The Impact of Organizational Boundaries on Healthcare Coordination and Utilization

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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 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 11% 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.

Keywords: organizations, fragmentation, healthcare, boundaries of the firm, transaction costs, communication
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Introduction

Transaction costs and imperfect information can make it difficult to coordinate production across firm boundaries (Coase 1937). In healthcare, these challenges 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 are employed by large practices or hospitals (Welch et al. 2013; Kocher et al. 2011), 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 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 be an important source of healthcare inefficiency. Organizational boundaries can affect the cost of coordination. For instance, healthcare firms often restrict information transmission to external providers by controlling the ease of information sharing 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. 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 speciality practice,

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 provide suggestive evidence 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 (2019) 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 high organizational concentration exit the market, their patients switch to more typical PCPs and subsequently experience higher healthcare utilization. Using this variation, we estimate that patients who switch to a PCP with 1 SD higher organizational concentration have 11% lower healthcare utilization. This finding is robust to controlling for the number and types of providers that the patient visits.

Our results indicate that organizational boundaries contribute an additional friction that lowers 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 PCPs' 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, as well as other PCP characteristics (residency training, experience, gender, practice size). 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 redundant testing. We find no evidence that changes in PCP organizational concentration predict changes in inpatient, emergency department or imaging utilization. However, for patients with diabetes, switching to a PCP with higher levels of organizational concentration leads to better compliance with recommended care guidelines. This finding from diabetes care provides suggestive evidence that greater organizational concentration may facilitate improved management of chronic conditions.

This paper contributes to a growing literature on how organizational structure affects healthcare productivity. 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 in new technology (Cutler and Morton 2013), empirical evidence of these benefits is lacking. For instance, recent work studying hospital mergers and acquisitions of physician practices suggest that they do not spur improvements in clinical quality or health outcomes (Beaulieu et al. 2020; Koch et al. 2018).[1]

Research using variation in organizational ties from mergers and acquisitions may not capture the potential benefits of organizational concentration for two reasons. First, mergers and acquisitions need not change patients' experienced organizational concentration even though they might change the market power of providers. The critical factor for care coordination is likely to be 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. Second, the process of organizational transformation is often slow, and large-scale mergers may not trigger an immediate change in clinical care processes. Financial integration may not facilitate coordination of care in practice, if the acquired units continue to function as separate organizations with little operational consolidation. Because this paper does not focus on short-run effects of mergers, the effects we study may reflect longer-run changes to care.

Prior research that investigates organizational boundaries outside of a merger context provides suggestive evidence of coordination challenges when healthcare is split across multiple firms. Multi-specialty practices participating in a consortium dedicated to quality and cost accountability provide higher quality, lower cost care on average (Weeks et al. 2010). Patients who seek healthcare both within and outside the Veteran's Health Administration system have higher rates of risky prescription drug combinations (Thorpe et al. 2017). How-

[1]These acquisitions may also raise costs, 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).

ever, in both these papers, patients endogenously sort into practices, making it difficult to disentangle coordination costs from differences in patients' demand for care.

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.

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 widely used in prior literature to measure the spread of patient care across providers.[2] Specifically, we use a Herfindahl–Hirschman Index (HHI) that calculates the spread of ambulatory care across organizations, analogous to how Agha et al. (2019) measures the spread of patient healthcare across providers. We measure organizational concentration using outpatient care, following previous literature examining continuity of care across individual physicians (Nyweide and Bynum 2017; Nyweide et al. 2013). This allows us to conceptually 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:

$$OrgConc_{it} = \sum_{j} share_{ijt}^2. \tag{1}$$

In general, the fewer organizations a patient visits, the higher is the organizational concentration. When a patient's 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 empirical analyses, we characterize the pattern of organizational concentration

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

at the PCP or hospital referral region level. To construct these measure of physician or regional organizational concentration, we average the patient-level measures across all patients attributed to that PCP, or within the relevant region. For regression analyses, we exclusively rely on jackknifed versions of these measures that omit the index patient to avoid bias driven by individual patient need for more specialized care.

In order to distinguish our findings from prior analyses of provider concentration, we study variation in organizational concentration conditional on the spread of patient healthcare across providers. We construct a parallel 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:

$$ProviderConc_{it} = \sum_{p} share_{ipt}^2. \tag{2}$$

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. 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 65–100 years old 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 care visits billed in the Carrier claims files, so we drop 223,822 beneficiaries who did not have any visits of this type. From this broad sample, we define two separate analytic samples for different purposes. First, we define a "Mover Analysis 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 define each of these samples below.

Mover Analysis Sample

We construct a Movers Analysis 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 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 Movers Analysis 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, and General Practice. Provider taxonomy codes are 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 his plurality PCP, defined as the provider who bills a plurality of the patient's Evaluation & Management (E&M) visits; 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 Calculating organizational concentration

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. 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. For our analysis of patient moves, we summarize each region's organizational concentration as the average organizational concentration across all patients residing in the HRR that year. For our PCP exit analysis, we calculate a PCP's tendency for organizational concentration as the average organizational concentration across all of their attributed patients. To construct these regional and 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 doctors' 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.

Earlier work by Baker et al. (2014), Austin and Baker (2015) and Baker et al. (2017) 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.

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.[3]

We also study the relationship between organizational concentration and several utilization-based measures of healthcare quality. Quality measures are calculated based on ICD-9 codes and/or HCPCS codes associated with visits. We study three measures related to the use of hospital care: inpatient hospital spending, 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 duplicated if it follows a prior test on the same body part with 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.

[3]Medicare 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 variation that is due to regional price adjustments.

3 Descriptive evidence on organizational concentration

3.1 Summary Statistics

Large variation between regions in healthcare usage suggest that some regions are inefficient (Skinner 2011), and work has sought to explain why this variation exists (e.g. Cutler et al. (2019); Molitor (2018); Frakes (2013); Finkelstein et al. (2016)). 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 are have lower organizational concentration.

Next, we examine how regional variation in organizational concentration is related to other regional characteristics. In Table 1, Columns 1 and 2, we split the sample at the median into HRRs with high and low organizational concentration. The average patient in a high organizational concentration HRR has an organizational concentration of 0.50, while in a low concentration region, the average patient has an organizational concentration of 0.43. Rates of chronic health conditions are slightly higher in low organizational concentration regions: patients in these low concentration regions are more likely to have diabetes (by 2 percentage points), hypertension (5 percentage points), and heart disease (4 percentage points). Similar patterns emerge when comparing patients treated by PCPs, split at the median into high and low average organizational concentration. As expected, there is more heterogeneity in organizational concentration across PCPs: we find a standard deviation of 0.16 across PCPs, as compared to a standard deviation of 0.05 across HRRs (see Appendix Table A4).

Figure 2 shows binned scatter plots relating organizational concentration and total healthcare spending. In the left Panel A, the observation is the regional (HRR) average, while in the right Panel B, the observation is the average of patients attributed to an individual 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 and table 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, Table 1 suggests that it will be important to separate organizational concentration from variation in provider con-

centration; we focus on residual variation in organizational concentration conditional on provider concentration. Finally, these results suggest a possible endogenous link between patient health status and organizational concentration, which motivates our econometric approaches. Both the patient mover and PCP exit strategies allow the inclusion of patient fixed effects, 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:

$$\begin{aligned} Y_{it} = \quad & \delta_1 \Delta OrgConc_{region(i)} \times post_{it} + \theta_2 \Delta ProviderConc_{region(i)} \times post_{it} \\ & + x'_{it}\beta + \alpha_i + \gamma_t + \tau_{(i,t)} + \epsilon_{it} \end{aligned} \tag{3}$$

where Y_{it} is the outcome of interest, $\Delta OrgConc_{region(i)}$ is the change in regional organizational concentration experienced when an patient i moves, $\Delta ProviderConc_{region(i)}$ is the change in regional provider concentration experienced when the individual moves. We also include: x_{it}, a vector of 5-year bin age fixed effects, 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 example, PCPs may deliberately choose whether or not to refer preferentially to other providers within a multi-specialty 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 his or her 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 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 healthcare utilization

needs. For instance, patients who have gotten sicker may deliberately sort to 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 organizational concentration of the original PCP. While we cannot test this assumption directly, we investigate event-study graphs to assess whether patients with different origin PCP concentration are on differential trends prior to that PCP's exit. The monotonicity assumption for this strategy requires that 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 should hold when patients use 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 and t index years, the difference-in-difference equation we estimate is :

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

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 $\Delta OrgConc_{PCP(i)}$ as the difference between the new PCP's organizational concentration minus the old PCP's organizational concentration. The new PCP is defined as the patient's plurality provider in the year following his original

PCP's exit. In all cases, the PCP's organizational concentration measures are defined in a jackknifed manner that omits the index patient from the calculation to avoid mechanical endogeneity. This is interacted with the indicator variable, $post_{it}$, equal to 1 in periods after a patient's origin PCP has exited, and zero otherwise. As a result, the coefficient δ_1 identifies how changes care utilization before and after PCP exit relate to changes in PCP organizational concentration practice style.

The regression controls 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 with exiting doctors, regardless of the exiting doctors' 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. For example, patients with new diagnoses requiring complex care may take the opportunity once their original PCP exits to switch to a PCP who shares the same network as the specialists they anticipate seeing. This pattern creates a correlation between a patient's change in health care demand and the change in PCP organizational concentration they experience once their original PCP exits. 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 mean reversion implies that a patient's lagged PCP exit will predict their care 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:

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

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.[4] 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. This assumption is directly testable.

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 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 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. This assumption states that 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

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

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 concentration as follows:

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

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:

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

Further, we test the robustness of our findings to adding controls for PCP characteristics and practice environment. These specifications control for PCP gender, experience, training (in internal medicine vs. family practice), 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

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 ahve 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.

To further quantify these patterns, we turn to Table 3 which presents the results of our instrumental variable strategy. We instrument for the change in organizational concentration with the level of organizational concentration at the origin 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 0.047 greater decrease in the subsequent PCP's organizational concentration. (Recall that the standard deviation of organizational concentration across PCPs is 0.16.) The associated second stage with this specification in Column 1 finds that about 20% of the variation in PCP organizational concentration practice style translates into the patient's individually experienced organizational concentration.

Our main results relating organizational concentration to spending are in Columns 2, 3, and 4. Below each second stage result is the associated first stage equation for that set of controls (see columns 6, 7, 8). (Note 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.). The IV regressions 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.

Column 2 reports that a 0.1 instrumented for increase in organizational concentration leads to a 7.9% decline in healthcare utilization. Column 3 shows that this 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 patterns 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, training (internal medicine or family medicine), and 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 or practice style.

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. Column 4 shows that a 0.1 increase in PCP organizational concentration is predicted to reduce health care spending by 7%. 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.

These findings can be contrasted with the difference in differences specifications reported in Appendix Table A5. 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 are are likely to 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.

Appendix Table A6 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.

Appendix Table A7 provides more detail on these specifications, specifically reporting our instrumental variable results on how changing the PCP's 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 the finding holds under a new identification strategy, using our instrumental variables approach. Interestingly, once

we add PCP organizational concentration as an additional endogenous variable in our IV framework, the estimated effect of provider concentration attenuates dramatically, as seen in column 2 of Appendix Table A7. By contrast, we saw relatively modest attenuation of the organizational concentration effect when we add provider concentration to the model (cf. columns 2 and 3 of Table 3). This pattern suggests that much of the prior relationship between provider concentration and care utilization may have reflected the challenges of coordinating care across firm boundaries, given that patients with many providers often consult providers practicing in different organizations. Adding controls for PCP characteristics and organization size further attenuates the estimated effect of PCP's provider concentration practice style, but does not attenuate the effect of PCP's organizational concentration.

Appendix Table A8 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 covers hospital billings. Patients treated by PCPs with higher organizational concentration incur lower utilization of professional services and lower spending on outpatient 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.

5.1 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, 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 hospitalization outcomes, though standard errors are large.

We next turn to imaging tests. We are specifically interested in the frequency of duplicated imaging tests, 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. We also report results on total imaging tests, as a less sensitive outcome that will indicate how the base number of images is changing and affect the number of opportunities for duplication. Switching to a PCP with 0.1 higher organizational concentration reduces the number of imaging tests per patient by 0.024 tests, from a base of 1.4 imaging tests annually; this small effect is not significantly different from zero). The coefficient on duplicate imaging is positive but very imprecisely estimated and not significantly different from zero.

Finally, we specifically 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 3 percentage point increase in HbA1c testing and 2 percentage point increase in LDL tests; these relationships are statistically significant at the 1% level. 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 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.

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 care providers have an impact on their total healthcare utilization.

Our estimated effect (11% 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. However, 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 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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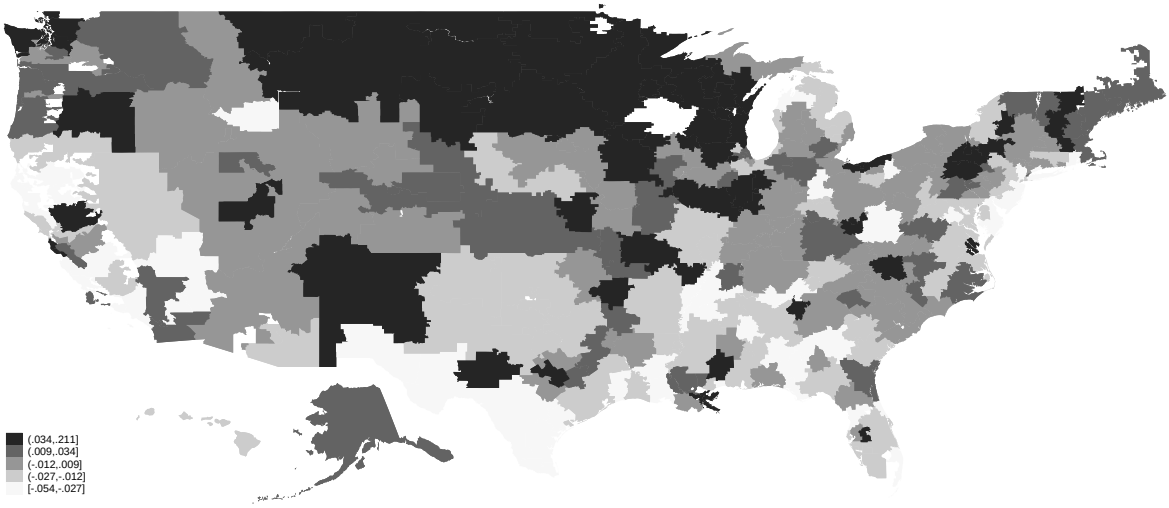
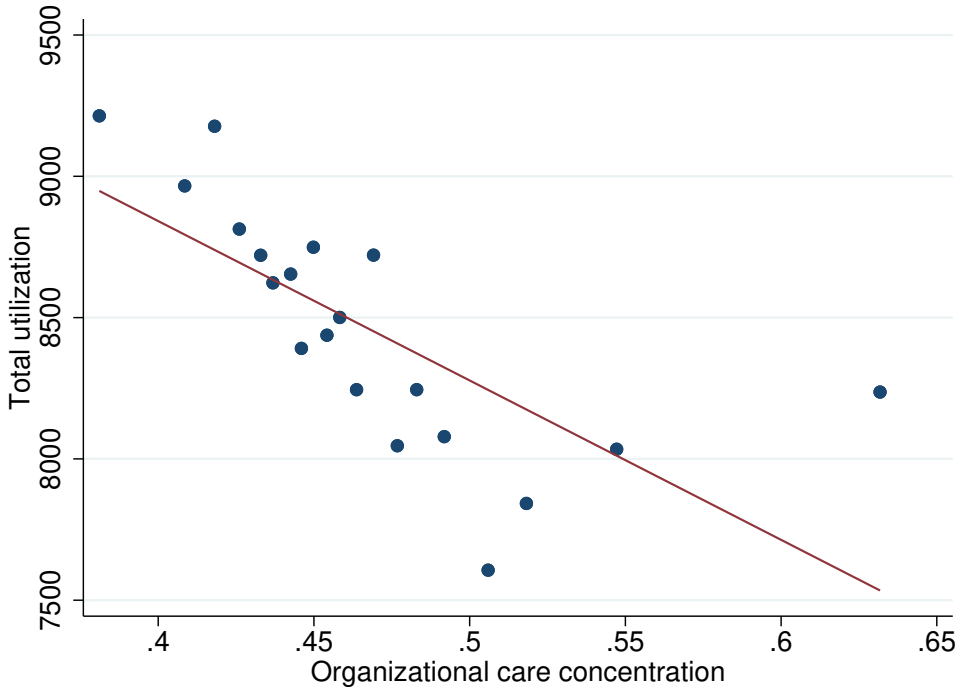
Figure 1: Residual of organizational concentration



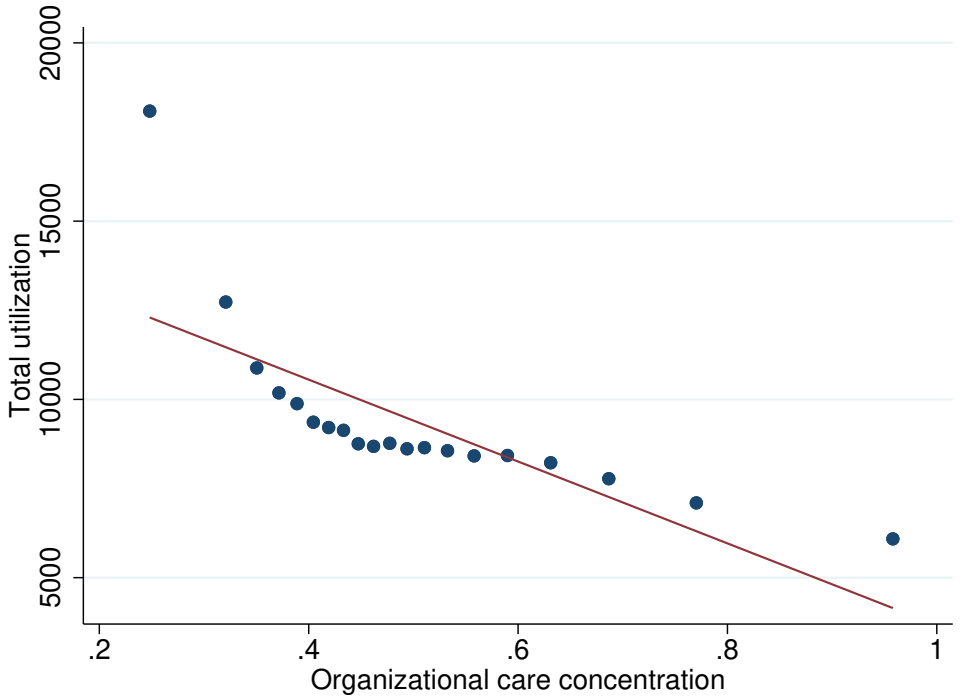
Notes: This map shows the mean residuals of patients' organizational concentration after regression adjustment for regional differences in average provider concentration, age, sex, and race. Organizational concentration and provider concentration are calculated as Herfindahl–Hirschman Index based on 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



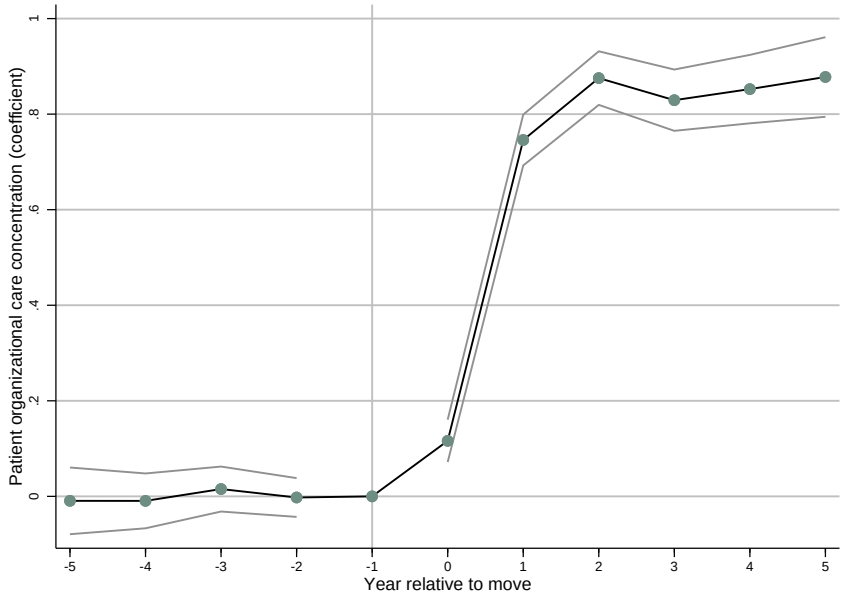
(B) PCP level



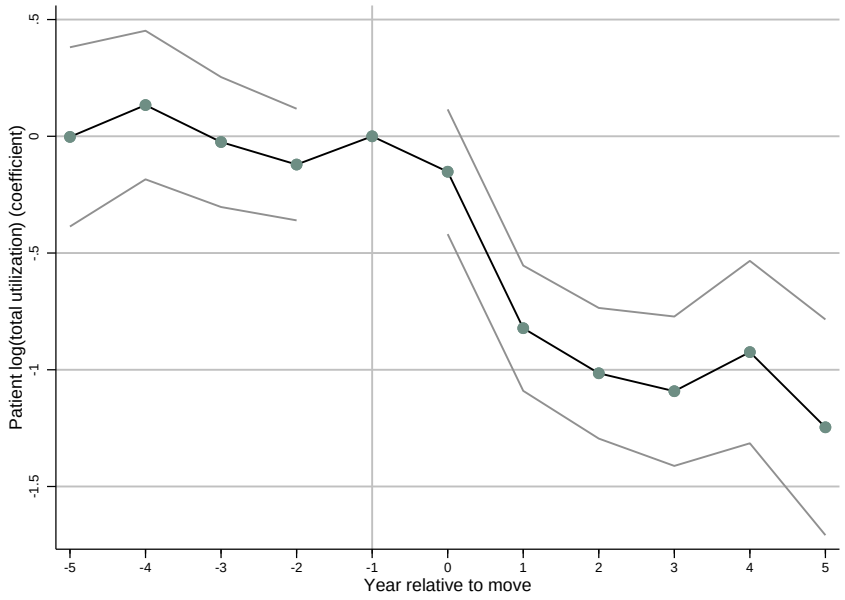
Notes: These binned scatterplots show the relationship between organizational concentration and total healthcare utilization. Panel (A) shows the relationship between these measures averaged at the Hospital Referral Region level, while Panel (B) shows the relationship between these measures averaged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



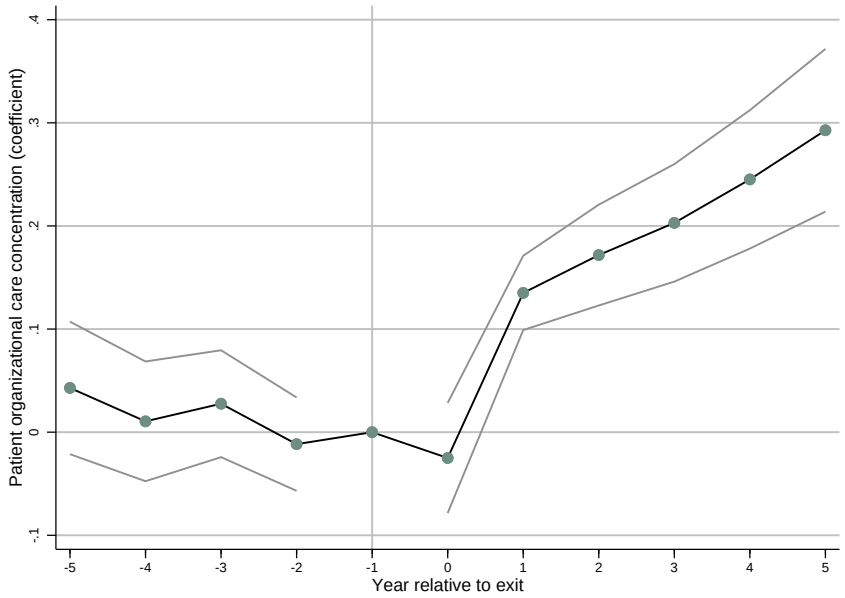
(B) Response of patients' total utilization to changes in regional organizational concentration



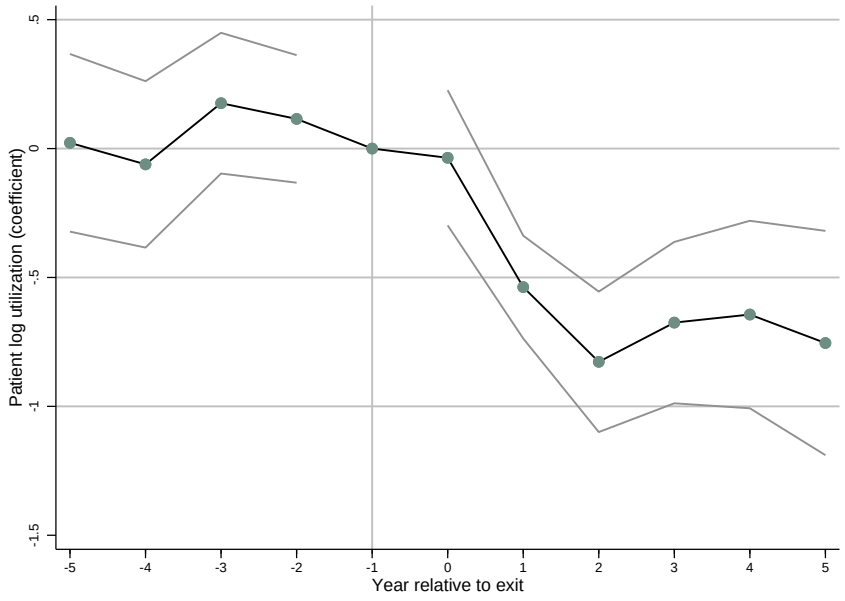
Notes: The two subplots show the estimates and 95% confidence intervals from two separate regressions. The dependent variables of subplot A and B are patients' organizational concentration and log utilization, respectively. Plots coefficient on the change in regional organizational concentration interacted 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 by level of organizational concentration

	(1)	(2)	(3)	(4)
	HRR		PCP	
	High	Low	High	Low
Organizational concentration	0.50	0.43	0.55	0.4
	(0.28)	(0.26)	(0.27)	(0.23)
Provider concentration	0.40	0.37	0.43	0.35
	(0.28)	(0.26)	(0.28)	(0.24)
Total utilization ($)	8208	8913	7328	8259
	(16,735)	(17,938)	(15,743)	(16,192)
Inpatient utilization ($)	3337	3409	3189	3360
	(10,999)	(11,182)	(10,585)	(10,703)
Carrier file utilization ($)	2895	3615	2639	3302
	(5226)	(5953)	(4334)	(4551)
Outpatient utilization ($)	1976	1889	1500	1597
	(6449)	(7598)	(6084)	(6460)
Age	76.13	76.09	76.08	76.57
	(7.5)	(7.46)	(7.48)	(7.52)
Female (%)	0.58	0.59	0.6	0.62
White (%)	0.87	0.86	0.8	0.89
Diabetes (%)	0.27	0.29	0.31	0.31
Hypertension (%)	0.58	0.63	0.66	0.70
Heart disease (%)	0.29	0.33	0.29	0.33
N of patient-year obs	18,695,293	29,741,228	8,060,958	14,129,655
N of patients	3,731,567	5,662,155	2,703,101	4,177,621
N of assigned PCP			95,308	95,307

Notes: This table reports means and standard deviations of patients' concentration measure, utilization, and demographics. Numbers in parentheses are standard deviations. For column (1) and (2), patients in the Full Sample are divided by the median of regions' organizational concentration of the Hospital Referral Region (HRR) they reside in. Column (3) and (4) are divided by the median of PCPs' organizational concentration that patients' are assigned to. Patients without assigned PCPs are excluded for column (3) and (4).

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***	-0.916***	-0.735***
	(0.021)	(0.099)	(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. 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)
	$OrgConc_{it}$	$Log(total\ utilization)_{it}$		
$\Delta OrgConc_{PCP(i)} \times post_{it}$	0.213***	-0.793***	-0.603***	-0.680***
	(0.017)	(0.090)	(0.211)	(0.207)
First stage	(5)	(6)	(7)	(8)
	$\Delta OrgConc_{PCP(i)} \times post_{it}$			
$OrgConc_{PCP(i)t-1} \times post_{it}$	-0.474***	-0.474***	-0.307***	-0.311***
	(0.006)	(0.006)	(0.007)	(0.007)
F-test	$1.0 * 10^5$	$1.0 * 10^5$	18,415	20,885
PCP provider concentration			X	X
PCP characteristics				X
PCP organizational size				X

Notes: Each column represents an instrumental variables regression, where the endogenous variable of interest is the current PCP's jackknifed organizational concentration. The 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, 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) Mean of dependent variable	(2) Coefficient on $\Delta OrgConc_{PCP(i)} \times post_{it}$
Dependent variable:		
A. Hospitalization outcomes		
Any inpatient visit	0.155	-0.001
		(0.060)
Any emergency department visit	0.259	-0.028
		(0.070)
B. Imaging use outcomes		
Number of imaging tests	1.387	-0.315
		(0.463)
Number of duplicated imaging tests	0.263	0.188
		(0.252)
C. Diabetes care outcomes		
Any HbA1C test	0.631	0.327***
		(0.154)
And LDL test	0.446	0.160***
		(0.168)

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. Panel A and B use the PCP Exit Sample (335,868 patient-year observations). Panel C 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

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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 statistics of different samples

	(1) Full	(2) Movers sample	(3) Movers	(4) PCP Exit sample
Organizational concentration	0.45	0.42	0.42	0.46
	(0.27)	(0.25)	(0.25)	(0.25)
Provider concentration	0.38	0.34	0.33	0.38
	(0.27)	(0.24)	(0.23)	(0.25)
Utilization (RBU)				
Total utilization ($)	8641	8673	9210	6512
	(17,487)	(17,127)	(16,435)	(12,722)
Inpatient utilization ($)	3381	3313	3697	2485
	(11,112)	(10,712)	(10,856)	(8617)
Carrier file utilization ($)	3337	3447	3648	2663
	(5694)	(5802)	(5253)	(3609)
Outpatient utilization ($)	1923	1913	1865	1364
	(7176)	(7133)	(5715)	(4358)
Age	76.1	76.34	78.65	77.19
	(7.48)	(7.38)	(7.35)	(7.18)
Female (%)	0.59	0.59	0.66	0.63
White (%)	0.86	0.87	0.9	0.86
Diabetes (%)	0.28	0.29	0.27	0.33
Hypertension (%)	0.62	0.65	0.67	0.73
Heart disease (%)	0.32	0.34	0.35	0.3
N of patient-year obs	48,436,521	7,576,900	195,489	335,868
N of patients	9,132,322	1,389,790	25,592	62,924
N of assigned PCP				52,981

Notes: This table reports summary statistics for the various analytic subsamples. Column 1 reports the full sample after initial restrictions. 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 A4: Summary stats of key variables at different levels

	(1)	(2)
	Mean	Std. Dev.
Patient level (N=9,132,322)		
Provider concentration	0.43	0.25
Organizational concentration	0.5	0.24
Total utilization	9116	14,800
PCP level (N=190,616)		
Provider concentration	0.39	0.15
Organizational concentration	0.5	0.16
Total utilization	9377	11,263
Regional level (N=306)		
Provider concentration	0.38	0.03
Organizational concentration	0.47	0.05
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, and reports the mean and standard deviation across PCPs. The bottom panel has one observation per Hospital Referral Region (HRR) and reports the mean and standard deviation across regions.

Table A5: Difference in differences analysis of PCP exits

	(1)	(2)	(3)	(4)
	$OrgConc_{it}$	$Log(total\ utilization)_{it}$		
$\Delta OrgConc_{PCP(i)} \times post_{it}$	0.245***	-0.456***	-0.049	-0.094
	(0.008)	(0.044)	(0.067)	(0.069)
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). Standard errors have two-way clustering at PCP and patient levels. The PCP Exit Sample has 335,868 patient-year observations.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A6: Instrumental variable analysis of PCP exits, controlling for number of physicians the patient consults

Instrumental Variables		
Second stage	(1)	(2)
	$Log(total\ utilization)_{it}$	
$\Delta OrgConc_{PCP(i)} \times post_{it}$	-0.680***	-1.272***
	(0.207)	(0.164)
First stage	(3)	(4)
	$\Delta OrgConc_{PCP(i)} \times post_{it}$	
$OrgConc_{PCP(i)t-1} \times post_{it}$	-0.311***	-0.310***
	(0.007	(0.007)
F-test	20,885	20,790
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 specification control for a 4-knot spline in the number of generalist providers (with family practice, internal medicine training, or gerontology training) and a 4-knot spline in the number of specialist providers (with any other training type).

Table A7: Impact of organizational concentration and provider concentration

Instrumental Variables			
Second stage	(1)	(2)	(3)
	Log(total utilization)$_{it}$		
$\Delta OrganizationConc_{PCP(i)} \times post_{it}$		-0.603***	-0.680***
		(0.211)	(0.207)
$\Delta ProviderConc_{PCP(i)} \times post_{it}$	-0.718***	-0.233	-0.086
	(0.076)	(0.193)	(0.189)
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. The PCP Exit Sample has 335,868 patient-year observations. See notes to Table 3 for further details.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A8: Instrumental variable analysis of PCP exits, spending decomposition

	(1) Mean of dependent variable (not log)	(2) (3) Sample size	Coefficient on $\Delta OrgConc_{PCP(i)} \times post_{it}$
Dependent variable:			
Log of Carrier claims (professional)	2663	335,868	-0.397**
			(0.160)
Log of outpatient claims (institutional)	1364	335,868	-1.105**
			(0.480)
Log of inpatient spending (hospital, if > 0)	16,507	35,002	-0.267
			(0.427)

Notes: See notes to Table 3. This table replicates the instrumental variable specification reported in Table 3 (4) and (8) with alternative outcome variables that decompose Medicare billing depending on the type of bill. Carrier claims are professional billings; outpatient claims are institutional ; inpatient claims are bills for inpatient hospital care. 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.