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ON HEALTHCARE COORDINATION AND UTILIZATION

Leila Agha
Keith Marzilli Ericson
Xiaoxi Zhao

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ABSTRACT

Patients often receive healthcare from providers spread across different firms. Transaction costs, imperfect information, and other frictions can make it difficult to coordinate production across firm boundaries, but we do not know how these challenges affect healthcare. We define and measure organizational concentration: the distribution across organizations of a patient's healthcare. Medicare claims show that organizational concentration varies substantially across physicians and regions, and that patients who move to more concentrated regions have lower healthcare utilization. Further, we show that when primary care physicians (PCPs) with higher organizational concentration exit the local market, their patients switch to more typical PCPs with lower organizational concentration and then have higher healthcare utilization. Patients who switch to a PCP with 1 SD higher organizational concentration have 10% lower healthcare utilization. This finding is robust to controlling for the spread of patient care across providers. Increases in organizational concentration have no detectable effect on emergency department utilization or hospitalization rates, but do predict improvements in diabetes care.

Leila Agha
Department of Economics
Dartmouth College
6106 Rockefeller Hall
Hanover, NH 03755
and NBER
leila.gha@dartmouth.edu

Xiaoxi Zhao
Boston University
xiaoxiz@bu.edu

Keith Marzilli Ericson
Boston University Questrom School of Business
595 Commonwealth Avenue
Boston, MA 02215
and NBER
kericson@bu.edu

Introduction

Transaction costs and imperfect information can make it difficult to coordinate production across firm boundaries (Coase 1937; Williamson 1985). The determinants of firm boundaries have been the subject of substantial theoretical and empirical investigation, particularly in the literature on vertical integration (Lafontaine and Slade 2007). Yet, we know less about how firm boundaries affect the firm performance (Mullainathan and Scharfstein 2001). and empirical studies from different industries find mixed results.¹

In healthcare, the challenges of cross-firm coordination are particularly salient; patient care is often produced with the input of many healthcare providers working in separate organizations. Geographically and over time, there is substantial variation in the organizational structures those providers operate in. An increasing fraction of US physicians is employed by large practices or hospitals (Welch et al. 2013), which may mitigate these coordination challenges. Integrated care organizations such as the Mayo Clinic, Intermountain Healthcare, and Kaiser Permanente are often held up as models of clinical efficiency and coordinated care (Enthoven 2009). Yet empirical evidence on how organizational boundaries affect healthcare productivity is limited.

In this paper, we investigate how organizational boundaries affect healthcare utilization. Existing evidence has shown that when coordination of care is more difficult, healthcare utilization tends to be higher. These coordination challenges can emerge when healthcare for an individual patient is spread across many individual providers (Agha et al. 2019; Frandsen et al. 2015), or when provider teams have fewer repeat interactions (Agha et al. 2018; Kim et al. 2020; Chen 2020). Cebul et al. (2008) argue that fragmentation across *organizations* may also be an important source of healthcare inefficiency. Organizational boundaries can affect the coordination costs; e.g., healthcare firms often restrict information transmission to external providers by limiting transfer across electronic medical record systems. Providers may invest in firm-specific relationships and infrastructure that improve productivity (Huckman and Pisano 2006). Finally, organizational fragmentation can affect incentives for clinical process improvement and other efficiency-enhancing investments due to common agency problems and spillovers that prevent firms from reaping the full benefit of their investments (Frandsen et al. 2019).

We introduce the concept of “organizational concentration,” which measures the distribution of a patient’s outpatient visits across organizations. A patient’s healthcare has maximal organizational concentration if all of their outpatient care is billed by the same organization.

¹For example, see Seru (2014); Pierce (2012); Stroebel (2016); Forbes and Lederman (2010); Forman and Gron (2011).

This construct builds on earlier work studying provider concentration (Pollack et al. 2016; Agha et al. 2019). Organizational concentration describes the realized experience of a given patient, and so is distinct from market concentration measures used in antitrust research, which instead measure provider market power for pricing. Patients who receive all their healthcare from one firm will have high organizational concentration even if there are many firms in the market. Conversely, a patient may have low organizational concentration in a highly concentrated market if they receive healthcare from many different specialty practices, even if each practice has a monopoly in that specialty.

To our knowledge, we are the first paper to measure organizational concentration systematically, so we begin with a detailed descriptive analysis. Using a 20% sample of insurance claims for Medicare fee-for-service enrollees from 2007-2016, we construct a measure of each patient’s experienced organizational concentration. There is substantial heterogeneity across regions in organizational concentration, even conditional on the spread of patient care across providers. Studying patients who move across regions, we find that moving to a location with a higher level of organizational concentration is associated with lower healthcare utilization. While these results suggest that organizational concentration leads to lower healthcare spending, they should be interpreted with caution because other attributes of regional practice style and place effects may be correlated with the level of organizational concentration.

To isolate variation in organizational concentration from other aspects of the local practice environment, we exploit quasi-experimental variation in patient assignment to physicians generated by physician exits. We examine the experiences of patients whose primary care provider (PCP) exits the local market, either due to a move or retirement, following recent work by Fadlon and Van Parys (2020) and Kwok (2019). Since patients may endogenously sort to new PCPs on the basis of changes in their health status, we use an instrumental variable strategy that leverages mean reversion to predict the change in a patient’s assigned PCP’s average organizational concentration, adapting the approach used by Laird and Nielsen (2017) and Abaluck et al. (2020). When PCPs with low organizational concentration exit the market, their patients switch to more typical PCPs with higher average concentration and subsequently experience lower healthcare utilization. Using this variation, we estimate that patients who switch to a PCP with 1 SD higher organizational concentration have 10% lower healthcare utilization in our preferred, most controlled specification. This finding is robust to controlling for the number and types of providers that the patient visits.

Our results indicate that organizational boundaries contribute additional frictions that lower the efficiency of healthcare provision, and this pattern does not simply reflect the challenges of spreading care across multiple providers. Although we cannot fully isolate

a PCP’s tendency for organizational concentration from every other possible dimension of PCP practice style, our estimated effect remains large in specifications that control for the spread of patient care across providers, the size of the PCP’s practice group, as well as other PCP characteristics (residency training, experience, gender). To the extent that observable variables are informative about selection on unobservables, this supports the claim that organizational concentration is an important independent contributor to spending variation (Oster 2019).

Finally, we investigate how organizational concentration influences quality of care. We use several measures related to distinct dimensions of healthcare quality, spanning gaps in primary care, appropriate management of chronic conditions, and repeated testing. We find no strong evidence that changes in PCP organizational concentration predict changes in inpatient or emergency department visits, or labs. However, for patients with a chronic condition (diabetes), switching to a PCP with higher levels of organizational concentration leads to better adherence to recommended care guidelines. This finding from diabetes care provides suggestive evidence that greater organizational concentration may facilitate improved management of chronic conditions. We also find suggestive evidence that spending higher organizational concentration reduces claims for diagnostic imaging.

High levels of organizational concentration arise when most of the providers a patient consults are integrated within the same firm. Our research is motivated by earlier work finding the effects of firm integration on productive efficiency are theoretically ambiguous. Bringing transactions into the same firm could improve communication (Arrow 1975) and reduce contracting barriers (Hart and Moore 1990; Hart and Holmstrom 2010). On the other hand, integration may also lead resources within the firm to be allocated less efficiently (Alonso et al. 2008; Friebel and Raith 2010). Moreover, integration may improve coordination in stable environments but lead to worse adaptation to change (Dessein 2014).

Empirical evidence from other industries on how integration affects firm performance has found mixed results. Mullainathan and Scharfstein (2001), Seru (2014), and Pierce (2012) document downsides to integration including less efficient capacity management, lower innovation, and insufficient knowledge sharing. By contrast, Stroebel (2016), Forbes and Lederman (2010), Forman and Gron (2011) find benefits of firm integration including superior information, better performance, and faster technology adoption. Atalay et al. (2014) argue that integration facilitates the efficient intrafirm transfer of intangible inputs, such as high quality managerial oversight and planning. We build on this literature by studying how firm boundaries affect health care delivery, a setting where the potential benefits of improved coordination, knowledge-sharing, and management are high, and rich insurance claims data allows us to track the production process.

Within healthcare, there is limited evidence on how the integration of healthcare providers affects care delivery. Although large consolidated practice groups argue they can deliver lower cost, higher quality healthcare through improved coordination, leveraging returns to specialization, and facilitating fixed cost investments, empirical evidence of these benefits is limited (Cutler and Scott Morton 2013). Recent work suggests that hospital mergers and acquisitions of physician practices do not spur improvements in clinical quality or health outcomes (Beaulieu et al. 2020; Koch et al. 2018).² We build on this research by studying changes in the extent to which individual patient care crosses firm boundaries, rather than focusing on short-run effects of mergers and acquisitions. Care coordination depends on the ease of communication across multiple providers who treat the same patient, but mergers may simply bring competing providers—who rarely would have treated the same patient—into the same firm. Further, the process of organizational transformation is often slow. Because this paper does not focus on short-run effects of mergers, the effects we study may reflect longer-run operational changes associated with integration.

This paper is also related to a growing literature investigating differences in practice patterns across individual physicians. Across a variety of care contexts, individual physician quality and practice style have important effects on care outcomes.³ Recent work by Kwok (2019) and Fadlon and Van Parys (2020) documents that primary care physicians in particular have substantial influence on patients’ healthcare spending. We build on this insight by investigating one important dimension of PCP practice environment and referral patterns, i.e. the PCP’s tendency to concentrate patient care within organizations.

The paper is organized as follows. Section 1 introduces our measure of organizational concentration. Section 2 describes our data and sample selection. Section 3 reports descriptive statistics on regional variation in organizational concentration and uses movers between regions to explore how regional variation in organizational concentration may contribute to regional variation in healthcare utilization. Section 4 lays out our main empirical strategy exploiting PCP exits to explore the impact of organizational concentration. Section 5 presents the results on how healthcare utilization and quality outcomes change when a patient switches to a PCP with a different level of organizational concentration. Section 6 concludes.

²These acquisitions may even raise healthcare spending, as physicians shift the site of care from doctors’ offices to hospital outpatient settings (Koch et al. 2017) and exploit reimbursement rules that allow hospital-owned physician practices to charge additional facility fees (Capps et al. 2018).

³For example, see Gowrisankaran et al. (2017); Molitor (2018); Chan et al. (2019); Currie and MacLeod (2017); Currie et al. (2016); Sahni et al. (2016).

1 Defining Organizational Concentration

In this project, we study the coordination frictions that arise when healthcare is spread across organizational boundaries. To do so, we define *organizational concentration*, adapting a concentration index that has been used in prior literature to measure the spread of patient care across providers.⁴ Specifically, we use a Herfindahl–Hirschman Index (HHI) that calculates how outpatient healthcare received by a patient is spread across organizations. We measure organizational concentration using outpatient care, following previous literature defining continuity of outpatient care across individual physicians (Nyweide and Bynum 2017; Nyweide et al. 2013). This allows us to consider the impact of outpatient organizational concentration on the likelihood that a patient requires an emergency department visit or hospitalization.

We calculate patient i 's share of outpatient visits at each organization j , in a year t . Organizational concentration is then defined as the sum of squared shares across all the organizations:

$$OrgConc_{it} = \sum_j share_{ijt}^2. \quad (1)$$

In general, organizational concentration is higher when a patient visits fewer organizations. When a patient's outpatient visits are uniformly distributed across N organizations, this measure is simply $1/N$. When a patient receives all the visits from one organization, this concentration measure will be 1. Lower values correspond to patient care that is spread more diffusely across organizations.

For some analyses, we aggregate organizational concentration up to at the hospital referral region (HRR) level. In our primary empirical strategy, we aggregate organizational concentration up to the PCP level.

Defining provider concentration

To distinguish our findings from prior analyses, we study variation in organizational concentration conditional on provider concentration: the spread of patient healthcare across providers. Following Agha et al. (2019), we construct a measure of provider care concentration where the $share_{ipt}$ measures the share of patient i 's outpatient visits in year t for each provider p :

$$ProviderConc_{it} = \sum_p share_{ipt}^2. \quad (2)$$

⁴Pollack et al. (2016) provides an overview and comparison of commonly used measures of care continuity.

This measure will capture the challenges of coordinating healthcare across many providers, thus allowing us to distinguish them from the frictions that are specific to crossing organizational boundaries.

2 Data and Sample Construction

2.1 Patient sample selection

Our primary source of data is a 20% sample of Medicare Fee-For-Service (FFS) Part A and Part B claims data from 2007-2016. The 10-year panel data allows us to observe both patient moves and PCP exits. We use the Carrier, Inpatient, and Outpatient claims files to measure care utilization and spending.⁵ Patient demographics (age, sex, zip code) and chronic conditions are extracted from the Master Beneficiary Summary file with the Chronic Condition segment. In the remainder of this section, we describe the sample restrictions implemented to construct our main analytic samples.

Initial sample restrictions

We restrict our sample to Medicare beneficiaries who are 66–99 years old (inclusive) and continuously enrolled in Medicare FFS. After these restrictions, our data covers 9,356,144 beneficiaries. Our organizational concentration measure is defined based on outpatient site of care visits billed in the Carrier claims files, so we drop 223,822 beneficiaries who did not have any visits of this type. This comprises our Broad Sample. From this broad sample, we define two separate analytic samples for different purposes. First, we define a “Patient Mover Sample” for a descriptive analysis studying regional variation in organizational concentration. Second, we define a “PCP Exit Sample” for our primary analysis studying the relationship between PCPs’ organizational concentration and patient care utilization. We describe each of these samples below.

Patient Mover Sample

We construct a Patient Mover Sample for our initial descriptive analysis. Sample restrictions defined here follow the construction process outlined in Agha et al. (2019). We assigned each patient to a hospital referral region (HRR) on an annual basis, using the zip code reported in

⁵The Inpatient file contains institutional inpatient claims, and the Outpatient file contains claims from institutional outpatient providers such as hospital outpatient departments or community mental health centers. The Carrier file contains non-institutional claims billed by individual providers such as physicians, and these claims can result from services provided at either outpatient or inpatient settings.

the Beneficiary Summary File. Further, we require that the patient received at least 75% of billed claims within that HRR; we drop beneficiaries who do not meet this requirement. To be included as a mover, the patient’s HRR must have changed once (and only once) in our 10-year period. Further, the beneficiary must be continuously in the sample from two years before their move to two years after. Our sample includes all moving patients who meet these criteria as well as a 25% random sample of non-movers (whose HRR never changed during this time period); non-movers contribute toward covariate identification. The final Patient Mover Sample includes 25,592 mover beneficiaries and 1,364,198 non-mover beneficiaries.

PCP Exit Sample

Next, we construct our PCP Exit Sample for our main analysis. This analysis focuses on beneficiaries who change their attributed PCP due to the original PCP’s relocation or retirement. We use provider taxonomies to distinguish primary care specialties from other types of providers. The provider taxonomy codes used for this categorization are reported in Table A1 and include codes for internal medicine, family medicine, pediatrics, geriatrics, and general practice. Provider taxonomy codes are the primary specialty code from the National Plan and Provider Enumeration System (NPPES), which is linked to our sample by providers’ National Provider Identifier (NPI). We attribute each patient to their plurality PCP in each year, defined as the provider who bills a plurality of the patient’s Evaluation & Management (E&M) visits that year; ties are broken randomly. We exclude patients who have no E&M visits and thus cannot be matched to a provider, as well as patients whose plurality provider does not report a primary care specialty. If a patient cannot be matched to a PCP according to this algorithm, they will be excluded from the PCP Exit Sample.

We limit this analysis to patients whose initial attributed PCP either moved (i.e. relocated once to a different HRR) or retired (i.e. bills no further Medicare claims). We also exclude patients who move across HRRs themselves or who have ever changed their PCP in our sample period prior to the exit of their assigned original PCPs. The PCP Exit Sample includes 62,924 beneficiaries and 335,868 beneficiary-year observations. These patients are initially attributed to one of 4365 relocating PCPs or 11,437 retiring PCPs; including both the exiting PCPs and the destination PCPs, this sample covers 52,981 PCPs.

2.2 Measuring organizational concentration

Measuring Organizations

The next step is to construct our measure of organizational concentration. We begin by identifying provider organizations delivering outpatient care to each patient. We limit to

provider services billed in the Carrier claims file and provided in an outpatient setting. The outpatient setting is identified using the place of service code listed on the Carrier file claims; a complete list of places of service codes is in Appendix Table A2. We then define a visit by aggregating claims to a unique provider-date pair. About 85% of visits measured in the Carrier claim file are classified as outpatient visits.

We use the federal tax ID numbers (TINs) associated with each Carrier file claim to identify provider organizations. Our sample covers 447,009 TINs. TINs provide a measure of financial organization, with integrated physician practices typically billing under a unique TIN, although some large provider groups may organize themselves into subsidiaries, billing under separate TINs (Baker et al. 2016). In these cases, TINs may still delineate organizational boundaries within the firm, even though they are not a perfect measure of firm boundaries.

We calculate organizational concentration at the patient-year level following the definition in equation 1 and the descriptions in Section 1. To construct these regional and shrunk PCP-level averages, we include our full initial sample of Medicare beneficiaries before implementing any of the specialized restrictions for the Mover or PCP Exit analysis samples.

We find that our baseline TIN-based measure of organizational concentration is highly correlated with an alternative definition based on physicians' reported organizational ties in the CMS Physician Compare database. Physician Compare data is only available for the final three years of our sample (2014-2016), so we cannot use it as our baseline analysis which tracks organizational concentration over a longer time period. In years where both measures are available, we use the affiliations reported in Physician Compare to construct an alternative measure of organizational ties, and compare this to our baseline TIN-based definition. The organizational concentration measures are correlated at 0.95 when averaged at the HRR level, and are correlated at 0.85 when averaged at the PCP level (prior to any shrinkage).

Earlier work by Baker et al. (2014), Austin and Baker (2015) and Baker et al. (2020) has also used TINs to measure local competition across physician provider groups. This research has shown that areas with higher market concentration pay higher prices for physician services. While this prior work suggests that providers sharing the same TINs are able to leverage oligopoly power in areas with high market concentration, our paper will test whether TIN-based measures of business organization are predictive of clinical integration that may yield offsetting benefits for patients and payers.

Aggregating organizational concentration to the HRR-level and PCP-levels

To characterize the pattern of organizational concentration at the hospital referral region (HRR) level we average the patient-level measures across all patients within the relevant region.

Our primary empirical strategy exploits variation in PCPs’ tendencies towards organizational concentration. The average patient in our sample is seen by a PCP who has 35 other attributed patients in the same year. To account for statistical noise in PCP organizational concentration, we apply a conventional empirical Bayes correction (Morris 1983). This correction shrinks the estimated PCP concentration towards the year-specific mean, in proportion to the amount of estimation error.⁶

To investigate the degree of shrinkage, we calculate “pseudo shrinkage coefficients” for organizational concentration, defined as each physician’s demeaned Bayesian posterior divided by the demeaned raw (not shrunk) estimate. A coefficient of one implies no shrinkage. The median coefficient is 0.89, with the 10th percentile at 0.63 and the 90th percentile at 0.99. This distribution suggests modest shrinkage, consistent with the high correlation (0.97) between the raw and shrunk measures.

For regression analyses at the HRR and PCP level, we exclusively rely on jackknifed versions of these organizational concentration measures that omit the index patient to avoid bias driven by an individual patient’s need for more specialized care.

Paralleling the procedure for organizational concentration, we calculate regional and provider level measures of provider concentration to include as a control in some regressions. This measure is also jackknifed, and the PCP level provider concentration is also shrunk with an empirical Bayes procedure.

2.3 Outcome measures

Our primary outcome variable is a patient’s annual healthcare utilization, which aggregates a patient’s spending across the Medicare Inpatient, Outpatient and Carrier claim files. Utilization measures are constructed using a fixed set of annual Medicare prices expunged of regional price adjusters.⁷

⁶To implement the empirical Bayes correction, we estimate a random effects model where patient-level organizational concentration depends on year fixed effects and PCP-year random effects. To achieve jackknifing, we omit the index patient from this regression. We recover empirical Bayes estimates of PCP-year organizational concentration as the sum of the year fixed effect and the best linear unbiased predictor of the PCP-year random effect.

⁷Medicare prices include some regional adjustments on the basis of local wage indices, and we do not want this source of regional variation in wage indices to confound the relationship between organizational concentration and spending. Following Finkelstein et al. (2016), we adjust total spending to strip away

We also study the relationship between organizational concentration and several utilization-based measures of healthcare quality. We study two measures related to the use of hospital care: a binary indicator for any inpatient hospitalization, and a binary indicator for any emergency department (ED) visit. Following Venkatesh et al. (2017), we define ED visits as any Carrier claim with a HCPCS code for E&M care in an ED setting. One potential cost of poorly coordinated care is additional low-value or duplicative imaging tests. We define an imaging test as repeated if it follows a prior test on the same body part with the same imaging modality within 30 days. Lastly, we examine the effects of organizational concentration on the indicators of healthcare quality for patients with diabetes: HbA1c test, and LDL test. These outcomes are only defined for the sub-sample of patients with diabetes, as defined by the Chronic Condition Warehouse; tests are identified with HCPCS codes.

3 Descriptive Evidence on Organizational Concentration

3.1 Summary statistics

Table 1 provides summary statistics for the Broad Sample (column 1), the Patient Mover Sample (column 2), and the PCP Exit Sample (column 3). Summary statistics suggest these samples are broadly similar. The average level of organizational concentration is 0.45, demonstrating that most patients regularly seek outpatient care across multiple organizations. The average level of provider concentration is lower than average organizational concentration at 0.38, as expected given that patients will often see multiple providers within the same organization. Average care utilization is \$8641 per year; utilization is lower in the PCP exit sample, perhaps in part due to the disruptive impact of PCP exits.

Appendix Table A3 further reports the mean and standard deviation of the patient-level, PCP level, and HRR level measures of organizational concentration, provider concentration, and total utilization. We use the standard deviations reported here to interpret the scale of our regression results. The empirical Bayes procedure recovers an estimate of the true standard deviation of organizational concentration across PCPs; as expected the adjusted standard deviation of 0.13 is slightly lower than that of the raw means (0.16).

Large variation between regions in healthcare usage suggests that some regions may be inefficient (Skinner 2011), and prior research has sought to explain why this variation exists (e.g. Cutler et al. (2019); Molitor (2018); Frakes (2013); Finkelstein et al. (2016)).

variation that is due to regional price adjustments.

We examine how organizational concentration varies across regions in Figure 1. This map displays residual variation in organizational concentration across regions, after accounting for the role of provider concentration, age, sex, and race. As shown in the map, the West and Upper Midwest have higher organizational concentration than would be predicted by their provider concentration and demographics, while the South and Mid Atlantic have lower organizational concentration.

Figure 2 shows binned scatter plots relating organizational concentration and total health-care spending. In Panel A, the observation is the regional (HRR) average, while in Panel B, the observation is the average of patients attributed to the same PCP. Panel A illustrates that regions with higher organizational concentration have lower levels of care utilization on average; we will investigate this relationship in more detail with our analysis of patients who move across regions, while Panel B shows that patients of PCPs with higher organizational concentration have lower levels of healthcare utilization. These patterns motivate our study of PCP exits in Section 4.

The patterns uncovered in these descriptive graphs motivate our analytic approach. First, they suggest a link between organizational concentration and care utilization, which we will investigate for the remainder of this paper. Second, it will be important to separate organizational concentration from variation in provider concentration; we focus on residual variation in organizational concentration conditional on provider concentration. Finally, given the possible endogenous link between patient health status and organizational concentration, we focus on econometric strategies which allow us to plausibly isolate the supply-side variation in organizational concentration from variation in patient demand for care.

3.2 Regional variation in organizational concentration and patient moves

Previous work has examined patients who move between regions to identify the effect of regional practice variation on spending (Finkelstein et al. 2016; Agha et al. 2019). Here, we use the same mover design to examine how regional organizational concentration correlates with the care received by moving patients. When moving between regions, patients are exposed to a change in the local pattern of organizational concentration. We provide descriptive evidence on the possible role of organizational concentration in shaping regional differences in care. Following prior work, we run regressions of the form:

$$\begin{aligned}
 Y_{it} = & \delta_1 \Delta \text{OrgConc}_{\text{region}(i)} \times \text{post}_{it} + \delta_2 \Delta \text{ProviderConc}_{\text{region}(i)} \times \text{post}_{it} \\
 & + x'_{it} \beta + \alpha_i + \gamma_t + \tau_{(i,t)} + \epsilon_{it}
 \end{aligned} \tag{3}$$

where Y_{it} is the outcome of interest, $\Delta OrgConc_{region(i)}$ is the change in regional organizational concentration experienced when patient i moves, and $\Delta ProviderConc_{region(i)}$ is the change in regional provider concentration experienced when the patient moves. We also include: x_{it} , a vector of age fixed effects (in 5 year bins); α_i , an individual fixed effect; γ_t , a year fixed effect; and $\tau_{(i,t)}$, a vector of event-time fixed effects indicating the year relative to the patient move.

Figure 3 presents event study graphs and shows that when patients move to a region with higher average organizational concentration, they experience an immediate and persistent increase in their individual organizational concentration. Table 2 reports the regression results, summarizing how changes in regional average organizational concentration translate into individual patients’ experiences when they move. If all regional variation were due to differences in the types of patients that lived in each region, then we would expect zero pass-through, while if movers fully adopted the average patterns of care in each region they lived, we would expect 100% pass-through. The regression in column 1 shows that about 80% of the regional difference in organizational concentration translates into patient-level changes in organizational concentration.

The final columns of Table 2 show how moving to a region with a different level of average organizational concentration is associated with changes in total care utilization. Column 2 shows that moving to a region with 1 standard deviation (SD) greater regional organizational concentration (an increase of 0.05) is associated with a 4.6% decline in total utilization. However, we know that changes in regional organizational concentration are also correlated with changes in regional provider concentration. Column 3 adds a control for the region’s provider concentration, and finds that the relationship between organizational concentration and total utilization diminishes only slightly: a 1 SD increase in regional organizational concentration is associated with a 3.7% decline in total utilization. These results suggest that the spread of patient care across distinct organizations is an important predictor of regional variation in health care utilization.

4 Identification Strategy: PCP Exits

In the previous section, we described how regional variation in organizational concentration predicts spending outcomes. The hurdle for interpreting these findings is that regional organizational concentration may also be correlated with other features of the local healthcare environment. To address this concern, we turn to our study of PCP exits. When a PCP exits a local market, due to a retirement or long-distance move, that PCP’s patients must find new care providers within their local market. This natural experiment allows us to

study exogenous variation in PCP practice style holding constant many features of the local healthcare market.

Organizational concentration may depend on a patient’s PCP for a few reasons. First, PCPs may deliberately choose to refer preferentially to other providers within a multispecialty practice. In addition, PCPs themselves may be affiliated with a large organization that is tied to many local specialists, increasing the organizational concentration that would occur even without preferential referrals. We characterize each PCP’s practice pattern with their average organizational concentration. We then test what happens to patient-level organizational concentration and healthcare utilization when a PCP exit forces the patient to switch to a new PCP with a different level of organizational concentration.

Our study of PCP exits thus analyzes how *changes* in the organizational concentration of a patient’s assigned PCP affects the patient’s outcomes. Because we observe patients who switch PCPs, we can include patient fixed effects in our regression model to control for any fixed patient attributes that influence their healthcare utilization. However, patients may endogenously sort to new PCPs on the basis of changes in their demand for care. For instance, patients who have gotten sicker may deliberately seek out multispecialty practices or well-known health systems when their original PCP exits. This type of sorting would bias our estimation of how organizational concentration affects healthcare spending within a difference-in-differences framework, since patient fixed effects would not adequately capture changes over time. As a result, we focus our analysis on an instrumental variables strategy adapted from Laird and Nielsen (2017) and Abaluck et al. (2020).

Our instrumental variables (IV) approach exploits the statistical property of mean reversion to predict the change in the organizational concentration of a patient’s assigned PCP after their original PCP exits. Patients whose initial PCP was highly concentrated will on average experience a decrease in their PCP’s organizational concentration when they switch providers. Patients whose initial PCP had low concentration will on average experience an increase in their PCP’s organizational concentration.

The exclusion restriction for this identification strategy requires that *changes* in patient demand for care are not endogenously related to the *level* of organizational concentration of the original PCP. While we cannot test this assumption directly, we investigate event-study graphs to assess whether patients with different original PCP organizational concentration are on differential trends prior to that PCP’s exit. The monotonicity assumption for this strategy requires that having an original PCP with high organizational concentration can only increase the probability that the patient experiences a decline in the PCP organizational concentration after the original PCP exits. This should hold when patients use a similar approach to selecting their second PCP as they applied when searching for the original PCP.

We discuss these IV assumptions in more detail in the next section.

4.1 Estimating equations

To fix ideas, we consider first a simple difference-in-difference regression, noting that the change in PCP organizational concentration is potentially endogenous. We then lay out our IV regression equations. Letting i index patients, t index calendar years, and τ index years relative to the exit of an patient’s PCP, the difference-in-difference equation we estimate is:

$$Y_{it} = \delta_1 \Delta \text{OrgConc}_{PCP(i)} \times \text{post}_{it} + x'_{it} \beta + \alpha_i + \gamma_t + \tau_{(i,t)} + \epsilon_{it} \quad (4)$$

where Y_{it} denotes a patient-level, time-varying outcome; in our baseline specifications, we consider two outcomes, the patient’s total healthcare utilization and the patient’s experienced organizational concentration. We define $\Delta \text{OrgConc}_{PCP(i)}$ as the difference between the destination PCP’s organizational concentration in the year after the move minus the origin PCP’s organizational concentration in the year before the move : $\Delta \text{OrgConc}_{PCP(i)} = \text{OrgConc}_{\text{destinationPCP}(i,\tau+1)} - \text{OrgConc}_{\text{originPCP}(i,\tau-1)}$. The new PCP is defined as the patient’s plurality provider in the year following his original PCP’s exit. This is interacted with the indicator variable, post_{it} , equal to 1 in periods after a patient’s original PCP has exited, and zero otherwise. As a result, the coefficient δ_1 identifies how changes in care utilization before and after PCP exit relate to changes in PCP organizational concentration practice style.⁸

The regression controls for individual patient fixed effects α_i and year fixed effects γ_t , as well a time-varying patient characteristic (age) in x'_{it} . The regression also includes a vector of event time fixed effects $\tau_{(i,t)}$ indicating the year relative to the PCP exit event; these controls will account for any differential trends or disruption in care when PCPs exit that are experienced uniformly by all patients whose physician exits, regardless of the exiting physician’s specific practice style.

The challenge to interpreting this difference-in-differences regression is that patients may endogenously sort to new PCPs on the basis of *changes* in their health status. To overcome this identification challenge, we do not estimate the difference-in-differences regression directly, but instead focus on an instrumental variables strategy.

When a patient’s PCP exits the market due to a retirement or long-distance move, the patient is forced to find a new provider. On average, patients tend to switch to more typical providers. This pattern implies that a patient’s lagged PCP exit will predict their care

⁸Recall, the PCP’s organizational concentration measures are defined in a jackknifed manner that omits the index patient from the calculation to avoid mechanical endogeneity.

utilization differentially depending on the organizational concentration of their exiting PCP. This insight underlies our instrumental variables strategy, which builds on recent work with similar instruments by Abaluck et al. (2020) and Laird and Nielsen (2017). Our first stage equation uses the initial PCP’s organizational concentration, denoted $OrgConc_{PCP(i),initial}$, to predict the change in organizational concentration when the initial provider exits:

$$\begin{aligned} \Delta OrgConc_{PCP(i)} \times post_{it} = & \delta_1^o OrgConc_{PCP(i),initial} \times post_{it} \\ & + x'_{it} \beta^o + \alpha_i^o + \gamma_t^o + \tau_{i,t}^o + \epsilon_{it}^o. \end{aligned} \tag{5}$$

With the fitted values from this first stage equation, we construct a two-stage least squares estimate of equation 4.

Interpreting δ_1 from our instrumental variable estimates as the average causal impact of the PCP’s organizational concentration on individual outcomes requires several assumptions, which we describe here. Under the assumption of constant treatment effects, assumptions 1 and 2 below suffice to recover treatment effects of being treated by a PCP with higher organizational concentration. If there are heterogeneous treatment effects, then assumptions 3 and 4 are needed to ensure that we recover average treatment effects.⁹ Finally, assumption 5 is needed to interpret PCP organizational concentration (rather than another correlated dimension of PCP practice style) as the underlying reason for the differences in patient care utilization.

1. **First stage:** The original PCP’s level of organizational concentration must predict the patients’ change in PCP organizational concentration after the original PCP exits, conditional on included covariates. This assumption is directly testable; we report first stage F-statistics along with our IV results.
2. **Exclusion restriction:** This assumption requires parallel trends among patients with different initial exposure to PCP organizational concentration. Specifically, patients who are initially attributed to PCPs with high levels of organizational concentration must be on the same counterfactual utilization trajectory as patients whose initial PCP has a lower level of PCP organizational concentration. We assess the plausibility of this assumption with event study graphs.
3. **Monotonicity:** Having an origin PCP with high organizational concentration can only increase the probability that the patient experiences a decline in the PCP organizational concentration after the original PCP exits. This is satisfied if patients

⁹Assumptions 3 and 4 together are similar to the fallback condition described in Abaluck et al. (2020).

use similar selection strategies to find a replacement PCP as they used to find their original PCP. For example, this assumption would be violated if some patients of high organizational concentration PCPs deliberately seek out a PCP with an even higher concentration due to their experience with the original PCP.

4. **No differential selection on gains:** Conditional variation in the original PCP’s organizational concentration must not predict the degree of selection on gains in choosing a new provider. The treatment effect of switching PCPs is independent of the exit timing and the practice styles of the exiting PCP.
5. **Organizational concentration selection on observables only:** Other factors that influence a PCP’s effect on patient care utilization must be uncorrelated with organizational concentration, after controlling for observed patient and provider characteristics. Without randomized manipulation of referral patterns, this is a strong assumption, and we discuss it in more detail below. When this assumption is violated, our estimate can be interpreted as the causal effect of switching to a higher organizational concentration PCP, rather than isolating the effect of organizational concentration from other dimensions of practice style.

Although the PCP exit strategy approach holds the regional practice environment fixed, PCP practice style is still multidimensional. A PCP’s organizational concentration may be correlated with other aspects of the PCP’s practice style, which would violate assumption 5 (selection on observables only) described above. In particular, physicians who make more referrals, ceding more of their patients’ care to other internists and specialists, will have more opportunities to reduce the organizational concentration. Prior research has documented that concentrating patient care within a narrow set of providers (provider concentration) is associated with lower levels of utilization (Agha et al. 2019; Hussey et al. 2014; Frandsen et al. 2015).

To establish that the impact of organizational concentration is distinct from the well-studied phenomenon of provider concentration, our main regression specifications include both measures. Moreover, we instrument for the change in provider concentration using an analogous approach to how we instrument for the change in organizational concentration: with the provider concentration practice style of the exiting PCP. Defining $\Delta ProviderConc_{PCP(i)}$ as the difference between the new PCP’s provider concentration and old PCP’s provider concentration, we estimate a new first stage for organizational concen-

tration as follows:

$$\begin{aligned} \Delta OrgConc_{PCP(i)} \times post_{it} = & \delta_1^o OrgConc_{PCP(i),initial} \times post_{it} \\ & + \delta_2^o ProviderConc_{PCP(i),initial} \times post_{it} \\ & + x'_{it} \beta^o + \alpha_i^o + \gamma_t^o + \tau_{i,t}^o + \epsilon_{it}^o. \end{aligned} \quad (6)$$

We also estimate a parallel first stage equation for $\Delta ProviderConc_{PCP(i)}$. Finally, we estimate the second stage equation, instrumenting for both endogenous variables:

$$\begin{aligned} Y_{it} = & \delta_1 \Delta OrgConc_{PCP(i)} \times post_{it} + \delta_2 \Delta ProviderConc_{PCP(i)} \times post_{it} \\ & + x'_{it} \beta + \alpha_i + \gamma_t + \tau_{i,t} + \epsilon_{it}. \end{aligned} \quad (7)$$

Further, we test the robustness of our findings to adding controls for PCP characteristics and practice environment. These specifications control for PCP gender, experience, residency training, and the size of the PCP’s practice organization. Larger firms may hire higher quality staff, have greater capital investment, or different managerial quality; by controlling for the size of the PCP’s practice organization, we can separate any general benefits of having a PCP who is employed by a large firm from the effects of organizational concentration.

5 Results

This section uses our instrumental variables strategy to show how PCP organizational concentration affects healthcare utilization. After discussing our baseline findings, we consider several alternative specifications, and then explore the relationship between organizational concentration and care quality.

5.1 PCP organizational concentration and utilization

To analyze how care patterns respond when a patient’s PCP exits, we begin by examining Figure 4. These graphs exploit the same variation underlying our instrumental variables approach, but instead of including a single indicator variable for the post period, they include a vector of fixed effects for each year relative to the PCP exit event. The endogenous variables of interest are the interaction of these relative event time fixed effects with the change in PCP organizational concentration, and the instrumental variables are the vector of interactions between these relative event time fixed effects and the original PCP’s organizational concentration.

The figure illustrates that when a patient’s PCP exits the local market, the patient’s care outcomes shift sharply towards the practice style of their new PCP. In Panel A, we show that if the new provider is predicted to have higher organizational concentration (so their patients receive care at fewer distinct organizations), the patient’s experienced organizational concentration also increases. This establishes that PCP organizational concentration plays an important role in shaping patient-level organizational concentration, even when the patient remains in the same geographic location. In Panel B, we show that if the new provider is predicted to have greater organizational concentration, the patient’s total healthcare utilization declines.

In both panels of this graph, we note an absence of pre-trends prior to the move. This demonstrates that patients whose original PCPs have different levels of organizational concentration are not on differential trends of care utilization prior to the original PCP’s exit. This pattern supports the exclusion restriction, described as assumption 2 above. We also see that in year 1, the first full calendar year after their PCP has exited, patients have the largest year-over-year change on both experienced organizational concentration and utilization. The new PCP’s influence may grow over time, as she gradually shapes the set of referred providers that the patient consults. In subsequent years 2 through 5, patients’ care evolves to conform more closely to the practice style of their new PCP.

Our IV regressions in Table 3 show that the effects of organizational concentration on utilization that are large and robust to accounting for other dimensions of PCP practice style, training, and practice setting. We instrument for the change in organizational concentration with the level of organizational concentration at the original PCP. The estimated first stage equation in column 5 is strong, and shows that coming from an origin PCP with a 0.1 higher organizational concentration predicts a 0.043 greater decrease in the new PCP’s organizational concentration. The associated second stage with this specification in Column 1 finds that about 29% of the variation in PCP organizational concentration practice style translates into the patient’s individually experienced organizational concentration.

Columns 2-4 contain our main results relating organizational concentration to spending, while columns 6-8 below each second stage result contain the associated first stage equation for that set of controls.¹⁰ Column 2 shows that a 0.1 instrumented for increase in organizational concentration leads to an 11% decline in healthcare utilization. The estimated standard deviation of organizational concentration across PCPs after applying Bayesian shrinkage is 0.13 (see Appendix Table A3), suggesting that a 1 SD increase in PCP organizational concentration leads to a 14% decline in utilization. Column 3 shows that this

¹⁰Note that columns 5 and 6 share a common first stage since they differ only in the choice of the dependent variable, so column 6 simply repeats column 5.

effect persists and is attenuated only slightly by the inclusion of provider concentration as an additional endogenous variable. Though the standard error on the estimate doubles, the relationship between organization concentration and care utilization remains statistically significant at the 1% level. This result shows that the frictions that arise when care crosses firm boundaries are distinct from previously studied concepts of provider concentration.

The main hurdle to interpreting this relationship as the causal effect of organizational concentration is that PCPs with more concentrated practice styles may differ along other dimensions besides their organizational concentration. By focusing on PCP exits experienced by patients who are not themselves moving, we are able to hold constant many features of the local healthcare environment. Nevertheless, PCPs' training, practice environment, and taste for aggressive care may covary with the PCP's tendency to concentrate care within an organization. To address this concern, we introduce controls for PCP gender, residency training, and experience (based on medical school graduation year). Further, we control for the size of the PCP's practice organization, as measured by the number of distinct providers billing to the TIN, as well as the number of claims billed to the TIN. By controlling for the organization size, we can account for the possibility that physicians working in larger practice groups have different quality, practice style, or access to capital inputs.

Reassuringly, we find no attenuation of the relationship between the PCP's organizational concentration and patient utilization once we account for PCP characteristics and practice size. Our preferred, most controlled specification (Column 4) shows that a 1 SD increase in PCP organizational concentration is predicted to reduce health care spending by 10%. The robustness of our findings to these controls provides evidence that our results are driven by differences in organizational ties, and are not an artifact of different practice settings, physician training, or experience.

5.2 Robustness and alternative specifications

Difference in differences results. These findings can be contrasted with the difference in differences specifications reported in Appendix Table A4. Without the instrumental variable approach, we estimate a smaller effect of PCP organizational concentration on care utilization. We believe these results are attenuated due to confounding. Patients who find themselves in worsening health are more likely to seek out care at large, integrated practices that include a wide array of specialists. PCPs affiliated with these practices are likely to have higher organizational concentration, but the patients who endogeneously select them may have increasing demand for health care services. This comparison highlights the motivation behind the instrumental variables approach. Specifically, a patient's choice of new PCP after

their original PCP exits is likely to be endogenous to changes in the patients' demand for care. By isolating the variation in PCP organizational concentration that is predictable due to mean reversion, the IV approach avoids relying on these endogenous selection patterns to estimate the impact of organizational concentration.

Exploring the role of PCP provider concentration. Appendix Table A6 provides more detail on our results, specifically reporting our instrumental variable results on how PCPs' provider concentration practice style affects care utilization. In column 1, we estimate an alternative specification that only includes PCP provider concentration as an endogenous variable, omitting organizational concentration from the model. As expected, patients whose PCPs tend to concentrate their patients' care within a smaller set of providers also have lower spending. This finding corroborates the pattern found in the earlier literature on provider fragmentation (Agha et al. 2019; Frandsen et al. 2015; Austin and Baker 2015), and shows that the finding holds under a new identification strategy—our instrumental variables approach. However, once we add PCP organizational concentration as an additional endogenous variable in our IV framework, the estimated effect of provider concentration attenuates and becomes statistically insignificant, as seen in columns 2 and 3. These results suggest that some of the spending previously attributed to the spread of care across providers may have actually reflected the challenges of coordination across organizations. Accounting for the role of organizational coordination diminishes the role of provider concentration.

Accounting for patient demand for specialized care. Appendix Table A5 establishes that the relationship we uncover is also robust to including detailed controls for the number and type of providers the patient consults. Specifically, we extend our instrumental variables specification to include additional controls for the number of generalist providers the patient sees, as well as the number of specialist providers the patient sees. The estimated effect of organizational concentration remains large and statistically significant; the point estimate is actually larger than that reported in Table 3. The larger coefficient suggests these results may in fact overstate the relationship between organizational concentration and care utilization. Specifically, patients with high organizational concentration PCPs who consult many doctors may have less underlying demand for care than patients who see more doctors with a low organizational concentration PCP. This could occur, for example, if large practices with greater organizational concentration (because they cover a wider breadth of specialists) also tend to rotate patients across providers more commonly.

Decomposing the source of utilization changes Appendix Table A7 disaggregates our findings on care utilization to identify how different types of care respond. Specifically, we consider three categories of utilization: Carrier file claims, which cover professional billings; Outpatient file claims, which cover institutional claims for outpatient care; and Inpatient file claims, which cover hospital billings. Patients treated by PCPs with higher organizational concentration have lower spending on professional services (carrier) and outpatient institutional care. Taken together, these results confirm that outpatient care utilization is lower when the PCP has high organizational concentration. The estimated effect on inpatient spending (conditional on having an inpatient admission) is also negative, but has a large standard error and is not statistically significant.

5.3 Organizational concentration and quality of care

In this section, we explore the relationship between organizational concentration and quality of care. While the quality of ambulatory care is multidimensional and difficult to quantify empirically, we present evidence on a variety of measures related to the provision of low-value care (duplicate imaging), high-value care (recommended monitoring of patients with diabetes), and use of intensive care settings (inpatient or emergency department) which may signal deficiencies in outpatient care. Results are reported in Table 4. In this table, we report our most controlled specification from Table 3, including PCP provider concentration as an endogenous variable and controlling for the full set of PCP characteristics and PCP organization size.

An important pathway by which organizational concentration could reduce total spending is by reducing the use of inpatient care. Recall that we define organizational concentration solely using outpatient provider interactions. As a result, there is no direct, mechanical relationship between organizational concentration and the PCP’s propensity to recommend hospitalization, since care delivered in the hospital setting will not contribute to the concentration measure. We do not find statistically significant effects of changes in organizational concentration on hospital-related outcomes, though standard errors are large.

Next, we investigate process of care measures for patients with diabetes. We rely on two quality of care measures, adapted from the HEDIS guidelines: receiving a regular HbA1c test and LDL test. Switching to a physician with 0.1 higher organizational concentration leads to a 4.5 percentage point increase in HbA1c testing and a 5.8 percentage point increase in LDL tests; these relationships are statistically significant at the 5% and 1% level, respectively. Patients with diabetes are more likely to receive guideline-concordant care when their PCP has greater organizational concentration. Recall that this specification does not simply reflect

the benefits of being treated in a large practice group (which might proxy for investment in clinical decision support or other electronic reminder system), because we control for the size of the PCP’s practice organization. Rather, this finding suggests that keeping the patient’s primary and specialty care integrated may lead to fewer gaps in care for chronically ill patients.

Finally, we turn to testing and imaging. Using BETOS codes, we identify Carrier claims for laboratory tests and diagnostic imaging. Changes in organizational concentration do not lead to statistically significant changes in the use of lab tests. By contrast, switching to a more concentrated PCP decreases the number of claims for imaging tests, with a 0.1 increase in organizational concentration reducing imaging claims by 5% (a decline of 0.2 claims from a base of 4.4, $P = 0.056$). We also specifically investigate a measure of repeated imaging, which we define as imaging of the same body part with the same imaging modality repeated within 30 days. While some duplication of this sort is clinically indicated, the measure will be sensitive to repeated imaging that occurs when patients seek care across different organizations that lack seamless systems for image transfer. The coefficient on repeated imaging is very imprecisely estimated relative to the mean and not significantly different from zero. These findings suggest that while reduced imaging may contribute to the utilization reductions, these reductions are not primarily driven by changes to repeated imaging tests.

Appendix Table A8 further investigates the relationship between organizational concentration and measures of preventive care provision. We find no consistent pattern between organizational concentration and preventive care. Higher organizational concentration predicts increases in mammogram and prostate cancer screenings, declines in colorectal cancer screenings, and little change in the provision of pap smears, pelvic exams, flu shots, and cardiovascular screenings.

6 Conclusion

In this paper, we explore the coordination challenges that arise when clinical care is split across firm boundaries. Firms may facilitate both informal relationships among care providers, as well as firm-specific investment in coordination technology. In the healthcare setting, coordination technology could include messaging systems, investments in health information technology, and established norms for passing off patient information across providers.

Studying patients who move regions, we document that regions with higher levels of organizational concentration also have lower levels of care utilization. This pattern suggests a role for organizational concentration in explaining regional variation in healthcare spending.

Our main analysis studies patients who stay in the same area after their PCP exits the local market due to a retirement or move. Patients who switch to a PCP with higher organizational concentration experience reductions in care utilization, relative to patients who switch to a PCP with lower organizational concentration. These relationships persist after conditioning on detailed measures of how many generalist and specialist providers the patient sees, and how concentrated the patient’s care is across those providers. This evidence indicates that the organizational ties between a patient’s healthcare providers have an impact on their total healthcare utilization.

Our estimated effect (10% decrease in utilization from a 1 SD increase in PCP organizational concentration) is large relative to other healthcare interventions. By way of comparison, Agha et al. (2019) find that moving to a region with 1 SD higher provider fragmentation increases care utilization by 10%. Clemens and Gottlieb (2014) estimate that a 2 percent increase in payment rates leads to a 3 percent increase in healthcare utilization. The introduction of a major policy initiative, Accountable Care Organizations and the Medicare Shared Savings Program, led to comparatively small reductions (less than 5%) in spending (McWilliams et al. 2018).

Although switching to a PCP with greater organizational concentration is associated with lower total utilization of physician services, we see no evidence that higher organizational concentration reduces quality of care. In fact, PCPs with greater organizational concentration perform better on these measures of effective care for patients with diabetes.

Taken together, these findings point to a potential mechanism by which higher organizational concentration lowers utilization. When providers share an organizational affiliation, they are likely to have lower barriers to information sharing and greater trust. These benefits may reduce gaps in care—e.g. resulting in better monitoring of diabetes patients—and improve hand-offs between providers. In turn, these improvements may allow providers to avoid unnecessary referrals, ensure that referred patients have already completed the requisite workup, and centralize follow-up care with the patient’s PCP. Each of these effects may reduce low-value visits that generate repeated contact with specialists.

It is also worth considering alternative explanations of these findings. Large organizations may hire higher-quality physicians. If this were the case, we would expect that our result would attenuate when we account for the size of the PCP’s organizational affiliation, but our empirical estimates show no such attenuation. Another possibility is that it may be more difficult to get a timely appointment in a large, multi-specialty practice, leading to lower care utilization. If this were the primary explanation, we might expect patients to substitute to more intensive forms of care that do not require appointments, such as emergency department visits; but, we find no evidence of substitution along this margin.

While our results suggest potential savings associated with care delivered at integrated multispecialty practices, any gains from reduced utilization would need to be weighed against the higher prices likely paid by private insurance providers to larger practices that have more bargaining power. The Medicare claims we study are paid at administratively set prices, so an investigation of countervailing price effects is beyond the scope of this paper. These results also raise the question of whether horizontal mergers that create multispecialty physician practices generate the savings from reduced utilization described here. If these gains occur, they may take time to develop as providers adapt to changing communication systems and adopt new referral patterns.

Our findings illuminate the role that firm boundaries play in organizing economic activity. Future research examining the detailed mechanisms of how these boundaries affect teamwork and care coordination may be able to show how some of the benefits of organizational concentration could be replicated without financial integration— for example, through better integration of health information technology systems, or by co-locating distinct provider groups.

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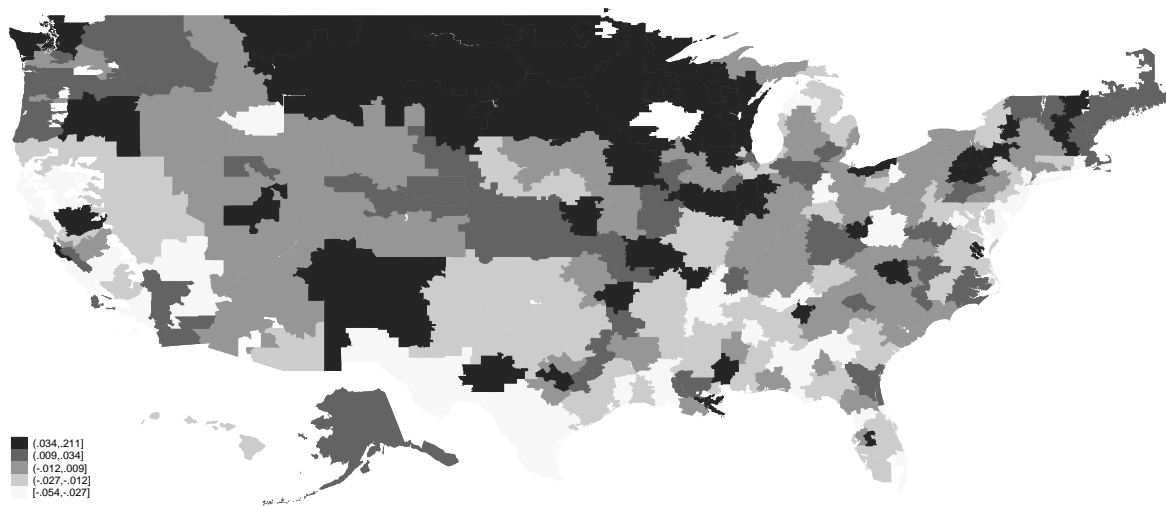
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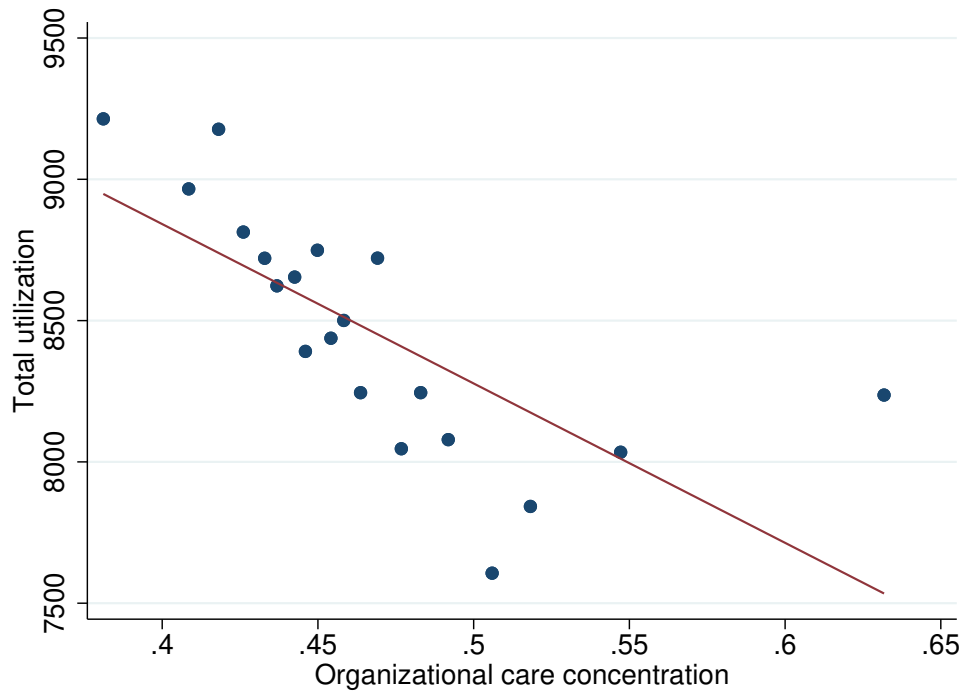
Figure 1: Residual of organizational concentration



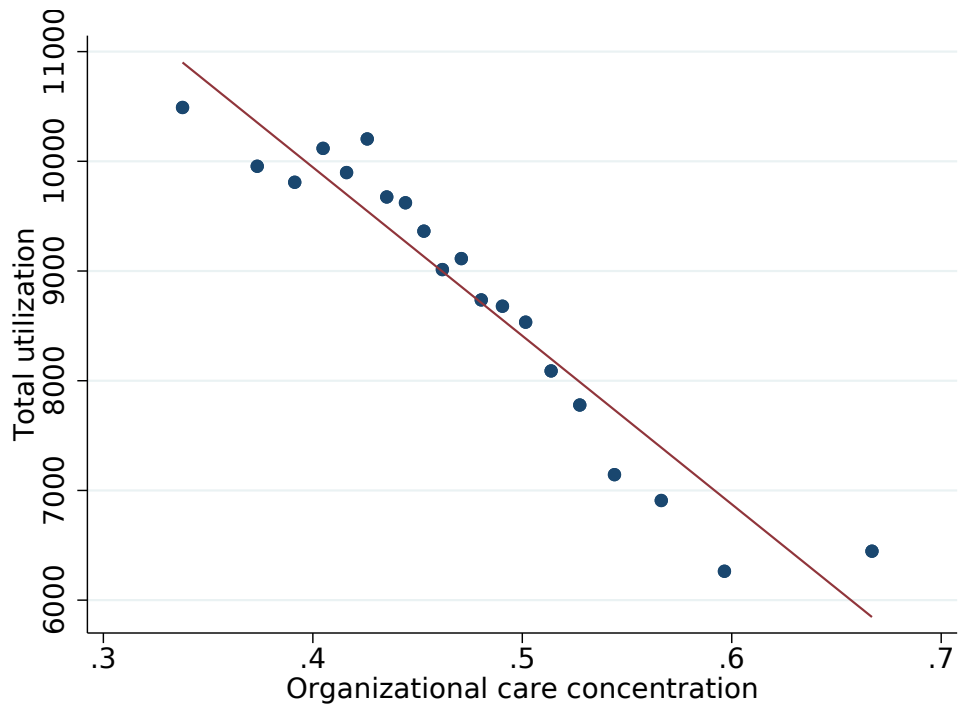
Notes: This map shows the mean residuals of patients' organizational concentration after regression adjustment for regional differences in average provider concentration, age, sex, and race. Organizational concentration and provider concentration are calculated as Herfindahl–Hirschman Index based on patients visits across healthcare organizations and providers, respectively. Hospital Referral Regions (HRRs) in darker gray have higher residual organizational concentration. Data is from the initial analytic sample, covering 9,132,322 beneficiaries.

Figure 2: Relationship between Organizational Concentration and Healthcare Utilization.

(A) HRR level



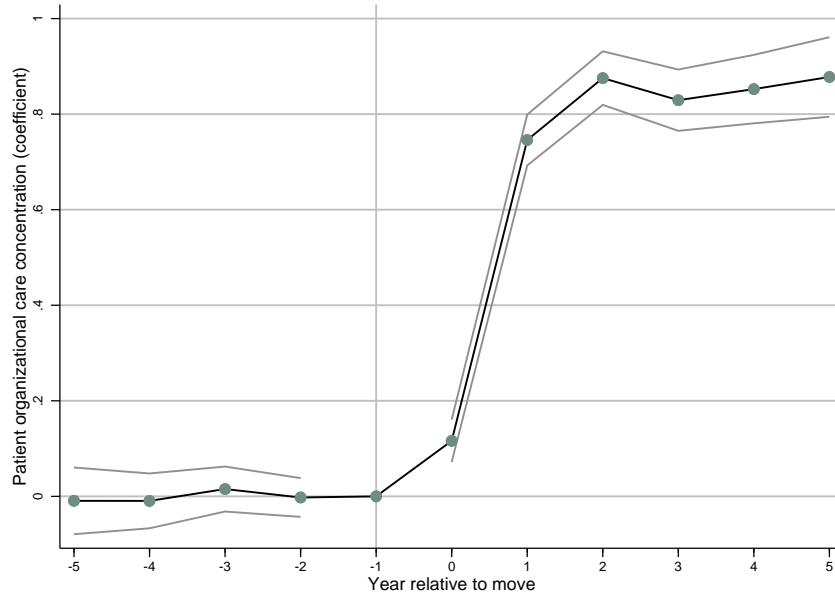
(B) PCP level



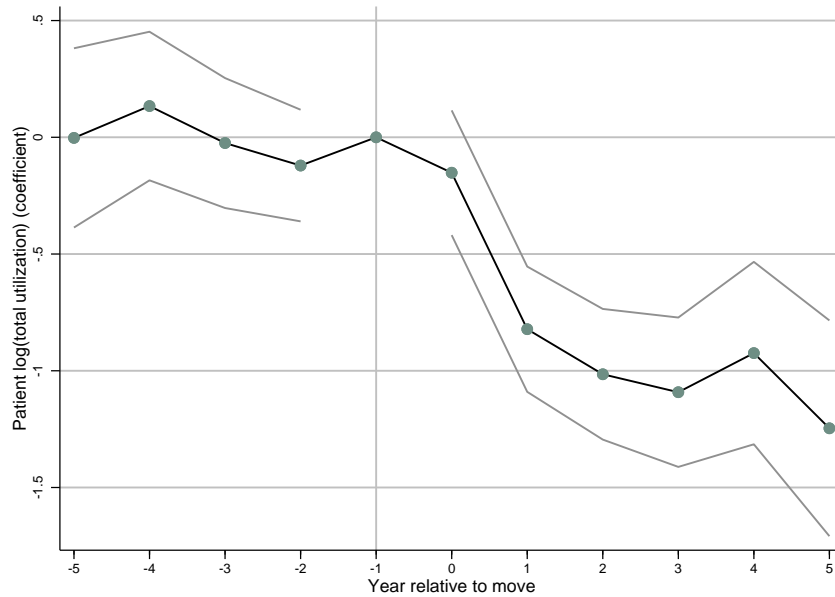
Notes: These binned scatterplots show the relationship between organizational concentration and total healthcare utilization. Panel (A) shows the relationship between these measures averaged at the Hospital Referral Region level, while Panel (B) shows the relationship between these measures averaged at the PCP level.

Figure 3: Event study figures. Based on patient movers.

(A) Response of patients' organizational concentration to changes in regional organizational concentration



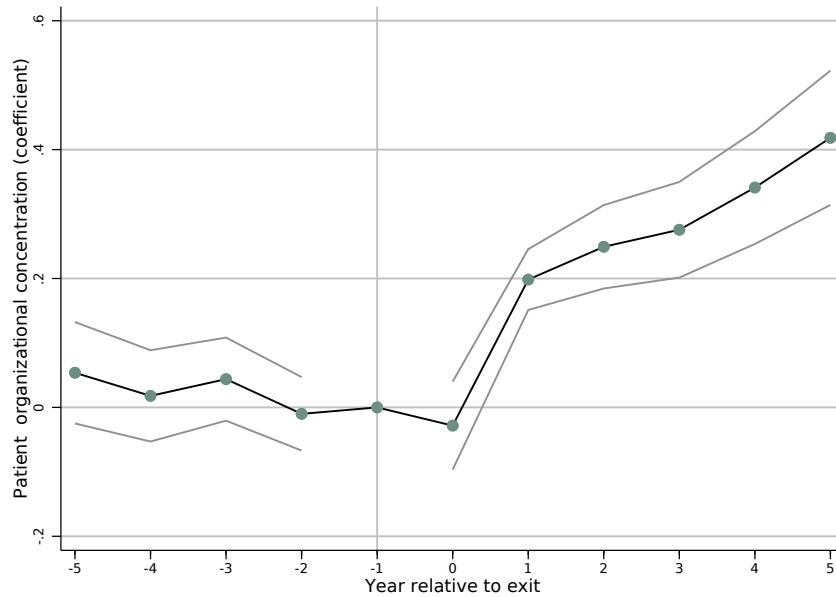
(B) Response of patients' total utilization to changes in regional organizational concentration



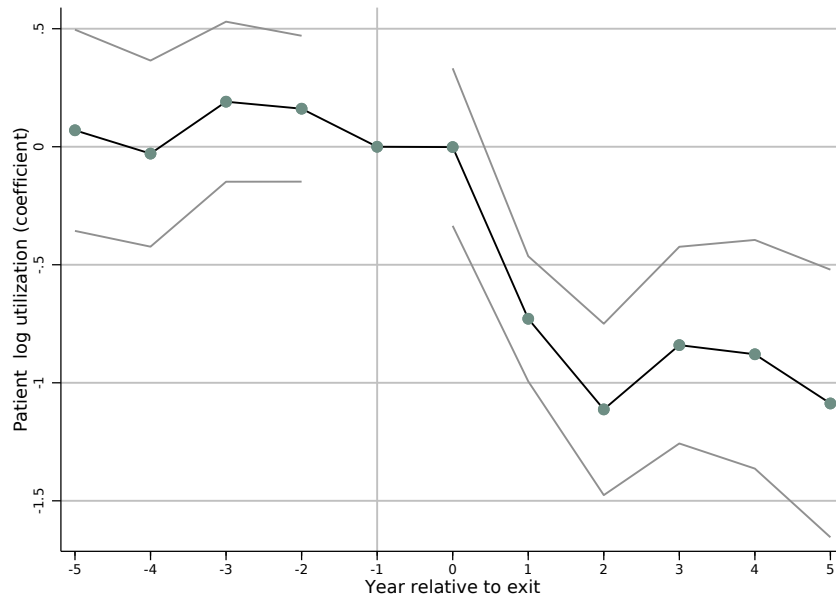
Notes: The two subplots show the estimates and 95% confidence intervals from two separate regressions. The dependent variables of subplot A and B are patients' organizational concentration and log utilization, respectively. Plots coefficient on the change in regional organizational concentration interacted with relative year. Both regressions control for patient age (five-year binned), calendar year fixed effects, and patient fixed effects. Standard errors are clustered at HRR and patient level.

Figure 4: Event study figures. Based on PCP exit.

(A) Response of patients' organizational concentration to changes in PCP organizational concentration



(B) Response of patients' total utilization to changes in PCP organizational concentration



Notes: The two subplots show the estimates and 95% confidence intervals from two separate regressions. The dependent variables of subplot A and B are patients' organizational concentration and log utilization, respectively. Regression specification matches the instrumental variable regressions in Table 3 column 1 (for Panel A) and column 2 (for Panel B), except that the post variable is now a vector of fixed effects for relative year. Both regressions control for patient age (five-year binned), calendar year fixed effects, and patient fixed effects. Standard errors are clustered at PCP and patient level.

Table 1: Summary statistics of different samples

	(1)	(2)	(3)
	Broad Sample	Patient Mover Sample	PCP Exit Sample
Organizational concentration	0.45 (0.27)	0.42 (0.25)	0.46 (0.25)
Provider concentration	0.38 (0.27)	0.34 (0.24)	0.38 (0.25)
Total utilization (\$)	8641 (17,487)	8673 (17,127)	6512 (12,722)
Age	76.1 (7.48)	76.34 (7.38)	77.19 (7.18)
Sex: Female	0.59	0.59	0.63
Race: White	0.86	0.87	0.86
Has Diabetes	0.28	0.29	0.33
Has Hypertension	0.62	0.65	0.73
Has Heart disease	0.32	0.34	0.3
N patient-year obs	48,436,521	7,576,900	335,868
N patients	9,132,322	1,389,790	62,924
N assigned PCPs			52,981

Notes: This table reports summary statistics for the various analytic subsamples. Column 1 describes the Broad Sample. Column 2 reports the sample underlying our mover analysis, including both patients who move and the 25% random sample of non-movers. Column 3 reports summary statistics only for patients who move. Column 4 reports summary statistics for the analytic sample underlying our analysis of PCP exits. This sample restricts to patients whose PCP exits the local market. The number of assigned PCP in column 4 includes exiting PCPs as well as the PCPs patients switched to.

Table 2: Patient movers and regional organizational concentration

	(1)	(2)	(3)
	$OrgConc_{it}$	$Log(total\ utilization)_{it}$	
$\Delta OrgConc_{region(i)} \times post_{it}$	0.797*** (0.021)	-0.916*** (0.099)	-0.735*** (0.113)
Regional provider concentration			X

Notes: All regressions control for patient age (five-year binned), calendar year fixed effects, relative year fixed effects, and patient fixed effects. Regional organizational concentration is jackknifed. Standard errors are clustered at HRR and patient level. Sample: Movers Analysis Sample, N=7,576,900 patient-year observations.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Organizational concentration and spending, identified from PCP exits

Instrumental Variables				
Second stage	(1)	(2)	(3)	(4)
	$OrgConc_{it}$	$Log(total\ utilization)_{it}$		
$\Delta OrgConc_{PCP(i)} \times post_{it}$	0.293*** (0.021)	-1.058*** (0.118)	-0.729*** (0.251)	-0.794*** (0.246)
First stage	(5)	(6)	(7)	(8)
	$\Delta OrgConc_{PCP(i)} \times post_{it}$			
$OrgConc_{PCP(i)t-1} \times post_{it}$	-0.432*** (0.006)	-0.432*** (0.006)	-0.295*** (0.007)	-0.299*** (0.007)
F-test	$1.0 * 10^5$	$1.0 * 10^5$	20,703	23,845
PCP provider concentration			X	X
PCP characteristics				X
PCP organizational size				X

Notes: Each column represents an instrumental variables regression, where instrumental variable is the exiting PCP's jackknifed organizational concentration multiplied by a post indicator. In specification (1), the outcome variable is the individual patient's realized organizational concentration and in specifications (2)-(4) the outcome variable is the patient's log of total utilization. All regressions control for patient age (five-year binned), calendar year fixed effects, relative year fixed effects, and patient fixed effects. Specifications (3) and (4) include PCP provider concentration as an additional endogenous variable, instrumented by the original PCP's provider concentration multiplied by a post indicator. Specification (4) controls for PCP characteristics: gender, experience quartile indicators, residency training indicators (internal medicine vs. family practice), and the PCP's organization size (log total number of claims billed to the PCP's TIN, and the log number of unique providers billing to the PCP's TIN). Standard errors have two-way clustering at PCP and patient levels. Cragg-Donald Wald F-test reported for first-stage. The PCP Exit Sample has 335,868 patient-year observations.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Organizational concentration and measures of quality

	(1)	(2)
	Mean of	Coefficient on
	dependent variable	$\Delta OrgConc_{PCP(i)} \times post_{it}$
Dependent variable:		
A. Hospital outcomes		
Any inpatient visit	0.155	-0.001 (0.072)
Any emergency department visit	0.259	-0.022 (0.083)
B. Diabetes care outcomes		
Any HbA1C test	0.631	0.452** (0.189)
Any LDL test	0.590	0.578*** (0.195)
C. Imaging use outcomes		
Number of lab test claims	14.245	0.358 (3.356)
Number of imaging test claims	4.417	-2.127* (1.112)
Number of repeated imaging tests	0.263	0.163 (0.294)

Notes: Each row corresponds to a regression. The specifications match that reported in column (4) of Table 3, but with alternative dependent variables. Specifically, all regressions control for changes in PCP provider concentration, PCP characteristics, PCP organization size, as well as patient age (five-year binned), calendar year fixed effects, relative year fixed effects, patient fixed effects. Both changes in PCP organizational concentration and changes in PCP provider concentration are instrumented for using the exiting PCP's practice style. Standard errors are clustered at PCP and patient level. Panels A and C use the full PCP Exit Sample (335,868 patient-year observations). Panel B uses the subset of the PCP Exit Sample of patients identified with diabetes as chronic condition (105,940 patient-year observations).

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The Impact of Organizational Boundaries on Healthcare Coordination and Utilization

Leila Agha, Keith Marzilli Ericson, Xiaoxi Zhao

December 2, 2020

A Online Appendix: Additional Tables and Figures

Table A1: Mapping from provider taxonomy codes to specialties

Specialty	Provider taxonomy codes
PCP	207Q00000X, 207QA0000X, 207QA0505X, 207QG0300X, 207R00000X, 207RA0000X, 207RG0300X, 208000000X, 2080A0000X, 208D00000X

Notes: These codes are used to define primary care specialties from the National Plan and Provider Enumeration System (NPPES).

Table A2: List of place of service codes included as outpatient care

Place of Service Code	Place of Service Name
05	Indian Health Service Free-standing Facility
07	Tribal 638 Free-standing Facility
11	Office
17	Walk-in Retail Health Clinic
20	Urgent Care Facility
22	On Campus-Outpatient Hospital
49	Independent Clinic
50	Federally Qualified Health Center
53	Community Mental Health Center
57	Non-residential Substance Abuse Treatment Facility
58	Non-residential Opioid Treatment Facility
62	Comprehensive Outpatient Rehabilitation Facility
65	End-Stage Renal Disease Treatment Facility
71	Public Health Clinic
72	Rural Health Clinic

Notes: These codes are used to identify claims in the Medicare Carrier File for services that take place in an outpatient facility.

Table A3: Summary stats of key variables at different levels

	(1)	(2)
	Mean	Std. Dev.
Patient level (N=9,132,322)		
Organizational concentration	0.50	0.24
Provider concentration	0.43	0.25
Total utilization	9116	14,800
PCP level (N=190,616)		
Organizational concentration (raw)	0.49	0.16
Organizational concentration (adjusted for statistical noise)	0.48	0.13
Provider concentration (raw)	0.39	0.15
Provider concentration (adjusted for statistical noise)	0.38	0.11
Total utilization	9377	11,263
Regional level (N=306)		
Organizational concentration	0.47	0.05
Provider concentration	0.38	0.03
Total utilization	8465	918

Notes: This table summarizes provider concentration, organization concentration, and utilization outcomes at different levels of aggregation. The top panel has one observation per patient, and reports the means and standard deviations across all patients. The middle panel has one observation per PCP (averaged across patient-year observations), and reports the mean and standard deviation across PCPs. The bottom panel has one observation per Hospital Referral Region (averaged across patient-year observations) and reports the mean and standard deviation across regions.

Table A4: Difference in differences analysis of PCP exits

	(1)	(2)	(3)	(4)
	$OrgConc_{it}$	$Log(total\ utilization)_{it}$		
$\Delta OrgConc_{PCP(i)} \times post_{it}$	0.340*** (0.010)	-0.623*** (0.057)	-0.088 (0.084)	-0.132 (0.086)
PCP provider concentration			X	X
PCP characteristics				X
PCP organizational size				X

Notes: This table shows the difference in differences estimates of equation 4 without using the instrumental variable strategy to predict variation in the change in organizational concentration after a PCP exit. In specification 1, the outcome variable is the individual patient's realized organizational concentration and in specifications 2-4 the outcome variable is the patient's log of total utilization in specifications. All regressions control for patient age (five-year binned), calendar year fixed effects, relative year fixed effects, and patient fixed effects. Specifications 3 and 4 include PCP provider concentration as an additional endogenous variable, instrumented by the original PCP's provider concentration multiplied by a post indicator. Specification 4 controls for PCP characteristics: gender, experience quartile indicators, training indicators (internal medicine vs. family practice), and the PCP's organization size (log total number of claims billed to the PCP's TIN, and the log number of unique providers billing to the PCP's TIN). There are 335,868 patient-year observations. Standard errors have two-way clustering at PCP and patient levels.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A5: Instrumental variable analysis of PCP exits, controlling for number of physicians the patient consults

Instrumental Variables		
Second stage	(1)	(2)
	$\text{Log}(\text{total utilization})_{it}$	
$\Delta \text{OrgConc}_{PCP(i)} \times \text{post}_{it}$	-0.794*** (0.246)	-1.451*** (0.195)
First stage	(3)	(4)
	$\Delta \text{OrgConc}_{PCP(i)} \times \text{post}_{it}$	
$\text{OrgConc}_{PCP(i)t-1} \times \text{post}_{it}$	-0.299*** (0.007)	-0.310*** (0.007)
F-test	23,845	23,733
PCP provider concentration	X	X
PCP characteristics	X	X
PCP organizational size	X	X
Spline N generalists seen by patient		X
Spline N specialists seen by patient		X

Notes: See notes to Table 3. For reference, specifications (1) and (3) replicate the results reported in (4) and (8) of Table 3. In specification (2) and (4), the regression adds new control variables that account for the number of distinct providers each patient sees. Specifically, these specifications control for a 4-knot spline in the number of generalist providers (as defined in Table A1: family practice, internal medicine training, or geriatrics training) and a 4-knot spline in the number of specialist providers (with any other training type). Standard errors have two-way clustering at PCP and patient levels.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A6: Impact of organizational concentration and provider concentration

A. Baseline estimates			
Instrumental Variables			
Second stage	(1)	(2)	(3)
	Log(total utilization) _{it}		
$\Delta OrganizationConc_{PCP(i)} \times post_{it}$		-0.729***	-0.794***
		(0.251)	(0.246)
$\Delta ProviderConc_{PCP(i)} \times post_{it}$	-1.072***	-0.453	-0.279
	(0.108)	(0.248)	(0.243)
PCP characteristics			X
PCP organization size			X

Notes: This table reports the results of instrumental variables regressions similar to those reported in Table 3, but now providing further detail on the relationship between PCP provider concentration and care utilization. Column 1 reports a specification similar to that in column 2 of Table 3, but replacing the endogenous and instrumental variables related to PCP organizational concentration with analogous variables describing PCP provider concentration. Columns 2 and 3 are identical to the specifications reported in columns 3 and 4 of Table 3, which include both PCP organizational concentration and PCP provider concentration as endogenous variables, but here we report the coefficient on PCP provider concentration. There are 335,868 patient-year observations. Standard errors have two-way clustering at PCP and patient levels. See notes to Table 3 for further details.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A7: Instrumental variable analysis of PCP exits, spending decomposition

	(1)	(2)	(3)
	Mean of dependent variable (not log)	Sample size	Coefficient on $\Delta OrgConc_{PCP(i)} \times post_{it}$
Dependent variable:			
Log of carrier spending (professional)	2663	335,868	-0.426** (0.189)
Log of outpatient spending (institutional)	1364	335,868	-1.397** (0.586)
Log of inpatient spending (hospital, if > 0)	16,507	35,002	-0.402 (0.538)

Notes: See notes to Table 3. This table replicates the instrumental variable specification reported in Table 3 columns (4) and (8) with alternative outcome variables that decompose Medicare billing depending on the type of bill. Inpatient billings are only defined among patients with at least one hospitalization. Sample size is 335,868 for carrier and outpatient claims; sample size is 35,002 for inpatient claims.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A8: Organizational concentration and preventive care

	(1)	(2)
	Mean of	Coefficient on
Dependent variable:	dependent variable	$\Delta OrgConc_{PCP(i)} \times post_{it}$
A. Preventive care for women ($N = 211,823$)		
Mammogram	0.567	0.423** (0.174)
Pap smear	0.165	-0.209 (0.129)
Pelvic exam	0.142	-0.006 (0.114)
B. Preventive care for men ($N = 124,042$)		
Prostate cancer screening	0.273	0.648*** (0.227)
C. Preventive care for full sample ($N = 335,868$)		
Flu shot	0.671	0.048 (0.119)
Colorectal screening	0.157	-0.581*** (0.097)
Cardiovascular screening	0.909	-0.239 (0.258)

Notes: Each row corresponds to a regression. The specifications match that reported in column (4) of Table 3, but with alternative dependent variables. Specifically, all regressions control for changes in PCP provider concentration, PCP characteristics, PCP organization size, as well as patient age (five-year binned), calendar year fixed effects, relative year fixed effects, patient fixed effects. Both changes in PCP organizational concentration and changes in PCP provider concentration are instrumented using the exiting PCP's practice style. Standard errors are clustered at PCP and patient level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$