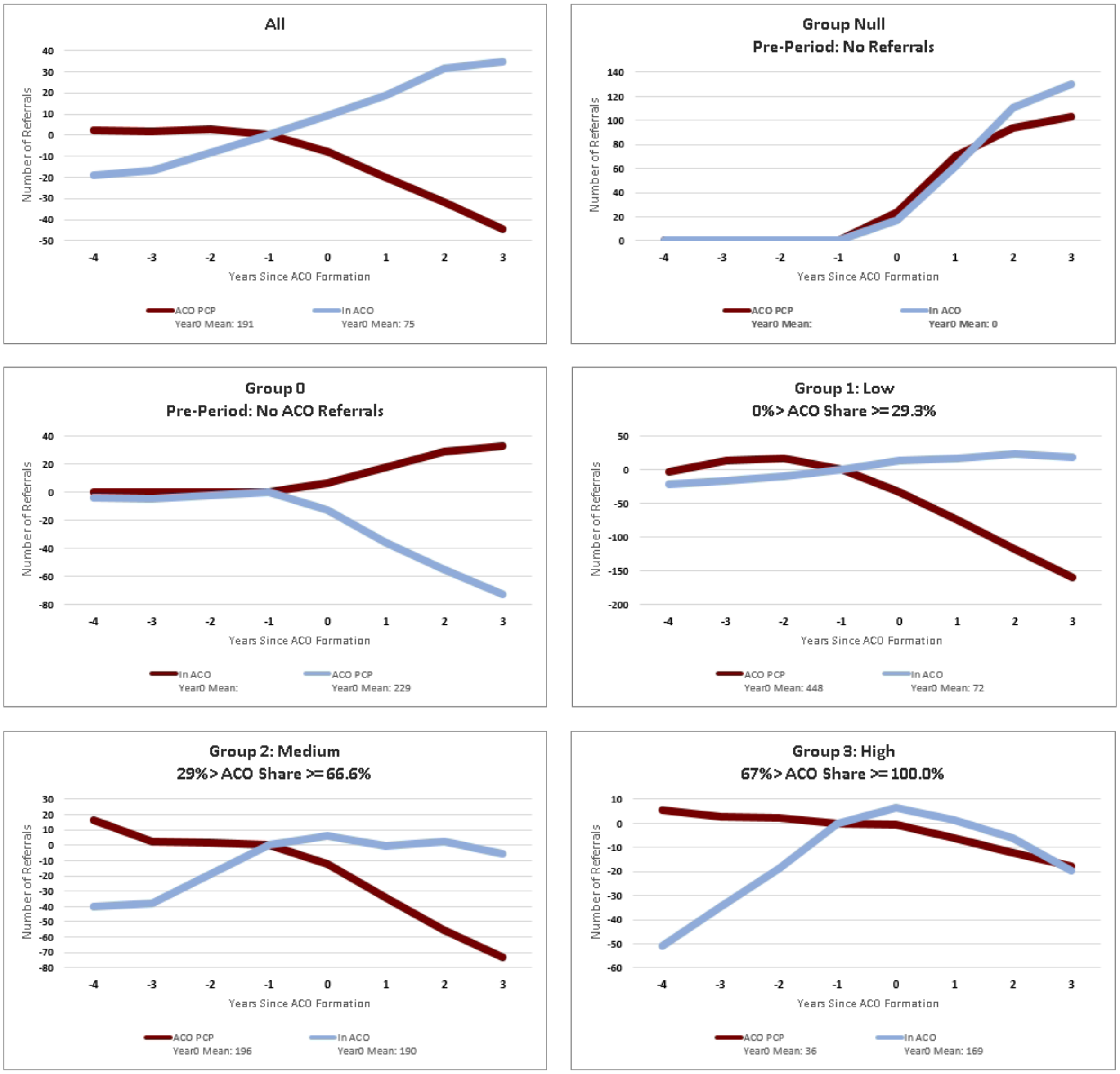
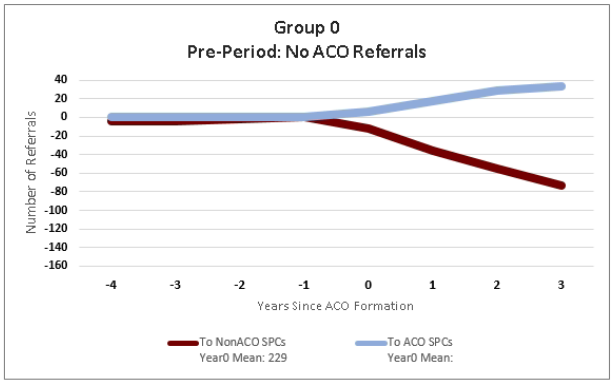
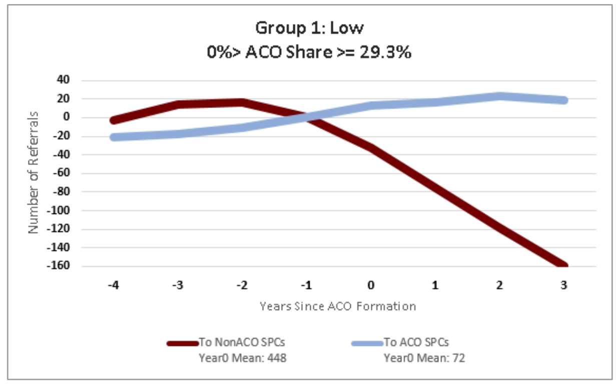
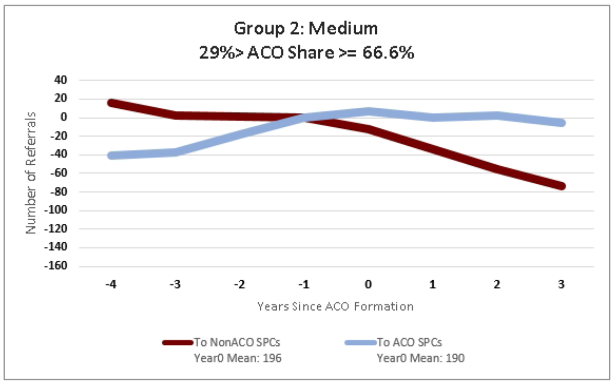


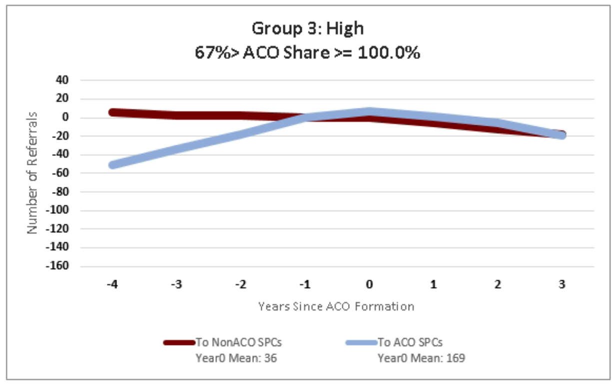
Figure 15: Number of referrals from ACO PCPs: to ACO Specialists vs non-ACO specialists

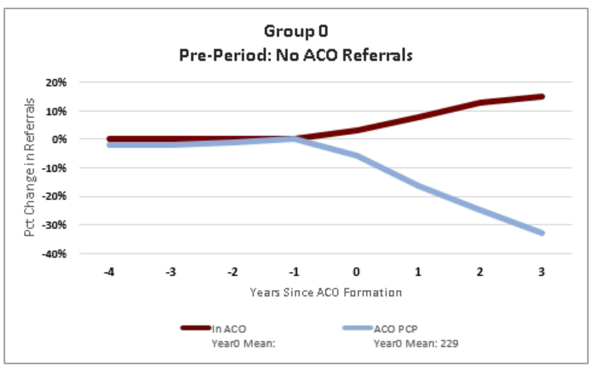


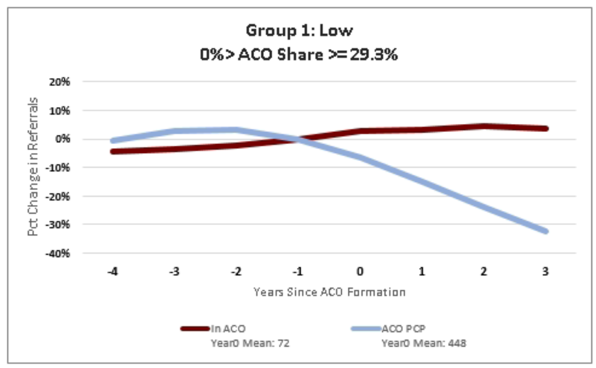

Group 0
Pre-Period: No ACO Referrals
Number of Referrals
Years Since ACO Formation
To NonACO SPCs
Year0 Mean: 229
To ACO SPCs
Year0 Mean:

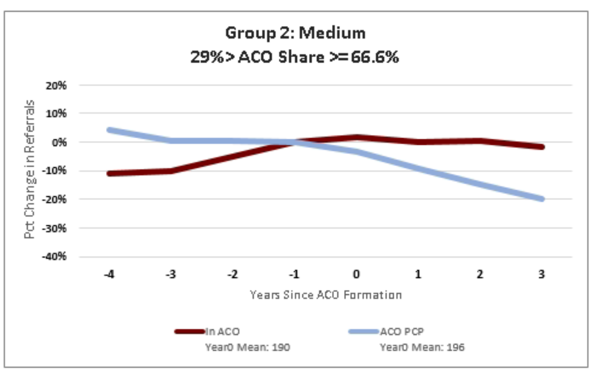

Group 1: Low
0%> ACO Share >= 29.3%
Number of Referrals
Years Since ACO Formation
To NonACO SPCs
Year0 Mean: 448
To ACO SPCs
Year0 Mean: 72

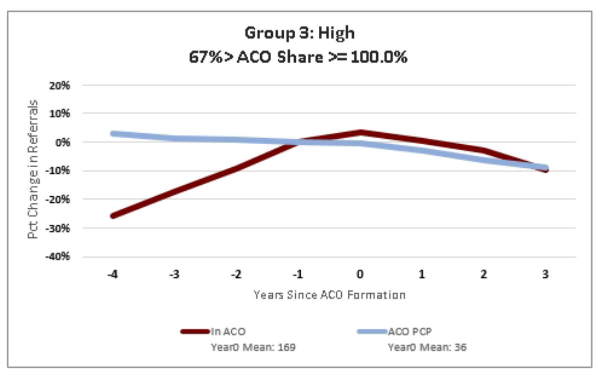

Group 2: Medium
29%> ACO Share >= 66.6%
Number of Referrals
Years Since ACO Formation
To NonACO SPCs
Year0 Mean: 196
To ACO SPCs
Year0 Mean: 190

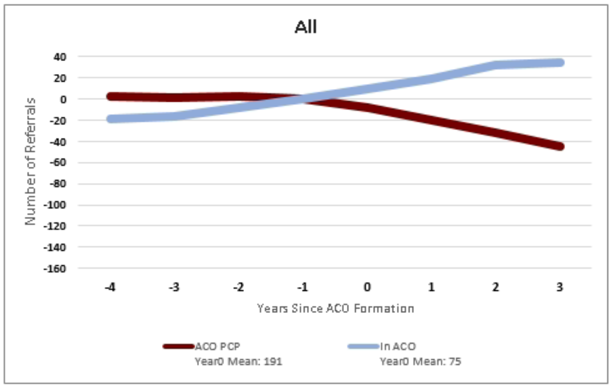

Group 3: High
67%> ACO Share >= 100.0%
Number of Referrals
Years Since ACO Formation
To NonACO SPCs
Year0 Mean: 36
To ACO SPCs
Year0 Mean: 169


Group 0
Pre-Period: No ACO Referrals
Pct Change in Referrals
Years Since ACO Formation
In ACO
Year0 Mean:
ACO PCP
Year0 Mean: 229


Group 1: Low
0%> ACO Share >= 29.3%
Pct Change in Referrals
Years Since ACO Formation
In ACO
Year0 Mean: 72
ACO PCP
Year0 Mean: 448


Group 2: Medium
29%> ACO Share >= 66.6%
Pct Change in Referrals
Years Since ACO Formation
In ACO
Year0 Mean: 190
ACO PCP
Year0 Mean: 196


Group 3: High
67%> ACO Share >= 100.0%
Pct Change in Referrals
Years Since ACO Formation
In ACO
Year0 Mean: 169
ACO PCP
Year0 Mean: 36


All
40
20
0
-20
-40
-60
-80
-100
-120
-140
-160
Number of Referrals
-4
-3
-2
-1
0
1
2
3
Years Since ACO Formation
ACO PCP
Year0 Mean: 191
In ACO
Year0 Mean: 75

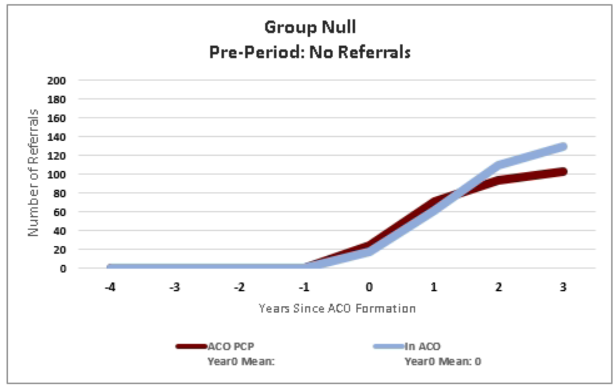
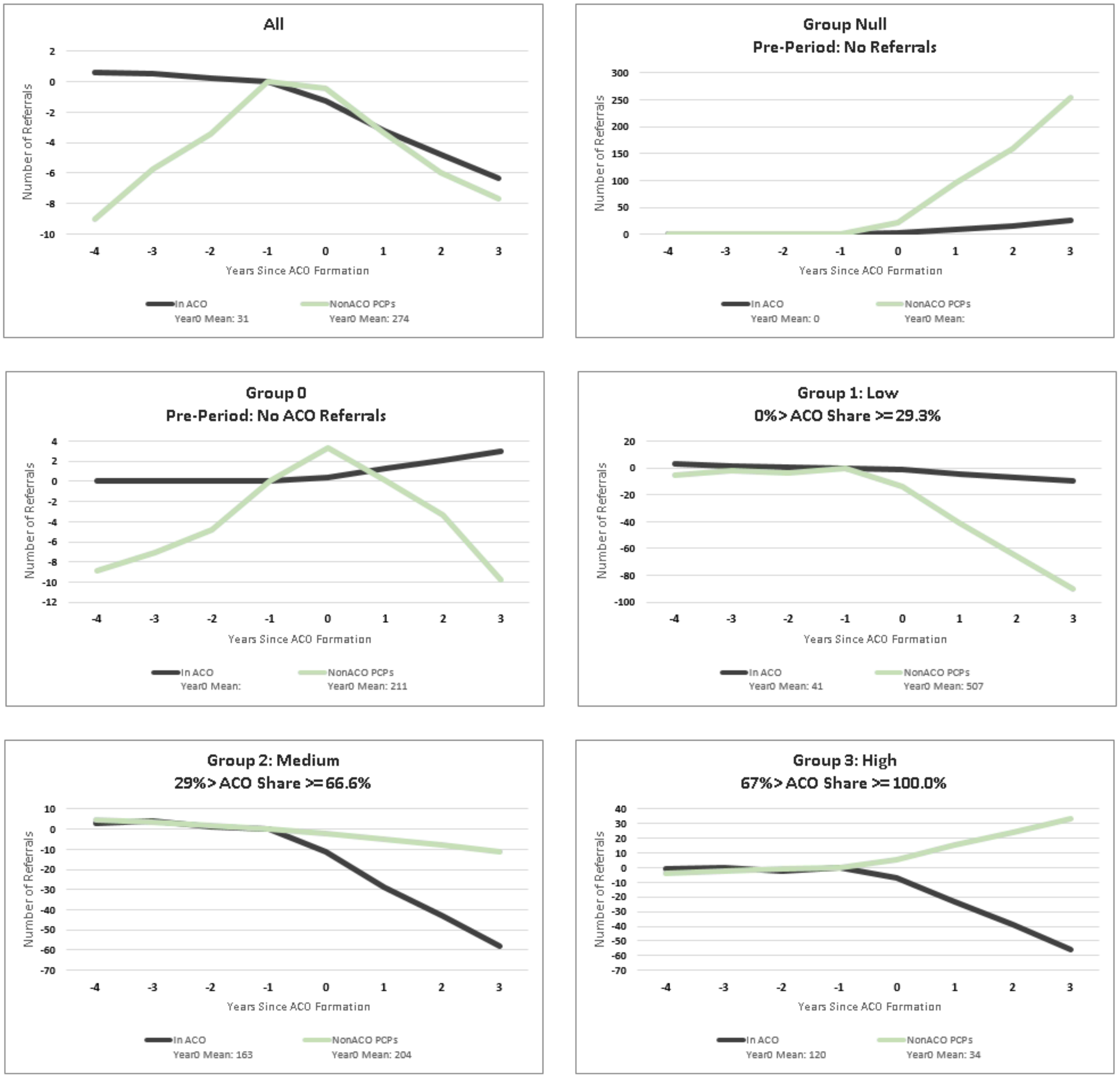
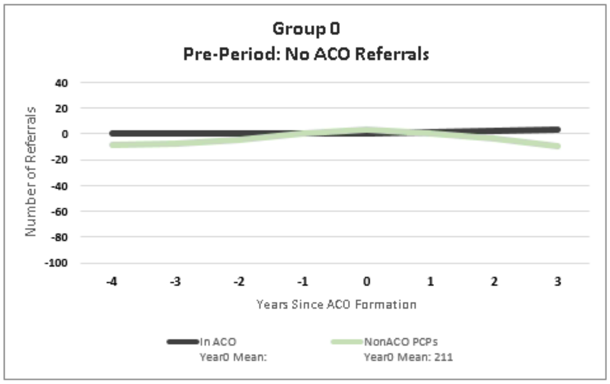
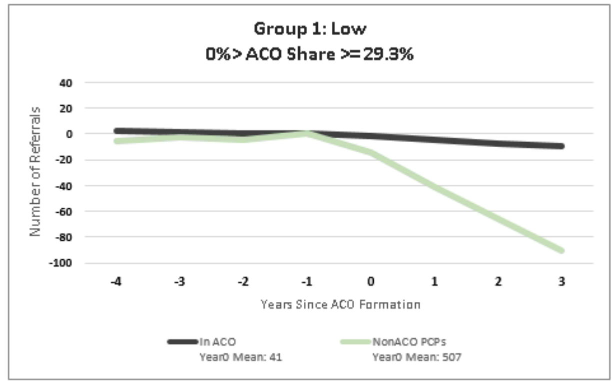

Group Null
Pre-Period: No Referrals
200
180
160
140
120
100
80
60
40
20
0
Number of Referrals
-4
-3
-2
-1
0
1
2
3
Years Since ACO Formation
ACO PCP
Year0 Mean:
In ACO
Year0 Mean: 0

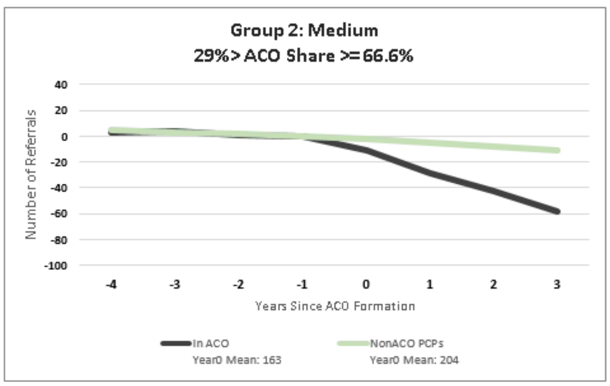
Figure 16: From non-ACO PCPs

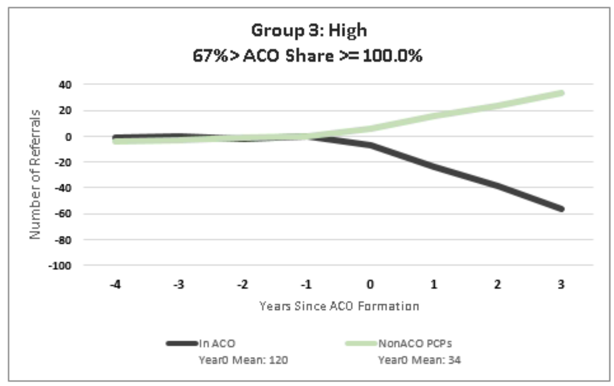


Below are figures with the same data, only with constant axes to better show the relative size of the impacts.

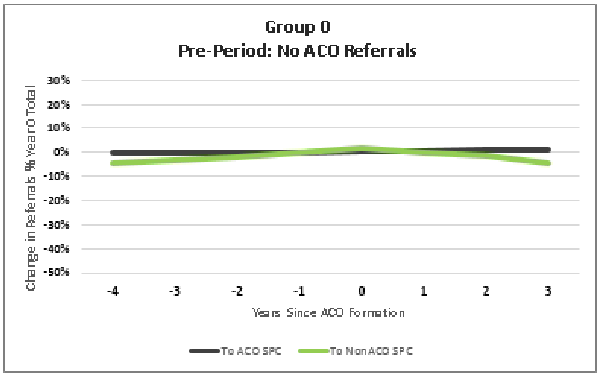


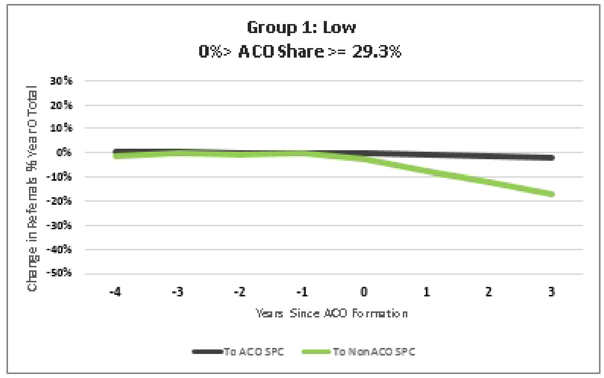


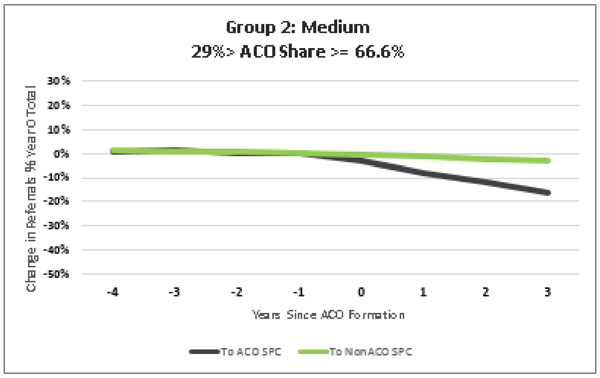




Finally, the same figures with constant axes expressed as a share of the year 0 total.







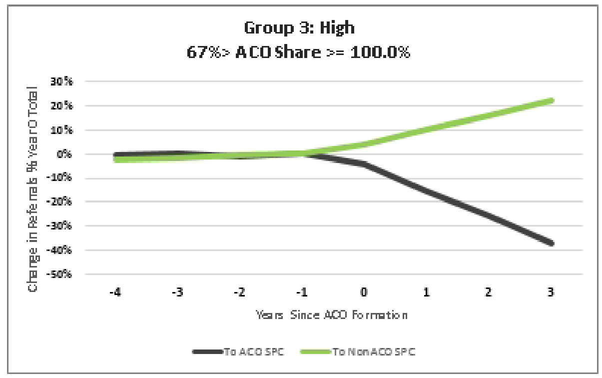
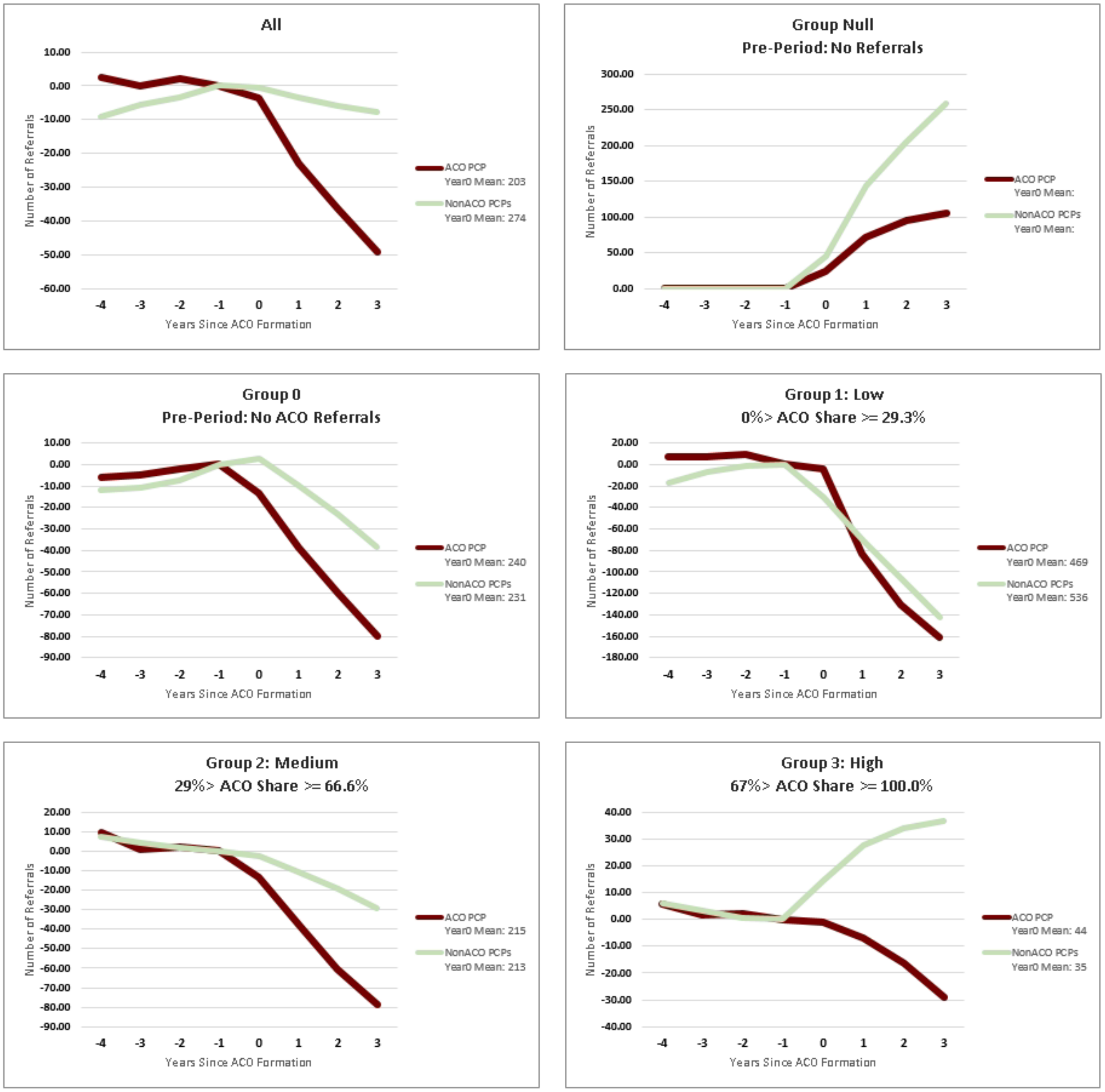


Figure 17: Number of Referrals to Non-ACO Specialists. ACO PCPs vs Non-ACO PCPs



Below are figures with the same data, only with constant axes to better show the relative size of the impacts.

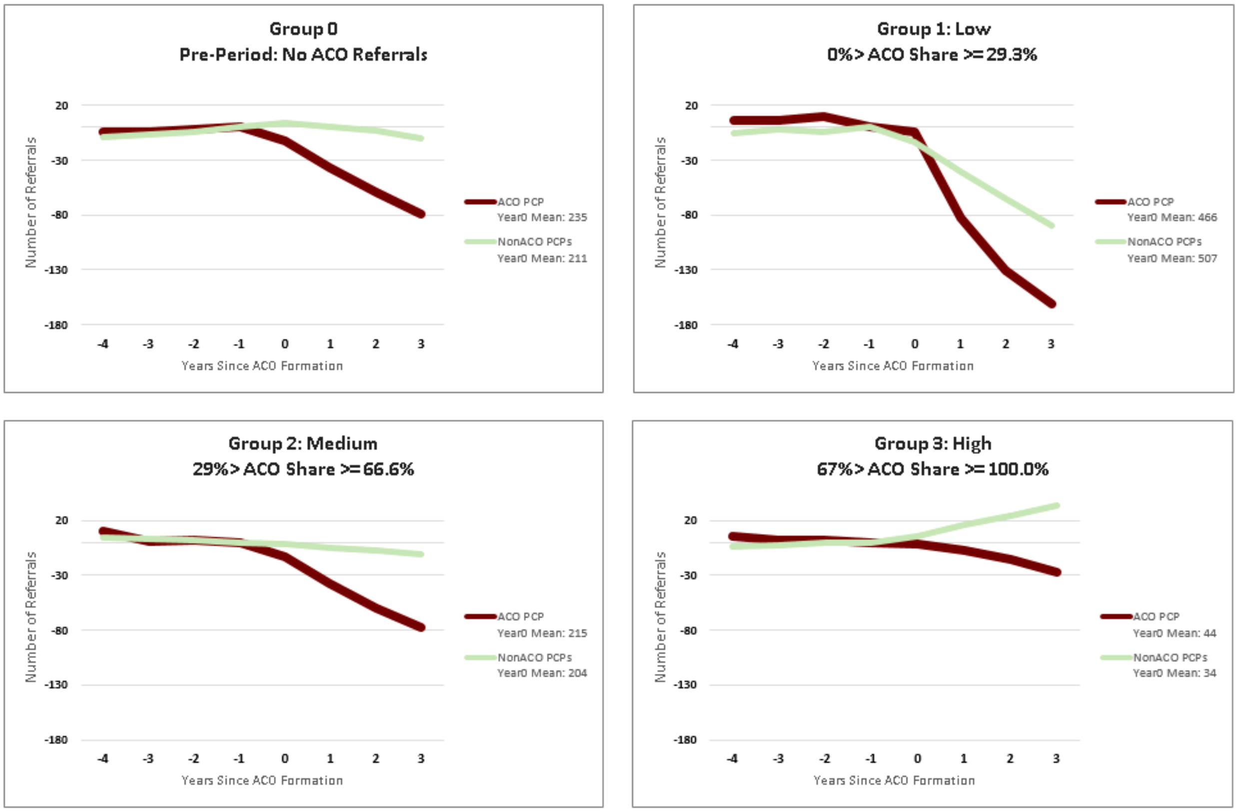


Figure 18: Total Number of Referrals. ACO PCPs vs Non-ACO PCPs

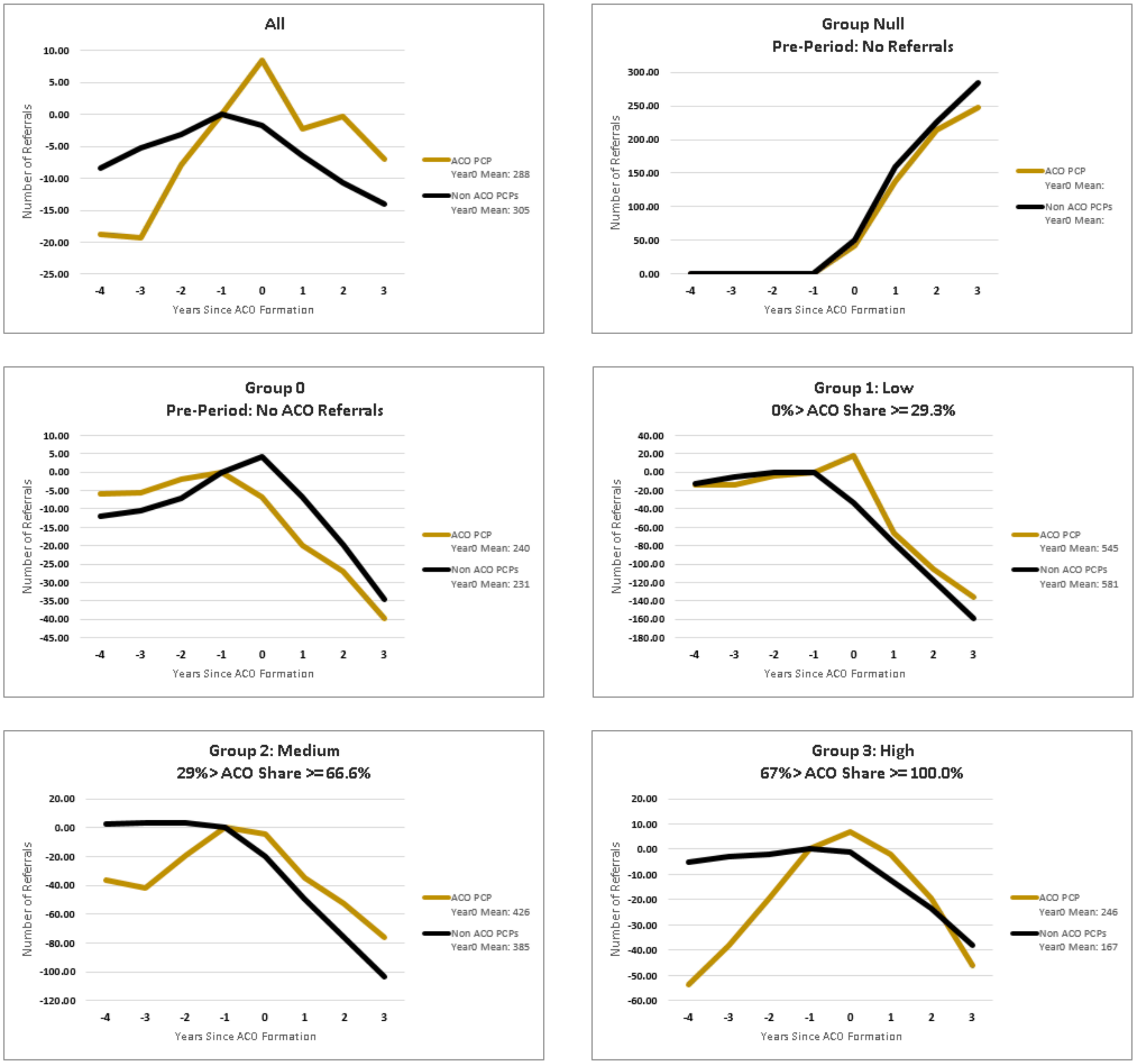


Figure 19: Share of Referrals from ACO PCPs to specialists in the same-ACO vs specialists in another ACO

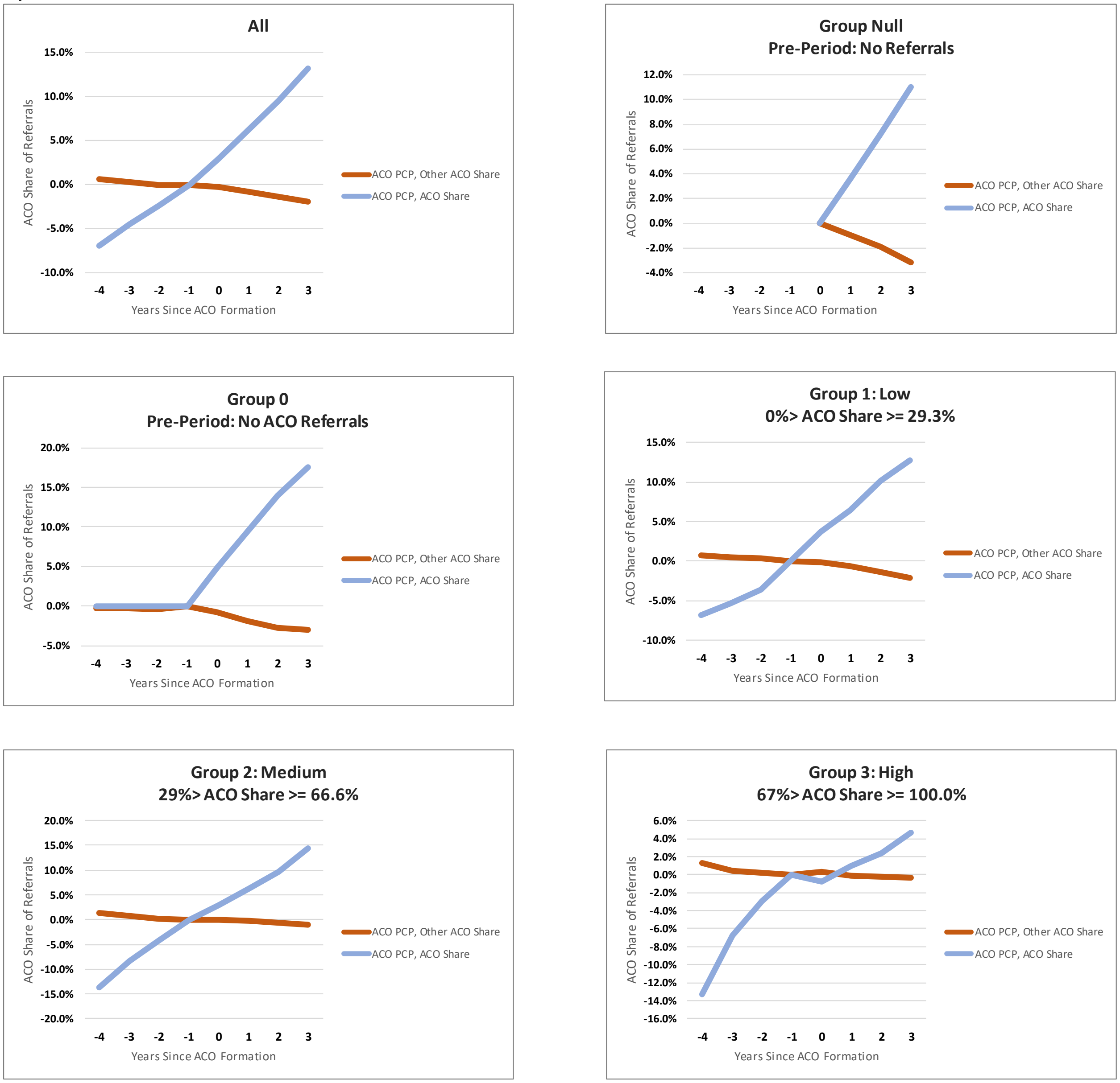


Figure 20: Referrals – difference from assumed attrition rate