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Fragmented Division of Labor and Healthcare Costs: Evidence from Moves Across Regions
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ABSTRACT

Policies aiming to improve healthcare productivity often focus on reducing care fragmentation. Care fragmentation occurs when services are spread across many providers, potentially making coordination difficult. Using Medicare claims data, we analyze the effect of moving to a region with more fragmented care delivery. We find that 60% of regional variation in care fragmentation is independent of patients' individual demand for care and moving to a region with 1 SD higher fragmentation increases care utilization by 10%. When patients move to more fragmented regions, they increase their use of specialists and have fewer encounters with primary care physicians. More fragmented regions have more intensive care provision on many margins, including services sometimes associated with overutilization (hospitalizations, emergency department visits, repeat imaging studies) as well as services associated with high value care (vaccines, guideline concordant for diabetics).

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1. Introduction

Healthcare spending accounted for 17.8 percent of the U.S. economy in 2015, nearly half of which was financed by federal, state, and local governments (CMS 2017). Spending on major healthcare programs made up 31 percent of federal budget expenditures in 2016 (CBO 2017). Reducing healthcare costs offers the possibility of reducing pressures on federal and state budgets, especially if it can be done with minimal effect on quality.

The academic and policy literature highlights two broad strategies for containing healthcare costs. The first strategy combines initiatives to discourage utilization with aggressive bargaining to reduce payments.[1] The second cost-containment strategy involves efforts to reorganize the delivery of care so that similar quality is delivered at lower cost. The belief that such efficiency-enhancing reorganization is possible has inspired important managerial and policy initiatives such as the integrated delivery networks of the 1990s and today's Accountable Care Organizations.

Empirical evidence that large-scale reorganization of delivery can successfully reduce costs is, however, limited.[2] The evidence that does exist is often indirect and much of it comes from studies of Medicare spending across regions in the United States. Medicare health care utilization exhibits high variation across U.S. regions, over half of which is unrelated to patients' clinical demand for care (Finkelstein, et al. 2016). Lower utilization regions, moreover, do not generally have worse patient outcomes (Skinner 2011). These Medicare variations are noteworthy because they are not the result of regional differences in prices or in payer policies

[1] There is growing evidence from cross-national studies, from studies of the U.S. healthcare system and from case studies that this approach can indeed reduce healthcare spending.The U.S. has substantially higher rates of healthcare spending than other high income countries. A recent cross-national comparison finds that many of the most noteworthy differences between the U.S. and other countries was the result of high prices in the U.S. (Papanicolas, Woskie and Jha, 2018). In their recent review of prior efforts to transform U.S. healthcare, Burns and Pauly (2018) observe that the cost-containment successes of the HMO revolution of the 1990s were largely the result of lower payments to providers and denying services to patients. Consumer driven health plans aim to discourage utilization via high deductibles. In her recent review, Bundorf (2016) finds that discouraging utilization in this way reduces health spending by approximately 5-15%. A more fine grained case study of a high deductible plan also finds evidence of substantial cost reductions, but little evidence that the high deductibles encourage wise decision making or improved shopping behavior among consumers (Brot-Goldberg, Chandra, Handel and Kolstad 2017).

[2] While it is still relatively early days, studies of Accountable Care Organizations suggest only very modest cost savings (Burns and Pauly, 2018, provide a review) and these have been concentrated among lower-risk patients suggesting that improved care coordination and management are not the major drivers (McWilliams, Chernew and Landon, 2017).

regarding utilization. The existence of large regional utilization differences in Medicare thus offers hope that strategies exist for organizing care delivery in more cost-effective ways.[3]

In this paper we explore the possibility that regional differences in the division of labor across providers contribute to regional differences in costs, utilization patterns, and outcomes. We focus on the distribution of care across distinct providers - a phenomenon often referred to as fragmented care delivery. It has long been an article of faith among healthcare analysts that fragmentation leads to poor care coordination and so to higher costs and uneven quality (see e.g. Bodenheimer 2008, Cebul et al. 2008, Stille et al. 2005). This belief has motivated important public policy initiatives aimed at improving care coordination, e.g. subsidizing investments in electronic health records and using public policy to encourage coordination-enhancing organizational forms such as Patient Centered Medical Homes and Accountable Care Organizations (ACOs).

To understand the issue of fragmentation from a clinical perspective, consider Press's (2014) account of treatment for a healthy 70-year-old patient suddenly presenting with pain and fever. A scan revealed these symptoms to be the result of a kidney stone and a liver tumor. Over the 80 days of treatment, the patient underwent five procedures and was seen by 12 clinicians. His primary care provider (PCP) took on the job of coordinating among these clinicians and communicated with them a total of 40 times over the 80 day period. In spite of this effort, coordination was not foolproof. The PCP picked up a problem with the patient's electrolytes resulting from a decision made by a cardiologist brought onto the case. Resolving this problem required additional calls, a change of medication, and additional lab tests.

The number of providers in involved in care delivery for this patient is not an anomaly: the median Medicare beneficiary is seen by 8 distinct providers each year, and 10% of patients are treated by over 21 providers. With so many information handoffs to manage, it is easy to understand why the medical literature has been concerned with the potential for fragmentation to complicate coordination and so to drive higher costs and diminished care quality through

[3] While regional cost differentials suggest the possibility of gains from more efficient care delivery, they are not a good guide to the magnitude of welfare gains from organizing care in more effective ways. As Chandra and Staiger discuss in their study of the treatment of heart attacks, once regions specialize in more or less costly styles of care, adoption of lower cost practice styles can lead to reductions in quality that partially or fully offset cost savings (Chandra and Staiger, 2007).

duplicative or unnecessary tests, medical errors, and adverse health outcomes (cf. McWilliams 2016, Milstein and Gilbertson 2009).

From an economist's perspective, the issue of fragmentation is best analyzed in terms of the trade off between specialization and coordination. Involving more specialized providers brings more expertise to the patient's care, but may also introduce coordination problems that can increase costs and/or reduce quality (Becker and Murphy 1992). The very localized nature of healthcare markets means that fragmentation is necessarily linked to geography. Geographic variation is further reinforced by "learning by doing" effects that spillover to all the doctors in a region (Chandra and Staiger, 2007). If by virtue of being in a fragmented region, specialists learn to better coordinate with primary care doctors, this will facilitate greater reliance on specialists for care delivery. Alternatively, if by virtue of operating in a less fragmented region, primary care providers learn to manage diverse conditions that might otherwise be referred to specialists, this will facilitate reduced delegation of care to specialists. The welfare consequences of the resulting regional variation in fragmentation is an empirical question that depends on the cost and quality of care produced by a region's division of clinical labor.

The empirical literature on fragmentation has focused on estimating how an individual patient's utilization varies with the fragmentation of care that individual received. Individual care fragmentation measures are typically a function of the number of providers and the distribution of care among them (see Pollack et al. 2013, Frandsen et al. 2015, Hussey et al. 2014, Nyweide et al. 2013, Baicker and Chandra 2004).[4] One important shortcoming of this approach is that patients who see more providers may do so because their clinical conditions are more complex; while prior research has controlled for observable comorbidities and demographics, cross-sectional comparisons are likely biased by omitted, patient-level factors. Another shortcoming is that individual care fragmentation measures do not capture cross-regional differences in the division of clinical labor, our key object of study.

The empirical approach we adopt in this paper aims to address both these shortcomings. We proceed in two steps. First we tackle the problem of unobserved and omitted patient characteristics by adopting the movers-based econometric approach developed by Skinner et. al.

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[4] Along these same lines Romano, Segal and Pollack (2015) report an association between measures of fragmented care delivery and the overuse of medical procedures.

(2010) and Finkelstein et. al. (2016). Like them, we focus on the change in outcomes as Medicare enrollees move across regions to identify causal region effects on fragmentation, utilization, and quality-of-care outcomes purged of fixed, patient-level confounders. The second step in our empirical approach is to examine how these causal effects of place vary with regional measures of fragmentation. Our empirical specification combines these two steps into one regression, but it is helpful to distinguish them because they rely on distinct identifying assumptions. We spell out these identifying assumptions more formally in Section 2.

Our results can be briefly summarized. First, we find that regions differ substantially in the degree to which the division of clinical labor is fragmented. Second, the region in which an individual receives care significantly affects the individual's care fragmentation: roughly 60% of the variation in fragmentation across regions is due to region effects rather than cross-regional variation in patient characteristics. Moving to a new region sharply shifts an individual's care fragmentation towards the fragmentation patterns prevalent in the destination region.

Third, we find that regions affect individual costs, utilization patterns, and outcomes, and that these region effects vary with the level of fragmentation prevailing in the region. A move to a region with a one standard deviation higher level of fragmentation leads to 10 percent higher annual care utilization for the mover. Patients who move to more fragmented regions increase their reliance on specialist providers while reducing their use of primary care. Patients moving to more fragmented regions make greater use of services often implicated in overutilization, including emergency department care, inpatient hospitalizations, and imaging studies; however, they also make greater use of high value services, including vaccinations, and guideline-concordant care for diabetic patients.

Our central finding, that the causal effects of location on both individual care fragmentation and utilization are positively correlated with regional fragmentation, supports the notion that regional practice styles matter. On this basis alone, public policy makers ought to pay careful attention to the causes and consequences of regional variation in the division of clinical labor. Drawing policy implications is complicated, however, by the tradeoff between the cost benefits of improved coordination and the likely quality benefits of enhanced specialization.

Indeed we find that for some measures, quality improvements are positively correlated with regional fragmentation and that for others we find no evidence of quality degradation.

If regional fragmentation correlates so strongly with policy-relevant outcomes can we also conclude that regional fragmentation per se causally affects these outcomes? As we analyze more fully below, in this study attributing a causal effect to regional fragmentation requires accepting very strong identifying assumptions. If these assumptions do not hold, we cannot rule out the possibility that unmeasured dimensions of regional practice patterns or institutions that are correlated with regional fragmentation drive the results. In this case regional fragmentation may nevertheless serve as a useful marker for further inquiry into the regional determinants of healthcare cost and quality.

The paper proceeds in four parts. Section 2 presents our data and empirical framework. Section 3 describes empirical results, robustness checks, and interpretation. In Section 4 of the paper we analyze the structure and potential impact of anti-fragmentation policies aimed at improving physician incentives. We conclude the paper by discussing the limitations of our analysis as well as directions for future research.

2. Data, Measurement, and Empirical Approach to Fragmentation

A. Data and fragmentation measures

The empirical analysis employs a 20% sample of Medicare fee-for-service beneficiaries from 2000 to 2010, including Part A and Part B claims. From these claims, we construct measures of care fragmentation, use of primary care and specialists, hospitalization rates, and cost-based utilization measures. The data tracks patients over time as long as they remain in fee-for-service Medicare, allowing us to study how care patterns evolve before and after a patient moves.

We restrict the sample to include only beneficiaries who are continuously enrolled in Medicare Parts A and B throughout the year, are between 65 and 99 years old, and have at least one claim. Of these, our sample includes all beneficiaries who move across hospital referral region (HRR) boundaries exactly once during our sample period and a 25% random sample of non-movers. We exclude from the sample beneficiaries who do not receive at least 75% of their claims in the indicated HRR of residence, except for movers during their year of move; this restriction purges beneficiaries who change the address on file with the Social Security Administration but continue seeking most of their medical care in their former location. The final sample includes approximately 70,000 moving beneficiaries and 860,000 non-moving beneficiaries.

We supplement this analysis with matched Medicare Part D claims from 2006-2010, for beneficiaries who are also Part D subscribers. The Part D claims allow us to track prescription drug use. For each patient, we count the number of unique drugs prescribed within a year using National Drug Codes to identify drugs. We also apply the Health Effectiveness Data and Information Set (HEDIS) criteria to measure use of high-risk medications in the elderly.[5]

As a first step in our analysis, we calculate a visit concentration index to measure the level of care fragmentation for each Medicare patient. A visit is defined as a provider-date pair, so that any bills generated by a single provider on a single day are counted as one visit. The provider is identified by the attending provider in the Outpatient and Inpatient claims, and as the performing provider in the Carrier claims.

The fragmentation measure is modeled on a standard Herfindahl-Hirschman concentration index.[6] We first calculate each provider's share of total visits associated with that patient's claims, and then sum the squared provider shares across all providers that a patient sees. The formula is below:

$$(1) \qquad fragmentation_{it} = 1 - \sum_{d=1}^{D} share_{itd}^2$$

where $fragmentation_{it}$ measures the level of care fragmentation for patient i in year t, who receives $share_{itd}$ of his care from each provider d, of D total possible providers. Note that we calculate one minus the usual HHI so that larger numbers correspond to a greater degree of care fragmentation, with 0 corresponding to having all care delivered by a single provider (or

5 Analysis is based on the 2012 HEDIS NDC list for high risk drugs in the elderly (DAE). These drugs are those which "should be avoided among patients 65 years of age or older, because the associated adverse effects outweigh potential benefits or because safer alternatives are available" (Qato and Trivedi, 2013). Examples include particular psychotherapeutic drugs, which have been linked to delirium

6 In the medical literature, fragmentation is sometimes discussed as creating a problem of "care continuity" and common measures of care continuity are essentially the same as measures of fragmented care delivery we employ in this paper. For a discussion of different measures of care fragmentation or care continuity see Pollack et al. (2013).

receiving no care at all) and fragmentation approaching 1 if the patient's care were split equally among a very large number of providers.

Unlike simple counts of providers per patient, this fragmentation measure reflects differences in care concentration. For example, it distinguishes between a patient whose care is equally divided across two providers and a patient who interacts almost exclusively with one provider but had a single consultation with an alternate provider. Concentrating patient visits with a single primary care physician should enable improved care coordination and will also reduce this measure of care fragmentation. Fragmentation has been validated in the medical literature as a summary measure capturing a bundle of practice patterns that together may predict coordination challenges (Pollack et al. 2013).

We further analyze two distinct manifestations of care fragmentation: primary care fragmentation, where patients split their primary care encounters across many providers; and specialty fragmentation, where patients split their care across many different types of specialists. Details of these measures and the accompanying analysis are reported in Section 3E.

Regional levels of care fragmentation are calculated by averaging these individual concentration measures within hospital service areas. For ease of interpretation, we normalize by dividing by the standard deviation of average regional fragmentation levels across regions. Much of our empirical work relies on the analysis of Medicare beneficiaries who move to regions with different levels of care fragmentation. For this reason, we define the regional level of fragmentation by averaging only over non-movers.

Our primary results use the Hospital Service Area (HSA) as our definition of a region. There are 3,436 HSAs in the United States as defined by the Dartmouth Atlas of Healthcare. The regions are constructed so that residents receive most of their hospitalizations within HSA boundaries. The Dartmouth Atlas also defines larger Hospital Referral Regions (HRR) in which patients are referred for major cardiovascular procedures and neurosurgery. As we report below, our results are not sensitive to using these larger regional definitions.

We are interested in understanding how regional practice style as captured by fragmentation may contribute to individual health outcomes. We estimate the relationship between care fragmentation and measures of utilization including both annual resource utilization and the log of annual utilization plus 1. These two utilization measures are constructed using a fixed set of Medicare prices expunged of regional price adjusters, and so should be interpreted as indices of resources used rather than as measures of actual costs or spending.[7]

Other supply-side features of a regions' health care system are potential confounders in our main analysis of care fragmentation. While we cannot refute the possibility that our finding is driven by other unmeasured feature of the local market, we estimate specifications that control for salient features of regional healthcare supply. We focus on four market-level characteristics that are plausibly related to fragmentation and costs: urbanicity, provider density, market concentration, and provider practice style.

To measure urbanicity at the HSA level, we link zip codes to the Census Bureau definitions of urbanized areas. We construct a continuous measure of urban status by calculating the fraction of the population within an HSA that lives in a Census-designated urban area zip code.

We apply measures reported in the Dartmouth Atlas of primary care physicians and specialists per 100,000 residents to estimate physician capacity in each HSA. The specialist density measures include 33 individual measures of density for each specific specialty reported by the Dartmouth Atlas.[8] These measures of physician capacity were originally derived from the 2006 American Medical Association Master File.

Next, we introduce controls for the market concentration of providers. Specifically, using tax IDs reported in the carrier claims file, we construct a Herfindahl Hirschman Index of market concentration at the HSA-level.

[7] Because Medicare prices include some regional adjustments on the basis of local wage indices, we want to avoid conflating high price regions with high utilization regions. Thus when analyzing price based utilization measures, we follow Finkelstein et al. (2016) and adjust total spending to strip away variation that is due to regional price adjustments.

[8] The complete list of physician types we control for is: allergists/immunologists, anesthesiologists, cardiologists, cardiothoracic surgeons, critical care physicians, dermatologists, emergency medicine physicians, endocrinologists, family practice physicians, geriatricians, general surgeons, gastroenterologists, hematologists/oncologists, infectious disease specialists, internal medicine physicians, neonatologists, neurosurgeons, neurologists, obstetricians/gynecologists, ophthalmologists, orthopedic surgeons, otolaryngologists, pathologists, pediatricians, plastic surgeons, psychiatrists, pulmonologists, radiologists radiation oncologists, physical medicine/rehabilitation physicians, rheumatologists, urologists, and vascular surgeons.

Finally, we add controls for "cowboy" and "comforter" provider preferences at the HRR level, using survey measures developed by Cutler et al. (2018). Because these survey measures are not available for all HRRs, including this control necessitates restricting the sample.

B. Summary graphs and statistics

Figure 1 presents the variation in care fragmentation across regions by shading Hospital Service Areas (HSAs) according to which tercile of the distribution of regional care fragmentation they belong. The map reveals heterogeneity in patterns of fragmentation, even within metro areas.

Table 1 presents a more detailed look at regional differences. The first panel presents our regional fragmentation scores and utilization measure for each tercile of the overall fragmentation measure. We report the standardized fragmentation measures, which have been demeaned (by the regional fragmentation level averaged across regions) and divided by the standard deviation (calculated across the regional average fragmentation levels). We find that the average individual fragmentation level is -0.01 in the lowest fragmentation tercile of HSAs, rising to 1.21 in the highest fragmentation tercile of HSAs.[9] The standard deviation of individual fragmentation within a regional tercile is approximately 4 times larger than the cross-regional variation, reflecting both the substantial heterogeneity in individual demand for medical care and local provider practice variation.

The remaining rows of Table 1 delve more deeply into resource utilization, describing the bundle of care patterns that underlie our fragmentation index. Total encounters in a year are higher in high fragmentation regions by over 4.9 visits per patient, from a mean of 21.9 annual encounters in the lowest tercile regions. Patients in regions with greater care fragmentation also see more unique providers on average, with patients in the lowest tercile seeing an average of 8.9 providers while those in the most fragmented tercile see 31% more providers. Despite the higher number of total visits, we find that patients in the most fragmented regions have 15% fewer primary care encounters than patients in the least fragmented regions.[10] This pattern raises the

[9] The average normalized fragmentation score in the lowest tercile (-.01) is so close to zero because (1) the normalization is done with equal weights for each HSA; (2) terciles are defined to have equal numbers of patients; and (3) the least populous HSAs tend to have lower fragmentation.

[10] Primary care visits are defined as any encounter with a physician listing family practice, primary care or internal medicine among his specialties.

possibility that specialized care is used as a substitute for primary care in these regions - an issue we explore in more detail below.

We note that average annual utilization in the highest fragmentation regions is also high - over $1,000 per beneficiary per year more than regions in the lowest fragmentation group. The positive relationship between average regional fragmentation and average regional spending is also evident in the scatter plot of HSA fragmentation and average utilization presented in Figure 2. Decomposing total utilization into the three sources of these bills reveals that increases in provider billings (from the Carrier file) account for most of the rise in total utilization, $870 higher in the top tercile relative to the bottom tercile regions. This increase is partially offset by a small decrease of $105 in hospital outpatient billings, which can cover many of the same services covered through provider bills. Hospital inpatient bills also increase, albeit more moderately, with the highest fragmentation tercile regions spending $320 more per beneficiary per year than the lowest fragmentation tercile regions.

The final panel of Table 1 presents patient characteristics. We find only modest differences in patient characteristics across regions with differing patterns of fragmentation. Patients residing in regions with the highest tercile of fragmentation are on average 0.28 years older than patients in the lowest fragmentation regions, and 2 percentage points more likely to be female. In all three terciles, 22% of patients have a diabetes diagnosis.

While these summary statistics do not suggest strong differences in patient selection across regions with different fragmentation levels, we nevertheless remain concerned that demand-side differences driven by patient needs or preferences could explain the cross-sectional differences in fragmentation and utilization. To investigate this issue, we turn to an analysis of Medicare beneficiaries who move between regions with different average levels of care fragmentation.

Our regression strategy requires that regional fragmentation patterns influence individual care patterns. Figure 3 visualizes this influence using binned scatterplots. Specifically, we divide our 70,000 moving beneficiaries into 20 equally sized groups according to the difference between fragmentation levels in the destination and origin regions. We then plot the average change in regional fragmentation at the HSA level along the x-axis, and the average change in individual fragmentation along the y-axis, for each vigintile. In examining this plot it is worth noting that regional fragmentation is calculated from data on stayers only so that the x and y axes are calculated using distinct populations of Medicare beneficiaries.

Patients moving to more fragmented regions clearly experience larger increases in their own fragmentation than beneficiaries moving to less fragmented regions, as evidenced by the strongly upward sloping pattern displayed in the plot.[11] Further, we find that beneficiaries who move to more fragmented regions experience larger increases in their health utilization relative to beneficiaries who move to less fragmented areas. These results suggest that regional factors may be important determinants of individual-level care fragmentation, and that regional fragmentation patterns are strongly associated with regional costs of care. We investigate these relationships in more detail using the regression strategy outlined in Section 2.C below.

C. Estimation strategy

Our empirical strategy identifies the contribution of fragmentation to regional effects on patient outcomes conceptually in two stages. The first stage identifies the causal effects of regions on health outcomes by exploiting variation from individuals who move across regions, adapting the event study methodology of Finkelstein et al. (2016). The second stage identifies the contribution of fragmentation to these regional effects by controlling for relevant observable regional characteristics. In practice, the two stages are estimated simultaneously in a single regression framework, but it is useful to discuss them separately as they rely on distinct identifying assumptions. This section describes these identifying assumptions using a potential outcomes framework.

If patient i were to receive care in region r in period t, she would experience potential outcome $Y_{it}(r)$. We denote the region where individual i actually receives care in period t by R_{it}. Individual i's observed outcome in period t is therefore $Y_{it} := Y_{it}(R_{it})$.

Our population consists of movers and non-movers. Let M_i be an indicator for whether individual i moves across regions during the study period. Let O_i be individual i's origin region

[11] Note that the y axis, the average change in individual fragmentation, is positive for all ventiles, This is because patients' care tends to become more fragmented as they age and movers are necessarily older in their destination region.

and D_i be the destination region. T_i is the period in which individual i moves (equal to infinity for non-movers).

The average causal effect among individuals who move from region o to region d in period t is given by the average difference between potential outcomes experienced by movers in the destination region in period t and potential outcomes had the individuals not moved:

$$\Delta(o,d,t) := E\left[Y_{it}(d) - Y_{it}(o) \mid O_i = o, D_i = d, T_i = t\right].$$

In general this average causal effect is specific to the moving period and the origin-destination pair. In order for comparisons of different average causal effects to have a causal interpretation, we assume that among movers the moving date and the specific origin and destination pair are not selected on the basis of the potential gain (or loss) from moving:

Assumption: No Selection on Gains. For all regions $d \neq o$,

$$E\left[Y_{iT_i}(d) - Y_{iT_i}(o) \mid M_i = 1, O_i = o, D_i = d, T_i = t\right] = E\left[Y_{iT_i}(d) - Y_{iT_i}(o) \mid M_i = 1\right].$$

This assumption says that the treatment effect of moving from o to d is independent of the moving date, actual origin, and actual destination, conditional on moving. The assumption is analogous to the conditional effect homogeneity assumption in Hull (2018). No Selection on Gains implies that comparisons of different regional moving effects have a causal interpretation as the effect of the destination region on outcomes.

The key challenge to identifying regional causal effects is that they involve the comparison of counterfactual potential outcomes, $Y_{iT_i}(o)$ and $Y_{iT_i}(d)$, at most one of which is observed. A straightforward way to overcome this challenge is to assume that the period-to-period change in outcomes that would have been experienced by movers had they not moved is equal on average to the observed change among individuals who did not move. Formally, this parallel trends assumption is given by:

Assumption: Parallel Trends. For all regions $d \neq o$ and all periods t,

$$E\left[Y_{it}(o) - Y_{it-1}(o) \mid R_{it-1} = o, R_{it} = d, T_i = t\right] = E\left[Y_{it}(o) - Y_{it-1}(o) \mid R_{it} = o, T_i \neq t\right].$$

This assumption means that the period-to-period change in potential outcomes in a given region does not (on average) depend on moving status. The parallel trends assumption can be assessed using the event-study approach we describe below, which examines whether prior to moving individuals who eventually moved followed similar trends to non-movers.

Under the parallel trends assumption the causal effect of moving between region *r* and *r'*, which we denote $\Delta(r,r')$, is identified via the difference in the observed change in outcomes between movers and stayers (including those who move in another period):

$$\Delta(r,r') = E\left[Y_{it} - Y_{it-1} | R_{it-1} = r', R_{it} = r, T_i = t\right] - E\left[Y_{it} - Y_{it-1} | R_{it-1} = r', T_i \neq t\right] \quad .$$

See the online Appendix for proofs of this and other results in this section. The Parallel Trends assumption as expressed above is quite strong. It allows movers on average to have different levels of outcomes from non-movers, but requires that trends in outcomes be no different on average between movers and non-movers. The assumption can be weakened to allow movers to be on different trends from non-movers, provided they are on parallel trends with other contemporaneous movers:

Assumption: Parallel Trends among Movers. For all regions *o*, *d*, *d'* and periods *t*,

$$E\left[Y_{it}(o) - Y_{it-1}(o) | R_{it-1} = o, R_{it} = d, T_i = t\right] = E\left[Y_{it}(o) - Y_{it-1}(o) | R_{it} = o, R_{it} = d', T_i = t\right].$$

Parallel Trends among Movers is implied by the stronger Parallel Trends assumptions, but does not imply it. This assumption, together with No Selection on Gains, identifies region effects via difference-in-differences among contemporaneous movers:

$$\Delta(r,r') = E\left[Y_{it} - Y_{it-1} | R_{it-1} = r_0, R_{it} = r, T_i = t\right] - E\left[Y_{it} - Y_{it-1} | R_{it-1} = r_0, R_{it} = r', T_i = t\right].$$

No Selection on Gains and Parallel Trends among Movers (possibly conditional on controls x_{it}) identify the average causal effect among movers of moving from one region to another. As only differences between regions are identified, we can normalize these effects to some reference region r_0 to define region causal effects:

$$\Delta_r := \Delta(r, r_0).$$

Many factors likely contribute to the region effects Δ_r, including the division of clinical labor in the region, institutional characteristics of the region, and infrastructure. Recall, however, that regional effects by definition do not reflect differences in patient health status across regions. To define the contribution of fragmentation to regional effects, let $\Delta_r(f)$ be the potential effect of region *r* if its fragmentation level were *f*. The region's observed fragmentation level is F_r. The realized region effect is $\Delta_r = \Delta_r(F_r)$, which is identified given Parallel Trends among Movers and No Selection on Gains as shown above. The average causal effect of a change in fragmentation from level *f* to *f'* is $E[\Delta_r(f') - \Delta_r(f)]$, where now the expectation is taken over regions. To identify the effect of fragmentation, consider the assumption that realized fragmentation is conditionally (mean) independent of potential regional effects given a vector of observable region characteristics:

Assumption: Fragmentation Selection on Observables. For observed vector X_r and for all fragmentation levels f we have $E[\Delta_r(f) | X_r, F_r] = E[\Delta_r(f) | X_r]$.

This assumption means that after controlling for X_r, further factors that influence a region's "place effect" are uncorrelated with its fragmentation level. This assumption can be assessed in several ways. First, a necessary (though of course not sufficient) condition for this assumption to hold is that controlling for additional variables beyond X_r that influence the outcome does not change the estimated effect of fragmentation. We augment the baseline regression specification to add several control variables describing other, likely impactful, supply-side features of the regional health care system. Second, economic theory may suggest that fragmentation will have a specific pattern of effects that omitted variables may not be expected to follow. For example, fragmentation across specialist types may increase use of specialist care while reducing utilization of primary care providers. One might expect omitted variables to be associated with increased utilization in all types of care. Third, Selection on Observables together with No Selection on Gains means that the change in fragmentation experienced by an individual moving across regions will not be related to the individual's health status. The Roy model of practice spillovers developed in the Online Appendix provides a plausible setting in which this will be true.

The assumptions needed to identify regional causal effects (No Selection on Gains and Parallel Trends among Movers) have been adopted previously in the literature to identify regional effects from variation induced by movers (Finkelstein, et al. 2016) and may be more plausible than the Selection on Observables assumption needed to further identify the causal effect of fragmentation. Without the Selection on Observables assumption our estimates can be interpreted as the causal effects of moving to regions with higher fragmentation, rather than the effect of fragmentation itself.

Given Parallel Trends among Movers, No Selection on Gains, and Fragmentation Selection on Observables, the effect of regional fragmentation on individual health outcomes is nonparametrically identified. In practice we estimate regression specifications that parameterize these assumptions. Conceptually, estimation can be thought of as occurring in two steps. First, region effects can be estimated from a differences-in- differences regression on region indicators controlling for covariates x_{it}, individual fixed effects α_i, time effects γ_t, and effects for periods relative to move ρ_p, in a specification such as the following:

$$Y_{it} = \sum_r \Delta_r 1\,(R_{it} = r) + x'_{it}\beta + \alpha_i + \gamma_t + \rho_{p(i,t)} + \varepsilon_{it}.$$

Second, estimates of the regional effects $\widehat{\Delta}_{R_{it}}$ can be regressed on the regional fragmentation measure in a similar specification, but with the region dummies replaced with the regional fragmentation measure:

$$\widehat{\Delta}_{R_{it}} = \delta F_{R_{it}} + x'_{it}\beta + \alpha_i + \gamma_t + \rho_{p(i,t)} + \varepsilon_{it}.$$

The coefficient on fragmentation identifies the effect of regional fragmentation on movers' health outcomes. The two-stage procedure conceptually distinguishes the identification of regional effects from the identification of fragmentation's contribution to the regional effects, but in practice we use the following single regression specification, which yields algebraically equivalent estimates of the effects of fragmentation and simplifies inference:

$$(1) \qquad Y_{it} = \delta \Delta fragmentation_i \times post_{it} + x'_{it}\beta + \alpha_i + \gamma_t + \rho_{p(i,t)} + \varepsilon_{it},$$

where Y_{it} is the outcome variable (such as care fragmentation or utilization) for beneficiary *i* in year *t*.[12] The key coefficient of interest is δ, which multiplies the interaction between $post_{it}$, an indicator variable that equals 1 for movers in the years following their move, and $\Delta fragmentation_i$, the change in average regional fragmentation for mover *i* calculated by the difference between destination and origin regions. The regression also controls for individual fixed effects α_i, calendar year effects γ_t, one-year bins for patient age x_{it}, and a vector of fixed effects for relative years $\rho_{p(i,t)}$. The relative event years indicate time relative to the move date,

[12] In estimating equations (10) and (11), we retain all Medicare Fee for Service beneficiaries who move exactly once during our study period, as well as a 20% sample of non-movers to identify control variables. We distinguish non-movers from movers in Medicare claims data by tracking changes in the beneficiary's address for Social Security payments from year to year. The recorded addresses report the address on file as of March 31st of each year, so we construct yearly estimates of fragmentation and utilization from April 1st through March 31st of the next year. All inference is clustered at the patient level, following Finkelstein, et al. (2016), whose patient-level bootstrap is asymptotically equivalent to clustering at the patient level.

with year -1 indicating the year before the move, year 0 indicating the year of the move, and so on. Note that $\Delta fragmentation_i$ and $\rho_{p(i,t)}$ are normalized to zero for non-movers.

Coefficient δ describes how an individual's outcome, Y_{it}, changes once he or she moves to a region with a different level of fragmentation. By controlling for beneficiary fixed effects, we can separate the effect of regional practice patterns from fixed patient-level factors. Of course, a patient's clinical situation or preferences can change over time and these fixed effects do not control for time-varying factors. We capture some of the time varying factors by including one-year bins for patient age, and fixed effects for years relative to move date. Because the parameter δ is identified solely by comparing movers to other movers, omitted time-varying patient factors only introduces a bias if they are correlated with the *change* in regional fragmentation following a move. For example, our identifying assumption would be violated if patients responded to negative health shocks by moving from their current region to a more highly fragmented region. Our assumption would not be violated, however, if the destination chosen by movers responding to a negative health shock were not influenced by fragmentation levels in the destination region.

We investigate the validity of this identifying assumption by replacing the single binary variable $post_{it}$ in equation (1) with a series of fixed effects for relative years $\theta_{p(i,t)}$

(2) $$y_{it} = \alpha_i + \theta_{p(i,t)}\Delta fragmentation_i + \tau_t + \rho_{p(i,t)} + x_{it}\beta + \varepsilon_{it} .$$

This specification allows us to observe any correlation between a patient's trends prior to a move and the change in fragmentation post-move in an event study framework. Finding that estimates of $\theta_{p(i,t)}$ from equation (2) are stable prior to the move would support our identifying assumption that trends are uncorrelated with ultimate changes in regional fragmentation.

In the next section we use parameter δ from various versions of equation (1) as our estimate of the magnitude of the effect of changes in regional care fragmentation. In addition, we use plots of estimates of $\theta_{p(i,t)}$ from equation (2) to investigate the validity of the parallel trends identifying assumption. Because we look at many outcome variables in this analysis, we apply Bonferroni (1937) corrections to our reported p-values and significance levels that correct for the multiplicity of tests within a domain; these corrections are applied based on the number of outcomes reported in each table.

We also consider a set of parallel specifications that differentiate the effects of fragmentation driven by reliance on specialists and the effects of fragmentation driven by low continuity within primary care providers. In these results, we replace the unitary measure of care fragmentation as the key independent variable of interest with two variables encoding the regional changes in primary care fragmentation and specialty fragmentation, respectively. The regression structure and identifying assumptions parallel those described above.

3. Regression Results

A. Regional fragmentation and care utilization

Figure 4 plots estimates of $\theta_{p(i,t)}$ from the event study specification in equation (2) for various individual outcomes. The purpose of these event study graphs is to probe the validity of our parallel trends assumptions. We then estimate the magnitude of region effects on care patterns and utilization using equation (1), and report the results in Table 2. Column 1 reports the baseline specification, which controls for patient fixed effects, year fixed effects, and patient age.

We begin with an analysis of how changes in regional fragmentation influence the fragmentation of care that individual patients receive. In Panel A of Figure 4 we see that estimates of $\theta_{p(i,t)}$ from equation (2) are quite flat prior to the move and rise sharply to a new equilibrium within 1-2 years after the move. This pattern supports our identifying assumption that fragmentation changes associated with a move are not related to differential trends in patients' health status. In row 1 of Table 2, we present estimates of the magnitude of the region effects from equation (1). We find that moving to a region that has one standard deviation greater care fragmentation increases the mover's individual care fragmentation by 0.60 standard deviations; this result is statistically significant at the 1% level.

Given the fact that physicians tailor care decisions closely to the medical needs and preferences of individual patients, the estimated effect of regional fragmentation on an individual's level of care fragmentation is strikingly large. One way to understand the magnitude of this coefficient is to assume, as described in Finkelstein, et al. (2016), that geographic variations in health care delivery can be decomposed into additively separable patient and place-based components. From this perspective, the coefficient of 0.60 suggests that 60% of the cross-regional variation in care fragmentation is due to region effects of the sort we model in Section 2. The finding that the fragmentation of a mover's care correlates so strongly with the level of fragmentation in the destination region lends credence to the idea that the regional division of clinical labor can shape individual outcomes.

Regional fragmentation provides a summary measure of a bundle of clinical practices that together may make coordination more challenging. In the next set of results, we unpack the specific care patterns that coincide with the documented fragmentation changes. Results reported in Table 2 column 1 find that a one standard deviation higher level of fragmentation is associated with 2.4 more encounters each year, 1.4 additional distinct providers, and 0.4 *fewer* encounters with a primary care physician. Panels B, C and D in Figure 4 reveal that these adjustments are rapid and remain quite stable after the move.

The fact that patients in fragmented regions *reduce* their use of primary care providers while increasing the number of visits and the number of distinct providers is noteworthy because it suggests some substitution away from primary care towards specialists in fragmented regions. One might have expected complementarity between the use of primary care and more specialized physicians, since primary care doctor visits can lead to the detection of a condition necessitating a specialized consultation. In addition, patients who see more specialists may also have a greater need for the care coordination services provided by a primary care provider – leading to additional PCP visits. Our findings instead suggest that in more fragmented regions, specialists take on the management of conditions that could otherwise be treated by primary care providers and this causes a decline in the utilization of primary care visits.

Next we examine the effects of regional fragmentation on resource utilization. Panel B of Figure 4 plots estimates of $\theta_{p(i,t)}$ from the event study specification in equation (2) with log of annual utilization as the outcome measure. As before, we see no trend in utilization prior to the move and a change immediately following the move that depends on the change in regional fragmentation. Estimates of equation (1) presented in Table 2, Panel B, row 1, reveal that moving to a region with one standard deviation higher fragmentation is associated with an 11% increase in utilization.

Decomposing these utilization changes by the source of the bill, we find that moving to a region with one standard deviation higher fragmentation increases individuals' physician and provider (Carrier) bills by \$471 and increases hospital inpatient bills by \$371 per year. We find that moving to more fragmented regions leads to a slight decrease in hospital outpatient bills of \$75 per year, which is not nearly enough to offset the large gains to spending in other categories. Because many of the same types of services can be billed to Medicare either through the Carrier file or the hospital outpatient file depending on the organizational structure and local billing practices, the opposing effects may reflect differences in billing practice for similar services between more and less fragmented regions.

Taken together the results in Panel B of Table 2 suggest the possibility of a link between fragmented division of clinical labor in a region and higher levels of utilization. Under assumptions of parallel trends and no selection on gains, these estimates demonstrate that regional fragmentation levels are strongly tied to the causal effect of place on overall care utilization. However, based on the evidence presented so far, we cannot refute the possibility that some other characteristic of regional institutions or practice style is correlated with regional fragmentation and drives the observed changes in the outcomes under study.

As described in Section 2.C, regional fragmentation may be correlated with other place-based factors that contribute to health utilization and outcomes, and these factors may bias our estimated results. While we do not have a source of quasi-random variation in regional fragmentation that is plausibly orthogonal to other characteristics of regional medical practice, we can endeavor to control for key features of local health care markets. In Table 2, columns 2 and 3, we report specifications that add new controls for other features of regional supply of care.

Column 2 introduces controls for urbanicity, 33 measures of provider density by specialty type, and the concentration of local provider markets, all at the HSA level. Urban areas may support higher levels of specialization that directly influence both levels of fragmentation and costs. This might happen, for example, if urban areas had better access to new technologies and tertiary care hospitals. For similar reasons, a greater density of specialists may influence levels of fragmentation and utilization, but in this case the causal channel would be specialist care per se not the degree of fragmentation with which care is delivered. Finally, we also control in these specifications for the concentration of the local provider market to allow firm structure to play a role in explaining regional place effects.

Specifications reported in Table 2 column 2 assess these alternative channels and find that controlling for urbanicity, provider density, and market concentration does not substantially alter the measured relationship between care fragmentation and our key utilization outcomes. In the baseline specification, moving to a region with 1 SD greater care fragmentation increases a patient's care utilization by 11.2%; this estimate attenuates to 9.4% after adding the density and concentration controls. There is similar attenuation to the estimated relationship between regional fragmentation and the number of visits, providers, and primary care encounters, suggesting that the local density of physicians may play a role in mediating the relationship between regional fragmentation and visit patterns. The general thrust of these results points to a persistent role for fragmentation even after including these controls.

Table 2 Column 3 reports specifications that add control variables for the regional preferences for cowboy or comforter care styles at the HRR level (the finest level for which these measures are available). The measures of cowboy and comforter preferences capture the extent to which primary care physicians and cardiologists recommend aggressive or palliative treatment for patients with serious chronic diseases. They do not directly capture referral decisions or fragmentation preferences, but rather measure a possibly distinct dimension of provider preferences for care style. Because these controls rely on survey measures from a relatively small sample of around 1500 physicians, practicing in 74 HRRs, they are noisy measures but have been demonstrated to be highly correlated with regional variation in utilization (Cutler et al. 2018).

Adding these controls has little effect on the estimated coefficients. The estimated impact of moving to a region with 1 SD higher regional fragmentation on individual fragmentation levels changes from 0.60 (baseline estimate) to 0.57 (adding urbanicity, provider density, and market concentration controls) and to 0.54 (also adding cowboy/comforter preferences). For our measures of care utilization, the estimates generally become slightly larger in magnitude with the addition of provider cowboy/comforter measures as controls. The exception is the outcome variable measuring the number of primary care visits; this coefficient drops in magnitude after the addition of the cowboy/comforter controls, which suggests that these measures capture an important dimension of primary care intensity.

Taken together, these regressions provide suggestive evidence that regional fragmentation may be the key driver behind the estimated effects of moving to a more fragmented region. However, we still cannot exclude the possibility that unmeasured dimensions of place-based institutions, local environment, or provider practice style contribute to these results.

B. Fragmentation and Care Process Measures

We now turn to investigating a series of care process measures that are sometimes linked to quality and system performance. We break these measures into four categories: hospitalizations, imaging use, prescription drug use, and process of care measures for diabetics.[13] Moving to a region with higher levels of our overall fragmentation measure is associated with increased care utilization within each of these categories, as column (1) of Table 3 reports.

Moving to an area with 1 SD higher fragmentation results in .036 more hospitalizations on average, from a base of 0.49 (a 7.3 percent increase). We find a fairly precisely estimated zero effect on hospitalizations for ambulatory care sensitive conditions, however.[14] While hospitalizations are sometimes interpreted as a sign that a patient's care was poorly managed in an outpatient setting, it can also simply be a signal of a more intensive practice style. Thus, the welfare implications of this change are unclear. Nevertheless, the finding demonstrates that increased frequency of hospitalization is one channel through which more highly fragmented regions have higher utilization.

We find that both total imaging use and repeated imaging increase by about 10% for every 1 SD increase in regional care fragmentation. Repeated imaging is defined when the same imaging modality (e.g. CT, MRI, x-ray, or ultrasound) is performed at least twice within a 30-day period. While this measure of repeated imaging may reflect increases in redundant scans

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[13] We examine diabetic care measures for two reasons: first, diabetes is an important chronic condition to study in its own right, and, second, diabetic process of care measures provide some of the few examples of reliable quality measures that can be constructed from claims records.

[14] Ambulatory care sensitive hospitalizations are those for conditions where hospitalizations are potentially preventable given appropriate ambulatory (outpatient) care. These conditions were established by the Agency for Healthcare Research and Quality (AHRQ) as part of its Prevention Quality Indicators.

triggered by communication failures, it will also capture settings where repeated imaging is clinically valuable and warranted.

Looking among the subsample of patients who fill prescriptions through Medicare Part D following its 2006 introduction, we find evidence that patients who move to more fragmented regions receive more prescription drugs. Applying the HEDIS measure of high risk drugs among elderly patients, we find no evidence of a statistically significant relationship between regional fragmentation and use of drugs that are typically contraindicated for elderly patients, and the confidence interval rules out effects larger than 15 percent of its low mean of .36.

Finally, we restrict attention to the subsample of patients with a current diagnosis of diabetes; this includes 6000 patients who move while retaining an active diabetes diagnosis both before and after the move. Specifically, we restrict the sample to patient-year observations in which the patient meets the CMS Chronic Conditions Warehouse criteria in Medicare billing records for diabetes. We then study three process of care measures defined by HEDIS as necessary for delivering high quality care to diabetic patients. First, diabetic patients are recommended to receive eye exams from an eye specialist annually, or every two years if the prior eye exam showed no sign of retinal disease. We code an eye exam measure that equals 1 if either the patient received an eye exam by a specialist that year or if they had an eye exam in the prior year and carry no diagnosis of retinal disease. Second, diabetic patients are recommended to receive LDL cholesterol test annually given the relationship between diabetes, high cholesterol levels and heart disease. Third, diabetic patients are recommended to receive an HbA1c test of blood sugar control at least once a year.

We find that when diabetic patients move to regions with 1 SD higher care fragmentation, they are 25% more likely to receive recommended HgA1c and LDL testing; the impact on eye exam compliance is also positive but not statistically significant. This finding raises the possibility that regions with fragmented care may actually manage care for patients with chronic conditions more effectively, contrary to the common presumption that care fragmentation necessarily reduces care quality (e.g., Stange, 2009). Through another lens, the prior results demonstrated that patients in more fragmented regions receive more total care across a number of broad measures (with the notable exception of primary care), and so the fact that they are also more likely to receive recommended diabetes care could be the result of the overall increase in care intensity.

These results suggest that moving to a high fragmentation region may lead to improved management of chronically ill patients even though these moves are associated with *fewer* primary care encounters and more encounters with specialists. Quality benefits of receiving care in a high fragmentation regions may offset some of the costs of additional utilization and some of these quality benefits may be due to specialists being more likely to provide guideline concordant care.

The results on these quality-related utilization metrics are similar in the more controlled specifications reported in Table 3 columns 2 and 3. Controlling for provider density and market structure changes attenuates the coefficients and increases the standard errors of our estimates, reducing the Bonferroni-corrected statistical significance of the findings on hospitalizations, imaging use and prescription drugs. However, the diabetes testing results remain highly consistent in magnitude and continue to be statistically significant at the 1% level through all three specifications.

C. Decomposing the effects on provider billings

Table 4 examines the increase in provider billings in more detail. Specifically we categorize provider-submitted carrier claims using Berenson-Eggers Type of Service (BETOS) codes. When investigating the effect of moving to a region with higher overall fragmentation, we find increased utilization in almost every category of provider bill, with the exceptions of cancer care and durable medical equipment which are less precisely estimated relative to their means. The largest increases (both in dollar terms and as a fraction of baseline spending) come from greater spending on evaluation and management services, as well as testing and imaging services. Spending on emergency room services, sometimes interpreted as an indicator of poorly coordinated outpatient care, increases by 9% with a move to a 1 SD more fragmented region, which is roughly proportional to the overall increase in fragmentation. These results largely remain statistically and economically significant after controlling for detailed measures of provider density and market structure in column 2 and for regional provider preferences in column 3.

One spending outcome analyzed here is vaccine spending, which increases modestly with a move to more fragmented regions in our baseline specification. Adding controls to the regression in columns 2 and 3 attenuates the result and it loses statistical significance. There are several vaccines indicated for elderly patients, including immunizations against pneumonia, the combined tetanus, diphtheria and pertussis immunization, shingles, and annual influenza vaccines. The vaccines are considered highly cost effective in this population, and compliance with vaccination guidelines has been used a measure of care quality.[15] These findings echo the earlier results on process of care outcomes for diabetic patients; regions with greater fragmentation are more successful at providing high-value care despite their reduced use of primary care services

Appendix Table A2 reports further results on detailed measures of care utilization, measuring the number of patient encounters with each of 18 commonly visited specialists. Moving to a region with higher levels of overall care fragmentation leads to increased encounters with most medical subspecialist types, especially those whose scope of practice overlaps with PCPs'.

D. Robustness Checks

In this section, we probe the robustness of our results to a number of alternative specifications. First, we explore the implications of varying the estimation sample. Second, we report results that measure regional fragmentation changes at the larger hospital referral region instead of the narrower hospital service area. Results from these alternative specifications are reported in Table 5.

Our main results combine the effects for two types of movers: those who move to more fragmented regions and those who move to less fragmented regions. This pooling may obscure different types of behaviors that could drive the estimated effects. A diabetic who changes HSA, for example, may simply find that she will be referred to specialists according to the style of care prevailing in the region in which see receives care. In this case the effect of moving from low to high fragmentation and high to low fragmentation should be symmetric. Alternatively it may be

[15] There are many medical studies that use vaccination rates among elderly patients as a quality of care measure; for example, see the meta-analysis by Peterson et al. (2006) or work on the quality of Veterans Health Administration care by Jha et al. (2003).

that a diabetic who is exposed to lots of specialty care comes to demand such care and will continue to see lots of specialists even if she moves to a lower fragmentation region. If this is the underlying behavior, then moves should have an asymmetric effect: moves towards higher fragmentation HSAs would increase individual fragmentation but moves in the other direction would have little effect.

In the second and third rows of Table 5 (the top row reproduces our baseline results from Table 2), we present disaggregated estimates for these two types of movers; all specifications naturally also include non-movers. The effects of moving to regions with higher and lower regional fragmentation on individual fragmentation are nearly identical for these outcomes.[16] This symmetric response indicates that regional effects are not the result of patients getting "locked in" to highly fragmented care patterns. Rather, individual patterns of care conform to styles prevailing in the region. The symmetry further suggests that our main findings are not driven by selection on gains from anticipation of healthcare demand; if patients in worsening health move to regions with more fragmentation we might expect to find larger effects of moves to higher fragmentation regions and smaller effects of moves to lower fragmentation regions.

Next we consider changing the window of time around the move included in the estimation sample. Our baseline results compare Medicare movers up to three years before and three years after the move, excluding the year of the move itself. This window is arbitrary and it is worth considering how sensitive our results are to this restriction. A narrower window around the move, for example, may reduce potential bias from differential trends across types of movers. Rows four through six of Table 5 show that narrowing to a 1-year window, expanding to a 5-year window, or restricting to a balanced panel of patients whom we observe for 3 years before and after the move does not change the interpretation of our results.

In Panel B of Table 5 we consider the sensitivity of our results to the definition of geographic areas. We continue to find a high degree of responsiveness to regional fragmentation patterns when we calculate regional fragmentation at the coarser hospital referral region (HRR) level rather than the hospital service area (HSA) level. The sample of movers is the same for both sets of estimates, since we required that movers change HRRs in order to be included in the

[16] A formal test fails to reject equality of the effects.

mover sample. Note that the scale of these numbers is not directly comparable to the HSA numbers reported earlier. The standard deviation across HRRs (0.034) is half as large as the standard deviation across HSAs (0.069), so the smaller estimated effect of a one standard deviation increase in fragmentation on total utilization is to be expected.

E. Granular measures of fragmentation

Standard measures of care fragmentation, like the measure described above, potentially conflate two different sources of variation in care organization. First, care may be fragmented because patients rely heavily on care from many different types of specialists. For many clinical conditions, primary care internists face a tradeoff between requesting specialized consultations or providing care directly; local norms and institutional structure may encourage greater use of specialists in some regions relative to others. It is possible that any costs associated with this type of specialty fragmentation may be offset by benefits from the greater expertise of specialist physicians.

A second source of fragmentation arises when care is divided among many providers with similar training and expertise. Fragmentation that occurs among providers with similar training may still confer benefits to patients, including potential advantages of location, scheduling, availability, as well as idiosyncratic differences in physicians' skill sets. That said, relative to specialty fragmentation, this type of fragmentation would likely confer smaller benefits from distinct provider expertise while still generating challenges for care coordination and possibly weakened patient-provider relationships.

To address these issues, we introduce two refined fragmentation indices: an across-specialty measure and a primary care measure. The across-specialty fragmentation measure categorizes each provider into one of 37 specialty types (see the Appendix for the categories). We determined specialty following Agha et al. (2018) by linking the provider's National Provider Identifier (NPI) to the National Plan and Provider Enumeration System (NPPES), which includes information on provider specialty.[17] The across-specialty fragmentation measure is constructed using the same rescaled Herfindahl-Hirschman concept as before, but it

[17] DesRoches, et al (2015) provide evidence validating the NPPES specialty data by showing agreement between it and other sources of specialty information.

treats each specialty type as a single entity. High scores on this cross-specialty fragmentation measure indicate settings where care involves a wider set of specialty types. We exclude the 5% of patients who do not encounter any specialized providers over a calendar year from the calculation of regional average specialty fragmentation.[18] We also control separately for the fraction of patients in the region who see no specialists.

The primary care fragmentation measure is constructed in the same way as our main fragmentation measure, but the variable is restricted to encounters with physicians who report having a primary care specialty (internal medicine, pediatrics, general practice, family medicine) and no further subspecialization or training. The primary care measure differs from our original fragmentation measure in that it is not influenced by the breadth of different specialist types involved in care. High scores along this measure indicate a setting where visits are spread out over a larger set of primary care physicians. We exclude the 26% of patients who do not have any encounters with primary care physicians in a given year from our calculation of primary care fragmentation.[19] We also control separately for the fraction of patients in the region who see no primary care physicians.

The regressions reported in Table 6 replace the overall fragmentation measure with the two new measures of within primary care fragmentation and across specialty fragmentation as the key independent variables of interest. Each row of Table 6 presents the results of single regression that includes both of the key fragmentation measures of interest. The row of the table also reports the p-value of a t-test for the equality of these fragmentation coefficients; this tests the null hypothesis that moving to a region with 1 SD greater primary care fragmentation has the same effect on the patient's outcome of interest as moving to a region with 1 SD greater specialty fragmentation. To correct for the multiple inferences we make across each table, we apply a Bonferroni (1937) correction to calculate a conservative p-value for each of these tests.

[18] When studying across specialty fragmentation as an outcome, we restrict to the sample of patients who see a specialist, although our findings are robust to using the full sample and coding patients who see no specialist as having the minimum specialty fragmentation level of 0.

[19] When studying within primary care fragmentation as an outcome, we restrict to the sample of patients who see at least one primary care doctor, although our findings are robust to using the full sample and coding patients who see no primary care doctor as maximally fragmented.

Controlling for primary care fragmentation in a region, Medicare enrollees who move to a region with 1 standard deviation higher across-specialty fragmentation experience a 0.32 SD increase in our overall fragmentation measure. Conditional on the changes in regional levels of across-specialty fragmentation, changes in regional primary care fragmentation do not predict changes in our overall fragmentation measure; moving to a region with 1 SD higher primary care fragmentation is associated with a 0.01 SD decrease in the overall fragmentation level. It thus appears that regional variation in the unitary measure of fragmentation is more strongly linked to differences in reliance on specialists than to differences in visit concentration among primary care encounters. A test for equality of the two coefficients on within primary care and across specialty fragmentation rejects the null of equality with $p<0.001$. [20]

The next two rows of Table 6 expand our prior result that the fragmentation of care received by individual movers to new regions comes to closely resemble the patterns that prevail in the destination region. Beneficiaries who move to a region with 1 SD higher across specialty fragmentation experience a 0.6 SD increase in their own across-specialty fragmentation. Beneficiaries who move to a region with 1 SD higher within primary care fragmentation experience 0.4 SD increase in their own primary care fragmentation.

Next, we consider the effects of regional fragmentation on visits with physicians and utilization. The results for specialty fragmentation look remarkably similar to our prior results on the unitary fragmentation measure. As with unitary fragmentation, we find that moving to a region with greater across-specialty fragmentation leads to more encounters, more distinct providers, fewer primary care visits, and overall increases in utilization.[21] The magnitude of the effect of moving to a region with 1 SD higher across specialty fragmentation is smaller than the magnitude of the effect of moving to a region with 1 SD higher unitary fragmentation, suggesting that further variation within specialty class in the division of labor might also be an important contributor to the total effect of fragmentation.

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[20] These findings are also consistent with correlational evidence reported in Table A1, showing a strong correlation between regional unitary fragmentation and regional across specialty fragmentation at 0.67; by contrast the correlation between regional unitary fragmentation and regional primary care fragmentation is only 0.04.

[21] As we report in appendix table A3, the quality results for specialty fragmentation are similar to those previously found for our unitary fragmentation measure - more guideline cordant care for diabetics in fragmented regions.

We find markedly different patterns when we investigate the impact of moving to a region with greater within primary care fragmentation, holding constant across specialty fragmentation. Patients moving to regions with fragmented primary care have more total primary care encounters, but this increase is more than offset by a reduction in the use of specialists, and so there is no increase in either unitary fragmentation or in total clinical encounters (including primary care and specialist). Moving to a region with higher primary care fragmentation is associated with 3.9% lower total care utilization.

The estimated coefficients on regional primary care fragmentation are consistently statistically distinguishable from the coefficients on regional specialty fragmentation, with a p-values of less than 0.2% after Bonferroni adjustment for all outcomes except inpatient and outpatient hospital billings (where the effects are imprecisely estimated). Taken together, the results in Table 6 suggest that the high fragmentation, high cost care patterns characterized by the earlier literature (e.g., Hussey, et al. 2014) are primarily driven by the use of specialists and subspecialists. Fragmentation within primary care, which is strongly associated with heavier use of primary care, is not associated with increases in utilization.[22]

4. Policies Aimed at Improving Physician Incentives

Given the strong association between fragmentation and utilization, it is worth asking why policies to promote care coordination have demonstrated only modest benefits to date (Peikes et al. 2009, McWilliams et al. 2015, McWilliams et al. 2016).

Perhaps the highest profile policy initiative to encourage better care coordination is the introduction of Accountable Care Organizations (ACOs). ACOs provide incentives against fragmentation by getting primary care providers to internalize some of the costs of specialist referrals. Current evidence suggests ACOs lead to modest reductions in spending at best (cf. McWilliams 2016), and this is consistent with other work that finds that the incentives in ACOs are almost surely too weak to affect large scale changes in practice patterns (see Frandsen et al. 2017 and Frandsen and Rebitzer 2014 for theory and evidence on this point).

[22] There is some evidence (presented in appendix table A3) that moving to a region with more primary care fragmentation is associated with some degradation in quality as measured by a decline in guidline concordant diabetes care.

Other large care coordination interventions have focused on programs to improve patient-provider communication (Peikes et al. 2009) or health information technology infrastructure to improve provider-provider communication (Agha 2014). These improvements in the communication infrastructure may, as a first order effect, improve the relative quality of treatment choices involving specialist referrals and so may *increase* the equilibrium level of care fragmentation as well as the cost of care. Any improvements in care quality enabled by the enhanced communication infrastructure are also typically harder to measure quantitatively.

We have documented that fragmentation alters visit patterns in complicated ways: more provider encounters, but fewer visits with primary care providers, and greater reliance on specialists - especially specialists whose scope of practice overlaps with a PCP's scope of practice. One possible set of interventions might be to introduce incentives that directly encourage continuity of care. Current Medicare reimbursement policy, for example, typically pays a higher rate for new patient visits, on the assumption that they take more time. If the reimbursement difference is not fully offset by the increased effort cost of seeing a new patient, the higher payment may distort incentives by encouraging providers to take on new patients rather than schedule repeat visits with old patients. Another possible policy to encourage care continuity would be to reduce patient out-of-pocket costs for repeat visits with an established primary care provider, while increasing patient cost sharing for specialists or new generalist providers.

Our findings also suggest a reason for caution in promoting reductions in care fragmentation as a policy goal. The evidence here suggests that care fragmentation is driven, in part, by increased use of different types of specialist providers, and that these care patterns are associated with more guideline-concordant care - at least for diabetic patients. While fragmented care is more costly and more intensive, there are situations where it also offers higher quality.

5. Conclusion

We use an analysis of Medicare movers to examine the possibility that regional differences in care fragmentation contribute to individual differences in costs, utilization patterns, and outcomes. Our findings can be briefly summarized. Moving to regions with higher levels of fragmentation causally affects the degree of fragmentation an individual Medicare patient experiences as well as individual costs, utilization patterns and quality outcomes. This association between a region's causal effects on outcomes and its fragmentation level persists even when controlling for a variety of regional health care market characteristics. Our results suggest that a fragmented division of clinical labor within a region may contribute to high healthcare costs. Fragmentation is closely associated with greater reliance on specialists and more intensive use of both high-value services (e.g. recommended testing for diabetics, vaccines) and services that are sometimes associated with overutilization or low value (e.g. emergency room utilization, repeated imaging, inpatient hospital stays). These findings are subject to three important limitations.

The first limitation concerns causation. The fact that causal regional effects are strongly correlated with regional fragmentation does not establish that the effects we observe are caused by regional fragmentation. Although the association persists even after we introduce controls for other important regional factors, the possibility of bias from omitted regional variables remains.

A second limitation of our study is that we do not directly observe *how* fragmented division of labor influences the provision and coordination of care across providers. For example, it would be useful to observe how many additional patient "handoffs" occur in highly fragmented regions and how these handoffs influence the problem of care coordination. Insurance claims data cannot provide such information so future analyses of care fragmentation may benefit from more narrowly targeted case studies across high and low fragmentation regions.

A third limitation of our investigation is that we do not offer an explanation for the cross-regional variation in fragmentation. Having such an explanation would be helpful for understanding the full consequences of regional fragmentation as well as the impact of anti-fragmentation policies on costs, quality and patient welfare. The development of a full blown theory of regional fragmentation is beyond the scope of this empirical study. In an online appendix, however, we sketch out a simple model of regional fragmentation.[23] The model analyses how providers balance the gains to patients from referrals to additional specialists

[23] The model we develop builds off of the Roy model presented in Chandra and Staiger (2007). The appendix is available at https://www.dropbox.com/s/d8fn0z9h534xy2d/onlineappendix.pdf?dl=0.

against the costs resulting from more difficult care coordination. In this model, regions are characterized by different levels of equilibrium care fragmentation. Anti-fragmentation policies can reduce regional fragmentation and costs but with some reduction in the quality of care. The net effect of these policies on patient welfare is complex. Understanding the conditions under which anti-fragmentation policies may improve patient welfare even as they reduce costs is an important area for future research.

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Tables

Table 1: Descriptive Statistics of care patterns by average region fragmentation

	Low fragmentation regions		**Medium fragmentation regions**		**High fragmentation regions**	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
	(1)	(2)	(3)	(4)	(5)	(6)
A. Visits and physicians						
Individual fragmentation	-0.01	3.73	0.70	3.47	1.21	3.24
Number of encounters	21.90	21.43	24.30	24.02	26.85	26.35
Number of unique providers	8.86	7.86	10.42	9.23	11.65	10.27
Number of primary care encounters	5.72	7.26	5.21	6.75	4.86	6.50
B. Utilization						
Total utilization ($)	7514	15192	8053	16188.8	8597	16920
Total inpatient hospital billings ($)	3961	11,697	4158	12483	4281	12954
Total provider billings ($)	2323	4171	2778	4675	3193	4986
Total outpatient hospital billings ($)	1228	3481	1117	3446	1123	3512
C. Patient characteristics						
Age	76.22	7.65	76.15	7.51	76.50	7.57
Female	0.58	0.49	0.59	0.49	0.60	0.49
Diabetes diagnosis	0.22	0.41	0.22	0.42	0.22	0.42
Number of patients	291,137		284,579		279,559	
Number of observations	1,447,625		1,455,237		1,457,094	

Notes: This table calculates summary statistics among non-movers. Beneficiaries are broken into 3 bins according to the average fragmentation level in their HSA. Fragmentation measures are calculated for non-movers. Fragmentation measures are normalized by first having been demeaned (by the regional average fragmentation level averaged across regions) and then divided by the standard deviation (calculated across the regional average fragmentation levels).

Table 2: Regression results describing care patterns after move to a region with different fragmentation levels

	Independent variable: Change in regional fragmentation		
Dependent variable	(1)	(2)	(3)
A. Visits and physicians			
Individual fragmentation	0.604***	0.567***	0.538***
mean: 10.59	(0.025)	(0.030)	(0.057)
Number of encounters	2.408***	1.941***	2.350***
mean: 24.41	(0.157)	(0.202)	(0.437)
Number of providers	1.415***	1.151***	1.224***
mean: 10.35	(0.061)	(0.077)	(0.164)
Number of primary care visits	-0.434***	-0.228***	-0.151
mean: 5.28	(0.055)	(0.068)	(0.135)
B. Utilization			
Log of total utilization	0.112***	0.094***	0.124***
mean: 7.8	(0.011)	(0.013)	(0.025)
Total utilization ($)	767***	548***	746
mean: 8114	(111)	(140)	(298)
Total inpatient hospital billings ($)	371***	220	324
mean: 4180	(88)	(110)	(232)
Total provider billings (carrier file) ($)	471***	304***	349***
mean: 2779	(32)	(41)	(91)
Total outpatient hospital billings ($)	-75***	24	74
mean: 1155	(22)	(27)	(55)
Controlling for density, provider concentration	No	Yes	Yes
Controlling for cowboy/comforter measures	No	No	Yes
Number of observations	4,607,987	4,328,271	2,443,249

Notes: Each cell reports the coefficient from a separate regression, where the dependent variable is noted in row and the independent variable of interest is the change in the regional fragmentation index interacted with a post-move dummy. The fragmentation indices are normalized by dividing fragmentation by the standard deviation of fragmentation across HSAs. The unit of observation is a beneficiary-year. All regressions control for calendar year fixed effects, fixed effects for years relative to move, one-year age bins, and individual beneficiary fixed effects. Regressions in column 2 and 3 add controls for the percent of the HSA that is urban, the HSA-level primary care providers and specialists density per capita, and the HSA-level HHI concentration index of providers. Column 3 regressions also control for HRR-level measures of providers' cowboy or comforter practice style, using survey measures developed by Cutler et al. (2018). Regressions include all movers, within 3 years before or after the move, excluding the year of the move itself, as well as a 20% subsample of non-movers. Standard errors clustered at the patient level are reported in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. Significance indicators in column are Bonferroni-corrected for multiple comparisons.

Table 3: Regression results describing care patterns after move to a region with different fragmentation levels

	Independent variable: Change in regional fragmentation		
Dependent variable	(1)	(2)	(3)
A. Hospitalizations			
Number of hospitalizations	0.036***	0.028*	0.032
mean: 0.49	(0.009)	(0.011)	(0.022)
Number of ACSC hospitalizations	0.002	0.004	0.012
mean: 0.06	(0.003)	(0.003)	(0.006)
Number of observations	4,607,987	4,328,271	2,443,249
B. Imaging use			
Total imaging studies	0.195***	0.096**	0.08
mean: 1.96	(0.027)	(0.034)	(0.073)
Repeated imaging studies w/in 30 days	0.065***	0.016	0.005
mean: 0.52	(0.016)	(0.021)	(0.044)
Number of observations	4,607,987	4,328,271	2,443,249
C. Prescription drug use			
Number of prescription drugs	0.500**	0.483	0.419
mean: 11.81	(0.163)	(0.213)	(0.407)
High-risk drugs among elderly	0.021	0.015	0.075**
mean: 0.36	(0.016)	(0.020)	(0.036)
Number of observations	927,202	861,717	494,318
D. Quality of care for diabetic patients			
Any HbA1c test	0.119***	0.115***	0.122***
mean: 0.48	(0.010)	(0.012)	(0.024)
Any LDL test	0.119***	0.102***	0.091***
mean: 0.44	(0.010)	(0.012)	(0.023)
Any indicated eye exam	0.019	0.021	0.000
mean: 0.48	(0.009)	(0.011)	(0.022)
Number of observations	1,017,515	957,561	547,253
Controlling for density, provider concentration	No	Yes	Yes
Controlling for cowboy/comforter measures	No	No	Yes

See notes to Table 2. Each cell reports the coefficient from a separate regression, where the dependent variable is noted in row and the independent variable of interest is the change in the regional fragmentation index interacted with a post-move dummy. Panel C restricts to patient-year observations with at least 1 billed Medicare Part D prescription. Panel D restricts to patient-year observations with an active diabetes diagnosis coded in the Chronic Conditions Warehouse. Standard errors clustered at the patient level are reported in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. Significance indicators are Bonferroni-corrected for multiple comparisons.

Table 4: Regression results describing care patterns after move to a region with different fragmentation levels

Dependent variable	*Independent variable*: Change in regional fragmentation (1)	(2)	(3)
A. Evaluation & management (E & M)			
Office E & M ($)	42.29***	20.84***	30.03***
mean: 445	(2.92)	(3.69)	(7.82)
Hospital E & M ($)	54.87***	33.52***	26.19
mean: 246	(7.17)	(9.39)	(19.66)
Specialist or consultation E & M ($)	50.51***	39.18***	45.92***
mean: 242	(3.06)	(4.02)	(8.92)
Emergency department E & M ($)	5.09***	3.19	2.97
mean: 57	(0.96)	(1.25)	(2.42)
Home or nursing home E & M ($)	21.29***	18.45***	17.68**
mean: 47	(2.39)	(3.12)	(7.28)
B. Imaging & testing			
Imaging & endoscopy ($)	102.30***	72.68***	83.79***
mean: 419	(5.09)	(6.26)	(13.55)
Testing ($)	58.40***	49.19***	59.86***
mean: 191	(2.20)	(2.86)	(6.59)
C. Procedures			
Major procedures & anesthesia ($)	22.66***	12.91	17.27
mean: 234	(5.12)	(6.37)	(12.84)
Other procedures & dialysis ($)	31.23***	19.23	14.75
mean: 301	(11.88)	(15.86)	(33.24)
Drugs and medical equipment			
Cancer claims ($)	12.26	-6.43	-27.59
mean: 174	(12.22)	(14.98)	(35.93)
Vaccines ($)	0.70***	0.32	0.4
mean: 12	(0.12)	(0.15)	(0.30)
Durable medical equipment ($)	2.12	1.92	9.79
mean: 2	(2.09)	(3.37)	(11.58)
Controlling for density, provider concentration	No	Yes	Yes
Controlling for cowboy/comforter measures	No	No	Yes
Number of observations	4,607,987	4,328,271	2,443,249

See notes to Table 2. Each cell reports the coefficient from a separate regression, where the dependent variable is noted in row and the independent variable of interest is the change in the regional fragmentation index interacted with a post-move dummy. These spending measures decompose provider-submitted carrier claims into categories on the basis of BETOS codes. Standard errors clustered at the patient level are reported in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. Significance indicators in column (1) are Bonferroni-corrected for multiple comparisons.

Table 5: Alternative Specifications and Robustness

	N	Fragmentation	Log(utilization)
		Dependent variable:	
		(1)	(2)
A. Alternative sample frames			
Baseline (within 3 years of move)	4,607,987	0.604***	0.112***
		(0.025)	(0.011)
Moves to lower fragmentation only	4,472,270	0.542***	0.072***
		(0.058)	(0.025)
Moves to higher fragmentation only	4,495,673	0.510***	0.079***
		(0.054)	(0.023)
Within 1 year of move	4,464,078	0.650***	0.135***
		(0.032)	(0.014)
Within 5 years of move	4,692,249	0.594***	0.109***
		(0.024)	(0.010)
Balanced panel (within 3 years of move)	4,366,717	0.791***	0.150**
		(0.155)	(0.065)
B. Alternative definition of regional fragmentation			
HRR fragmentation (rather than HSA)	4,716,739	0.791***	0.083***
		(0.155)	(0.007)
Controlling for density, provider concentration		No	No
Controlling for cowboy/comforter measures		No	No

Each cell reports the coefficient from a separate regression, where the dependent variable is noted in the column header andthe independent variable of interest is the change in the regional fragmentation index interacted with a post-move dummy. Panel A explores robustness to alternative definitions of the regression sample. Baseline results include movers within 3 years of their move and all non-movers. Alternative specifications limit to 1 year before and after the move and 5 years before and after the move. Next, we restrict the sample to patients who survive during the entire study period. Finally, the balanced panel requires all movers to remain in the sample for 7 years, including all 3 years before and 3 years after the move. Panel B reports results where we describe regional fragmentation at the more aggregate HRR level in the key independent variable of interest. Note that we continue to normalize fragmentation measure by the regional standard deviation; a 1 standard deviation change in HRR fragmentation is 0.069, whereas a 1 standard deviation change in HSA fragmentation is 0.034. Standard errors clustered at the patient level are reported in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 6: Analysis of more granular measures of specialty and primary care fragmentation

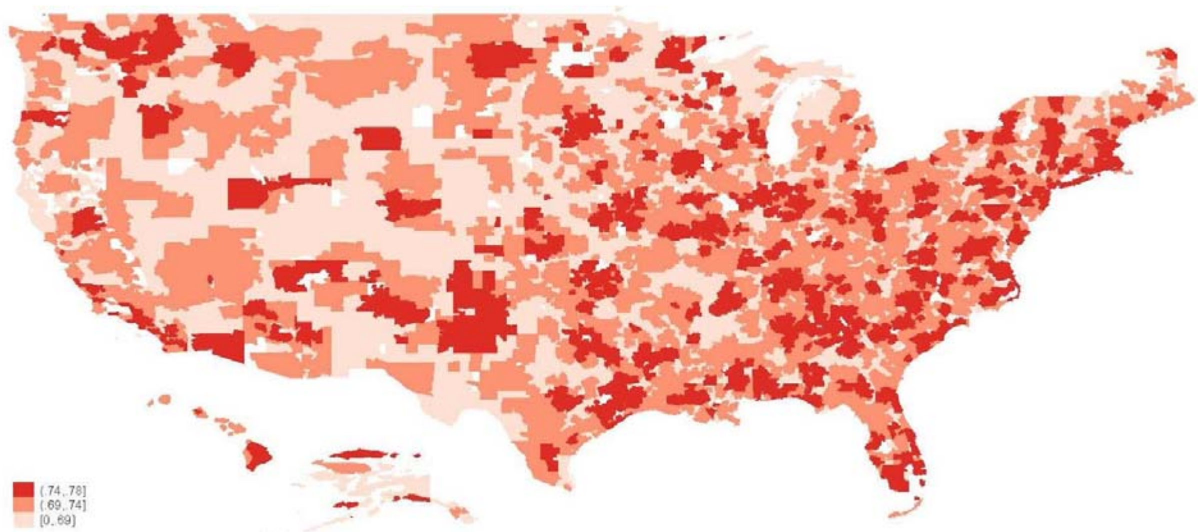
	Specification with two fragmentation measures:			
	Change in regional across specialty fragmentation	Change in regional within primary care fragmentation	Test of coefficient equality (p-value)	Test of coefficient equality (Bonferroni p-value)
Dependent variable	(1)	(2)	(3)	(4)
Individual fragmentation				
Fragmentation	0.324***	-0.01	0.000	0.000
mean: 10.59	(0.027)	(0.023)		
Across specialty fragmentation †	0.597***	0.029	0.000	0.000
mean: 6.56	(0.029)	(0.025)		
Within primary care fragmentation ‡	0.022	0.389***	0.000	0.002
mean: 2.17	(0.025)	(0.022)		
Visits and physicians				
Number of encounters	1.297***	-0.409*	0.000	0.000
mean: 24.41	(0.169)	(0.155)		
Number of providers	0.816***	0.156*	0.000	0.000
mean: 10.35	(0.066)	(0.060)		
Number of primary care visits	-0.279***	0.284***	0.000	0.000
mean: 5.28	(0.059)	(0.052)		
Utilization				
Log of total utilization	0.055***	-0.039***	0.000	0.000
mean: 7.8	(0.012)	(0.010)		
Total utilization ($)	432***	-212	0.000	0.002
mean: 8114	(123)	(108)		
Total inpatient hospital billings ($)	207	-38	0.068	0.540
mean: 4180	(95)	(84)		
Total provider billings (carrier file) ($)	258***	-223***	0.000	0.002
mean: 2779	(35)	(31)		
Total outpatient hospital billings ($)	-33	48	0.071	0.557
mean: 1155	(33)	(24)		
Number of observations	4,607,987			

Notes: Each row reports the coefficients from a single regression, where the dependent variable is noted in row and the independent variables of interest are the change in the regional across specialty group fragmentation and within primary care fragmentation, both interacted with a post-move dummy. All fragmentation indices are normalized by dividing fragmentation by the standard deviation of fragmentation across HSAs. The unit of observation is a beneficiary-year. All regressions control for calendar year fixed effects, fixed effects for years relative to move, one-year age bins, and individual beneficiary fixed effects. All regressions include movers as well as a 20% subsample of non-movers. Regressions include all movers, within 3 years before or after the move, excluding the year of the move itself, as well as all non-movers. Standard errors clustered at the patient level are reported in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. Significance indicators in column (1), (2), and (4) are Bonferroni-corrected for multiple comparisons.

†This regression excludes patients who have no specialist encounters and so do not have a defined level of across-specialty group fragmentation. The sample size is 4,360,169. ‡This regression excludes patients who have no primary care encounters and so do not have a defined level of primary care fragmentation. The sample size is 3,395,372.

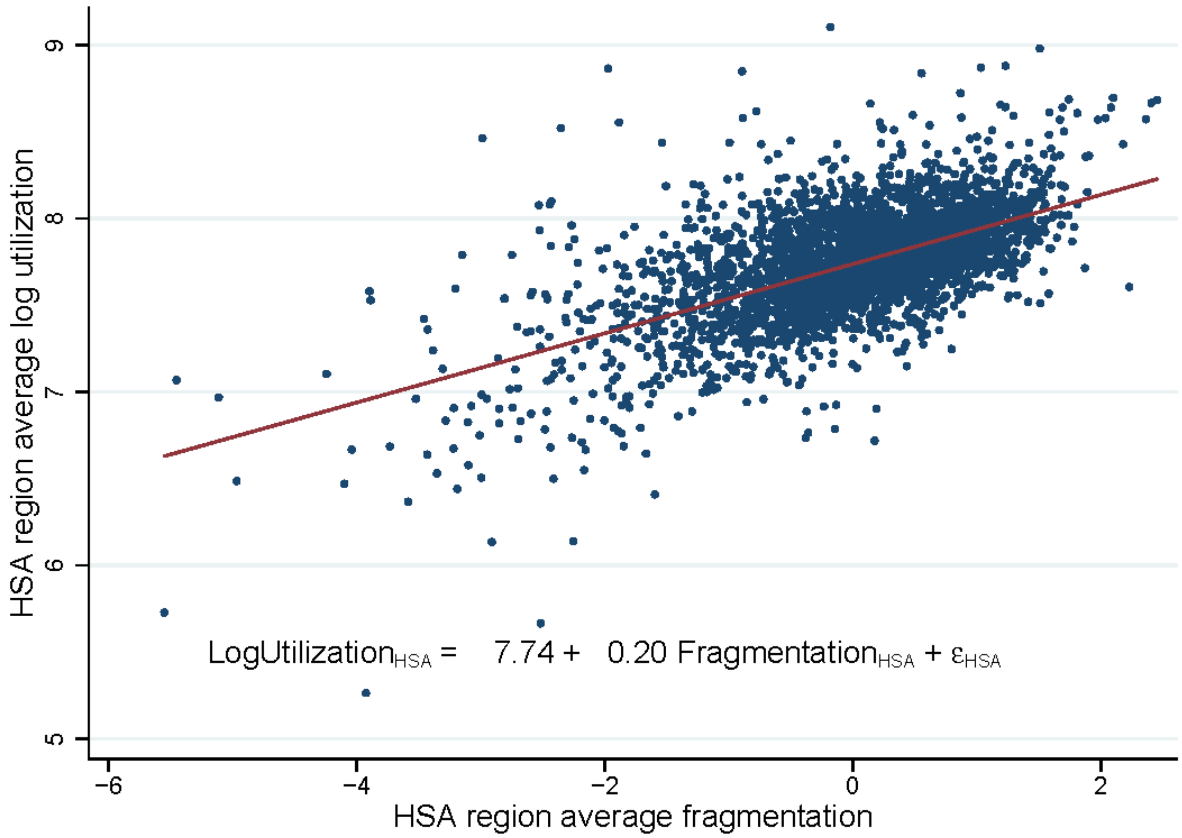
Figures

Figure 1: Fragmentation Index by Hospital Service Area



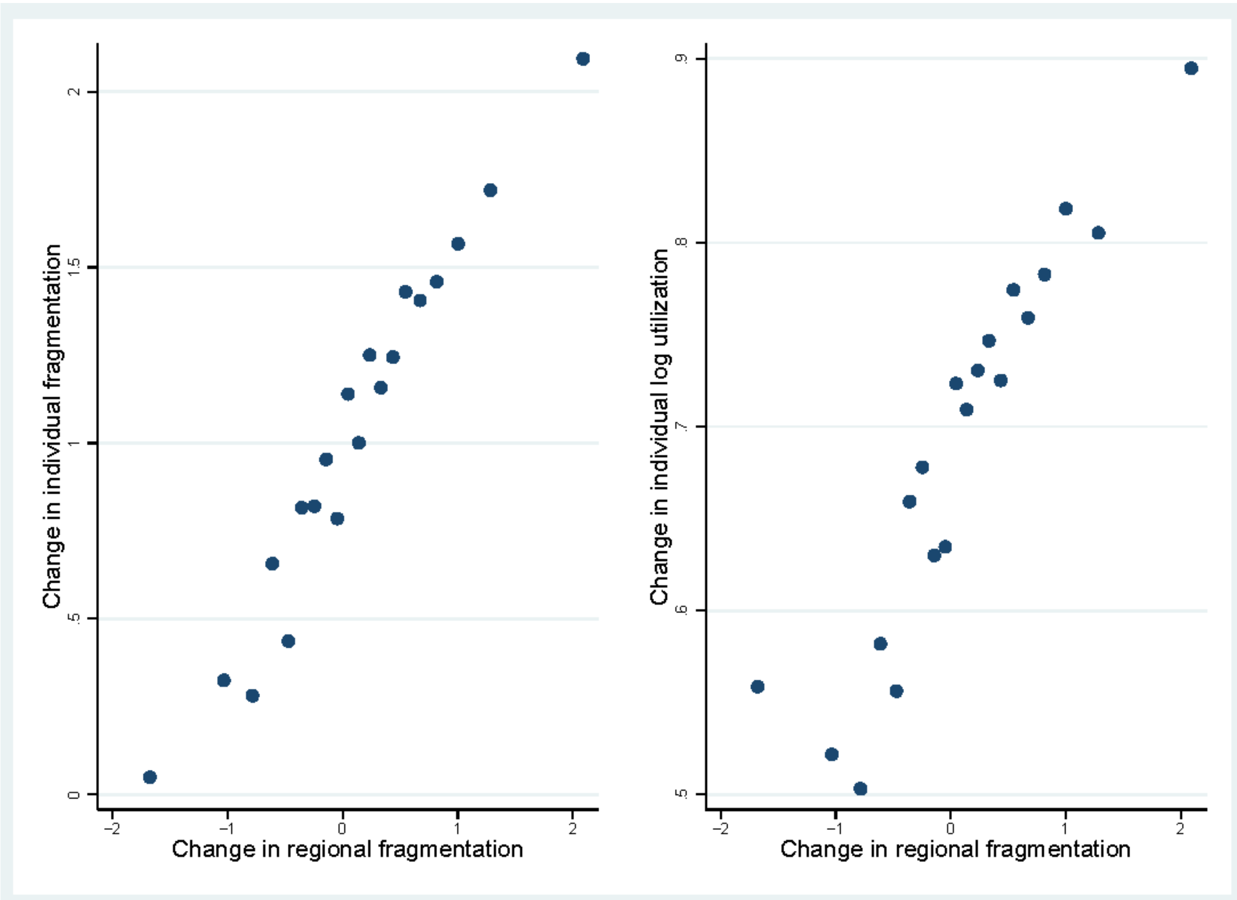
Notes: This map illustrates regional variation in care fragmentation across hospital service areas (HSAs). HSAs shaded in darker red have higher average levels of care fragmentation. Care fragmentation is calculated as one minus the Herfindahl-Hirschman concentration index describing visit concentration across providers, following equation (9) in the text. Data are from Medicare Part A and B claims from 2000-2010.

Figure 2: Scatterplot of HSA average utilization by HSA average fragmentation index



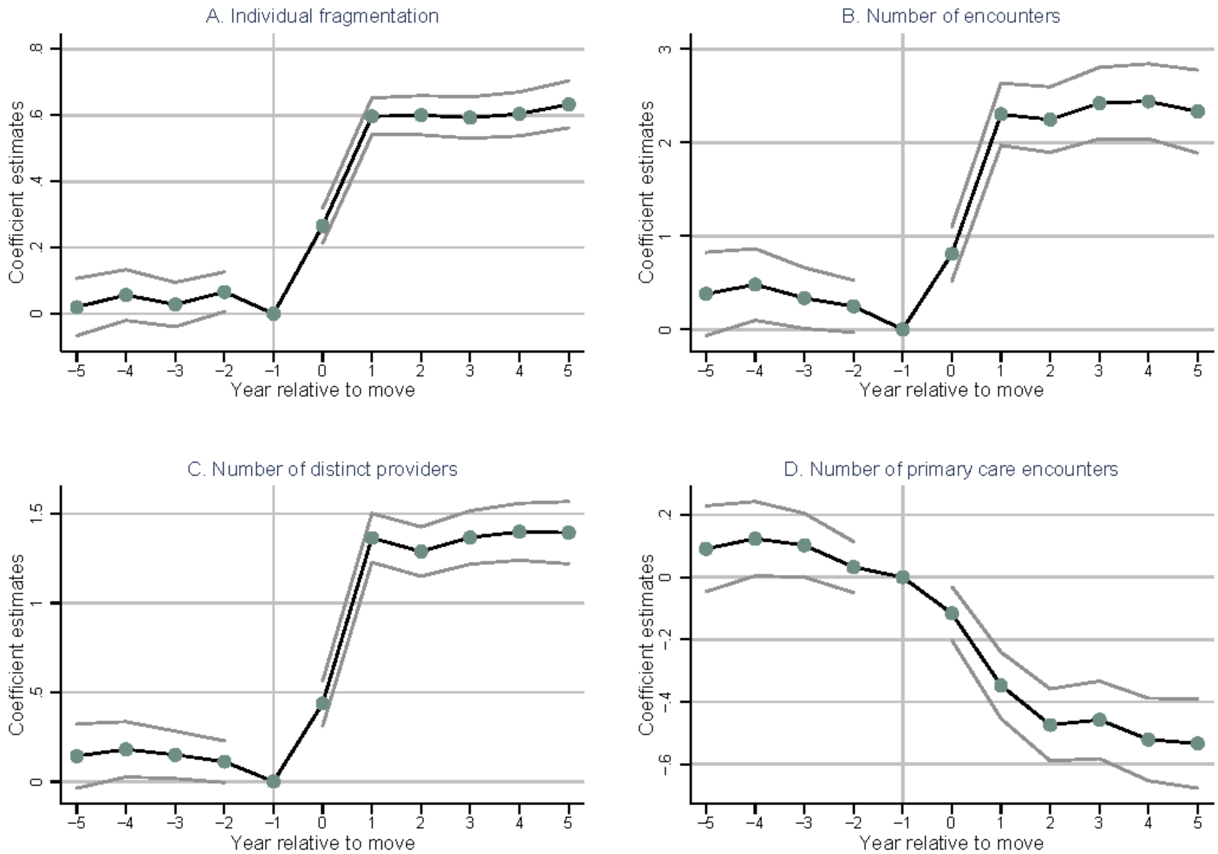
Notes: For each hospital service area, this scatterplot displays the regional average patient fragmentation index along the x-axis and the regional average annual per-patient utilization (in dollars) along the y-axis. Data are from Medicare Part A and B claims from 2000-2010.

Figure 3: Binned scatterplot of change in regional fragmentation index vs. change in individual care fragmentation and individual log utilization



Notes: These scatterplots divide the population of beneficiaries who move across regions into 20 bins according to the change in regional fragmentation levels experienced as a result of the move. For example, -1 along the x-axis would indicate the patients in this bin moved to destination regions with 1 standard deviation lower fragmentation than the patients' regions of origin on average. Along the y-axis, we have plotted the average change in the individual patients' fragmentation indices (left panel) and log utilization (right panel), averaging the three years after the move and comparing to three years before the move. The upward sloping relationship reveals that patients moving to more fragmented regions experience larger increases in individual fragmentation and log utilization after their move. Similarly, patients moving to less fragmented regions experience larger declines in individual fragmentation and utilization. Data are from Medicare Part A and B claims from 2000-2010.

Figure 4: Event study graphs



Notes: Each graph reports the coefficients and 95% confidence intervals from a separate regression, where the dependent variable is noted in the title and the independent variable of interest is the change in regional fragmentation associated with the beneficiary's move interacted with event time dummies. The fragmentation index is normalized by dividing fragmentation by the standard deviation of fragmentation across HSAs. Year 0 is the year of the move, and year -1 indicator is excluded. All regressions control for calendar year fixed effects, fixed effects for years relative to move, one-year age bins, and individual beneficiary fixed effects. Standard errors are clustered at the patient level. There are 4,607,987 beneficiary-year observations.

Online Appendix for Fragmented Division of Labor and Healthcare Costs: Evidence from Moves Across Regions

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1 Specialty categories for across-specialty fragmentation measure

Allergy & Immunology

Anesthesiology

Clinical Neuropsychologist

Clinical Pharmacology

Colon & Rectal Surgery

Dermatology

Electrodiagnostic Medicine

Emergency Medicine

Family Medicine

General Practice

Hospitalist

Independent Medical Examiner

Internal Medicine

Legal Medicine

Medical Genetics

Neurological Surgery

Neuromusculoskeletal Medicine & OMM

Neuromusculoskeletal Medicine, Sports..

Nuclear Medicine

Obstetrics & Gynecology

Ophthalmology

Oral & Maxillofacial Surgery

Orthopaedic Surgery

Otolaryngology

Pain Medicine

Pathology

Pediatrics

Phlebology

Physical Medicine & Rehabilitation

Plastic Surgery

Preventive Medicine

Psychiatry & Neurology

Radiology

Surgery

Thoracic Surgery

Transplant Surgery

Urology

2 Appendix Tables

Table A1: Correlation among HSA-level fragmentation measures

	Overall fragmentation	Primary care fragmentation	Specialist fragmentation
Overall fragmentation	1		
Primary care fragmentation	0.0391	1	
Specialist fragmentation	0.6776	0.1234	1

Notes: The table reports the Pearson correlations among the HSA-level mean non-mover fragmentation measures listed in the columns and row headings, weighted by number of beneficiaries.

Table A2: Regression results describing changes in specialist visits after regional fragmentation change

	Independent variable: Change in regional fragmentation		
Specialty:	(1)	(2)	(3)
Radiology (diagnostic)	0.1784***	0.102	0.123
mean: 1.99	(0.0243)	(0.1000)	(0.1950)
Cardiology	0.2503***	0.161	0.049
mean: 1.56	(0.0270)	(0.1170)	(0.2690)
Ophthalmology	0.0332	0.065	0.049
mean: 1.03	(0.0131)	(0.0500)	(0.1140)
General surgery	0.0124	0.04	0.112
mean: 1.02	(0.0184)	(0.0680)	(0.1680)
Emergency	0.0226	0.021	-0.032
mean: 0.66	(0.0119)	(0.0440)	(0.0750)
Podiatry	0.0655***	0.182**	0.291
mean: 0.63	(0.0122)	(0.0600)	(0.1480)
Dermatology	0.0687***	0.065	0.109
mean: 0.35	(0.0084)	(0.0280)	(0.0520)
Urology	0.0463***	0.052	0.064
mean: 0.34	(0.0098)	(0.0360)	(0.0690)
Gastroenterology	0.0860***	0.086	0.085
mean: 0.33	(0.0090)	(0.0360)	(0.0580)
Anesthesiology	0.0633***	0.023	0.019
mean: 0.28	(0.0097)	(0.0240)	(0.0490)
Pathology	0.0423***	0.016	0.018
mean: 0.27	(0.0064)	(0.0210)	(0.0510)
Neurology	0.0536***	0.01	-0.014
mean: 0.24	(0.0089)	(0.0260)	(0.0540)
Psychiatry	0.0433***	0.021	0.116
mean: 0.19	(0.0100)	(0.0340)	(0.0680)
Otolaryngology	0.0035	-0.016	-0.05
mean: 0.18	(0.0112)	(0.0380)	(0.0420)
Obstetrics & gynecology	0.0076	-0.011	0.019
mean: 0.14	(0.0072)	(0.0230)	(0.0330)
Endocrinology	0.0275***	0.047	0.104
mean: 0.12	(0.0061)	(0.0340)	(0.0720)
Radiation Oncology	0.0195	0.024	-0.098
mean: 0.12	(0.0099)	(0.0400)	(0.0890)
Controlling for density, provider concentration	No	Yes	Yes
Controlling for cowboy/comforter measures	No	No	Yes
Number of observations	4607987	957561	547253

Notes: See notes to Table 2. Each cell reports the coefficient from a separate regression, where the dependent variable is the number of visits with a specialist type noted in row and the independent variable of interest is the change in the regional fragmentation index interacted with a post-move dummy. Standard errors clustered at the patient level are reported in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. Significance indicators in column are Bonferroni-corrected for multiple comparisons.

Table A3: Analysis of more granular measures of specialty and primary care fragmentation

	Specification with two fragmentation measures:			
	Change in regional across specialty fragmentation	Change in regional within primary care fragmentation	Test of coefficient equality (p-value)	Test of coefficient equality (Bonferroni p-value)
Dependent variable	(1)	(2)	(3)	(4)
A. Hospitalizations				
Number of hospitalizations	0.013	0.001	0.380	0.987
mean: 0.49	(0.010)	(0.008)		
Number of ACSC hospitalizations	0.000	-0.003	0.454	0.996
mean: 0.06	(0.003)	(0.002)		
Number of observations: 4,607,987				
B. Imaging use				
Total imaging studies	0.107***	-0.032	0.001	0.007
mean: 1.96	(0.029)	(0.026)		
Repeated imaging studies w/in 30 days	0.036	-0.007	0.088	0.562
mean: 0.52	(0.018)	(0.017)		
Number of observations: 4,607,987				
C. Prescription drug use				
Number of prescription drugs	0.269	-0.114	0.147	0.761
mean: 11.81	(0.178)	(0.165)		
High-risk drugs among elderly	-0.006	0.004	0.699	1.000
mean: 0.36	(0.017)	(0.014)		
Number of observations: 927,202				
D. Quality of care for diabetic patients				
Any HbA1c test	0.046***	-0.051***	0.000	0.000
mean: 0.48	(0.011)	(0.010)		
Any LDL test	0.051***	-0.058***	0.000	0.000
mean: 0.44	(0.011)	(0.009)		
Any indicated eye exam	0.033***	-0.003	0.009	0.081
mean: 0.48	(0.010)	(0.009)		
Number of observations: 1,017,515				

Notes: Each row reports the coefficients from a single regression, where the dependent variable is noted in row and the independent variables of interest are the change in the regional across specialty group fragmentation and within primary care fragmentation, both interacted with a post-move dummy. All fragmentation indices are normalized by dividing fragmentation by the standard deviation of fragmentation across HSAs. The unit of observation is a beneficiary-year. All regressions control for calendar year fixed effects, fixed effects for years relative to move, one-year age bins, and individual beneficiary fixed effects. All regressions include movers as well as a 20% subsample of non-movers. Regressions include all movers, within 3 years before or after the move, excluding the year of the move itself, as well as all non-movers. Standard errors clustered at the patient level are reported in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. Significance indicators in columns (1), (2), and (4) are Bonferroni-corrected for multiple comparisons.

3 Empirical Approach: Notation and Proofs

Our empirical strategy identifies the effects of fragmentation on patient outcomes conceptually in two stages. The first stage identifies the causal effects of regions on health outcomes by exploiting variation from individuals who move across regions. The second stage identifies the contribution of fragmentation to these regional effects by controlling for relevant observable regional characteristics. In practice, the two stages are estimated simultaneously in a single regression framework, but it is useful to discuss them separately as they rely on distinct identifying assumptions. This section describes these identifying assumptions in a potential outcomes framework.

If patient i were to receive care in region r in period t she would experience potential outcome $Y_{it}(r)$. We denote the region where individual i actually receives care in period t by R_{it}. Individual i's observed outcome in period t is therefore $Y_{it} := Y_{it}(R_{it})$.

Our population consists of movers and nonmovers. Let M_i be an indicator for whether individual i moves across regions during the study period. Let O_i be individual i's origin region and D_i be the destination region. T_i is the period in which individual i moves (equal to ∞ for nonmovers).

The average causal effect among individuals who move from region o to region d in period t is given by the average difference between the potential outcome experienced by the mover in the destination region in period t and the potential outcome had the individual not moved:

$$\Delta(o,d,t) := E\left[Y_{it}(d) - Y_{it}(o) \,|O_i = o, D_i = d, T_i = t\right].$$

In general this average causal effect is specific to the moving period and the origin-destinatin pair. In order for comparisons of different average causal effects to have a causal interpretation, we assume that among movers the moving date and the specific origin and destination pair are not selected on the basis of the potential gain (or loss) from moving:

Assumption: No Selection on Gains For all $d \neq o$,

$$E\left[Y_{iT_i}(d) - Y_{iT_i}(o) \,|M_i = 1, O_i, D_i, T_i\right] = E\left[Y_{iT_i}(d) - Y_{iT_i}(o) \,|M_i = 1\right].$$

This assumption says that the treatment effect of moving from o to d is independent of the moving date, actual origin, and actual destination, conditional on moving. The assumption implies that comparisons of different moving effects have a causal interpretation (see proof below):

$$\Delta(o,d,t) - \Delta(o,d',s) = E\left[Y_{iT_i}(d) - Y_{iT_i}(d') \,|M_i = 1\right].$$

Since under No Selection on Gains, different average causal mover effects can be compared causally, we can define the causal effect of a move between any two regions as

$$\Delta(r,r') := E\left[Y_{iT_i}(r) - Y_{iT_i}(r') \,|M_i = 1\right].$$

The key challenge to identifying regional causal effects is that they involve the comparison of counterfactual potential outcomes, $Y_{iT_i}(r)$ and $Y_{iT_i}(r')$, at most one of which is observed. A straightforward way to overcome this challenge is to assume that the period-to-period change in outcomes that would have been experienced by movers had they not moved is equal on average to the observed change among individuals who did not move. Formally, this parallel trends assumption is given by:

Assumption: Parallel Trends For all regions $o \neq d$ and all periods t,

$$E\left[Y_{it}(o) - Y_{it-1}(o) \,|R_{it-1} = o, R_{it} = d, T_i = t\right] = E\left[Y_{it}(o) - Y_{it-1}(o) \,|R_{it} = o, T_i \neq t\right].$$

This assumption means that the period-to-period change in potential outcomes in a given region does not (on average) depend on moving status. The parallel trends assumption can be assessed using the event-study approach we describe below, which examines whether prior to moving individuals who eventually moved followed similar trends to non-movers.

Under the parallel trends assumption the causal effect of moving is identified (see below for the proof) via the difference in the observed change in outcomes between movers and stayers (including those who move in another period):

$$\Delta(r, r') = E[Y_{it} - Y_{it-1} | R_{it-1} = r', R_{it} = r, T_i = t] - E[Y_{it} - Y_{it-1} | R_{it-1} = r', T_i \neq t].$$

The Parallel Trends assumption as expressed above is quite strong. It allows movers on average to have different levels of outcomes from nonmovers, but requires that trends in outcomes be no different on average between movers and nonmovers. The assumption can be weakened to allow movers to be on different trends from nonmovers, provided they are on parallel trends with other contemporaneous movers:

Assumption: Parallel Trends among Movers For all regions o, d, d' and periods t,

$$E[Y_{it}(o) - Y_{it-1}(o) | R_{it-1} = o, R_{it} = d, T_i = t] = E[Y_{it}(o) - Y_{it-1}(o) | R_{it-1} = o, R_{it} = d', T_i = t].$$

Parallel Trends among Movers is implied by the stronger Parallel Trends assumptions, but does not imply it. This assumption, together with No Selection on Gains, identifies region effects via difference-in-differences among contemporaneous movers (see below for proof):

$$\Delta(r, r') = E[Y_{it} - Y_{it-1} | R_{it-1} = r_0, R_{it} = r, T_i = t] - E[Y_{it} - Y_{it-1} | R_{it-1} = r_0, R_{it} = r', T_i = t].$$

No Selection on Gains and Parallel Trends among Movers (possibly conditional on controls x_{it}) identify the average causal effect among movers of moving from one region to another. As only differences between regions are identified, we can normalize these effects to some reference region r_0 to define region causal effects:

$$\Delta_r := \Delta(r, r_0).$$

Many factors likely contribute to the region effects Δ_r, including regional practice styles, institutional characteristics of the region, and infrastructure. Recall, however that regional effects by definition do not reflect differences in patient health status across regions. To define the contribution of fragmentation to regional effects, let $\Delta_r(f)$ be the potential effect of region r if its fragmentation level were f. The region's observed fragmentation level is F_r. The realized region effect is $\Delta_r = \Delta_r(F_r)$, which is identified given Parallel Trends among Movers and No Selection on Gains as shown above. The average causal effect of a change in fragmentation from level f to f' is $E[\Delta_r(f') - \Delta_r(f)]$, where now the expectation is taken over regions. To identify the effect of fragmentation, consider the assumption that realized fragmentation is conditionally (mean) independent of potential regional effects given a vector of observable region characteristics:

Assumption: Fragmentation Selection on Observables For observed vector X_r and for all fragmentation levels f we have

$$E[\Delta_r(f) | X_r, F_r] = E[\Delta_r(f) | X_r].$$

This assumption means that after controlling for X_r, further factors that influence a region's "place effect" are uncorrelated with its fragmentation level. This assumption can be assessed in several ways. First, a necessary (though of course not sufficient) condition for this assumption to hold is that controlling for additional variables beyond X_r that influence the outcome does not change the estimated effect of fragmentation. Second, economic theory may suggest that fragmentation will have a specific pattern of effects that omitted variables may not be expected to follow. For example, fragmentation across specialist types may increase use of specialist care while reducing utilization of primary care providers. One might expect omitted variables to be associated with increased utilization in all types of care. Third, the selection-on-observables assumption together with no selection on gains means that the change in fragmentation experienced by an individual moving across regions will not be related to the individual's health status. The Roy model of practice spillovers developed in the appendix provides a plausible setting in which this will be true.

Given Parallel Trends among Movers, No Selection on Gains, and Fragmentation Selection on Observables, the effect of regional fragmentation on individual health outcomes is nonparametrically identified. In practice we estimate regression specifications that parameterize these assumptions. Conceptually, estimation can be thought of as occurring in two steps. First, region effects can be estimated from a differences-in-differences regression on region indicators controlling for covariates x_{it}, individual fixed effects α_i, time effects γ_t, and effects for periods relative to move ρ_p, in a specification such as the following:

$$Y_{it} = \sum_r \Delta_r + x_{it}'\gamma + \alpha_i + \gamma_t + \rho_{p(i,t)} + \varepsilon_{it}.$$

Second, estimates of the regional effects $\hat{\Delta}_{R_{it}}$ can be regressed on the regional fragmentation measure in a similar specification, but with the region dummies replaced with the regional fragmentation measure:

$$\hat{\Delta}_{R_{it}} = \delta F_{R_{it}} + x_{it}'\gamma + \alpha_i + \gamma_t + \rho_{p(i,t)} + \varepsilon_{it}.$$

The coefficient on fragmentation identifies the effect of regional fragmentation on movers' health outcomes.

The two-stage procedure conceptually distinguishes the identification of regional effects from the identification of fragmentation's contribution to the regional effects and lends itself to graphical analysis, but in practice we use the following single regression specification, which yields algebraically equivalent estimates of the effects of fragmentation and simplifies inference:

$$Y_{it} = \delta \Delta F_i \times post_{it} + x_{it}'\gamma + \alpha_i + \gamma_t + \rho_{p(i,t)} + \varepsilon_{it}.$$

Theorem 1 *Suppose No Selection on Gains holds. Then* $\Delta(o,d,t) - \Delta(o,d',s) = \Delta(d,d')$.

Proof. No Selection on Gains implies

$$\Delta(o,d,t) = E\left[Y_{iT_i}(d) - Y_{iT_i}(o)\,|M_i = 1\right]$$

and

$$\Delta(o,d',s) = E\left[Y_{iT_i}(d') - Y_{iT_i}(o)\,|M_i = 1\right],$$

and thus the difference is

$$\begin{aligned} & \Delta(o,d,t) - \Delta(o,d',s) \\ = \; & E\left[Y_{iT_i}(d) - Y_{iT_i}(o)\,|M_i = 1\right] - E\left[Y_{iT_i}(d') - Y_{iT_i}(o)\,|M_i = 1\right] \\ = \; & E\left[Y_{iT_i}(d) - Y_{iT_i}(d')\,|M_i = 1\right]. \\ = \; & \Delta(d,d'). \end{aligned}$$

■

Theorem 2 *Suppose Parallel Trends and No Selection on Gains hold. Then*

$$\Delta(r,r') = E\left[Y_{it} - Y_{it-1}|R_{it-1} = r', R_{it} = r, T_i = t\right] - E\left[Y_{it} - Y_{it-1}|R_{it-1} = r', T_i \neq t\right].$$

Proof. Adding and subtracting $Y_{it}(r')$ in $E\left[Y_{it} - Y_{it-1}|R_{it-1} = r', R_{it} = r, T_i = t\right]$ yields

$$\begin{aligned} & E\left[Y_{it} - Y_{it-1}|R_{it-1} = r', R_{it} = r, T_i = t\right] \\ = \; & E\left[Y_{it}(r) - Y_{it}(r')\,|R_{it-1} = r', R_{it} = r, T_i = t\right] + E\left[Y_{it}(r') - Y_{it-1}(r')\,|R_{it-1} = r', R_{it} = r, T_i = t\right]. \end{aligned}$$

Parallel Trends implies the second term on the right-hand side of this equation is equal to

$$\begin{aligned} & E\left[Y_{it}(r') - Y_{it-1}(r')\,|R_{it-1} = r', T_i \neq t\right] \\ = \; & E\left[Y_{it} - Y_{it-1}|R_{it-1} = r', T_i \neq t\right]. \end{aligned}$$

Thus, the right hand side of the theorem's conclusion becomes

$$\begin{aligned} & E\left[Y_{it}(r) - Y_{it}(r')\,|R_{it-1} = r', R_{it} = r', T_i = t\right] \\ = \; & E\left[Y_{iT_i}(r) - Y_{iT_i}(r')\,|M_i = 1\right] \\ = \; & \Delta(r,r'), \end{aligned}$$

where the first equality follows from No Selection on Gains and the second equality is by definition. ■

Theorem 3 *Suppose Parallel Trends among Movers and No Selection on Gains hold. Then*

$$\Delta(r, r') = E[Y_{it} - Y_{it-1} | R_{it-1} = r_0, R_{it} = r, T_i = t] - E[Y_{it} - Y_{it-1} | R_{it-1} = r_0, R_{it} = r', T_i = t].$$

Proof. Adding and subtracting $Y_{it}(r_0)$ in the first term of the right hand side of the theorem's conclusion yields

$$\begin{aligned} & E[Y_{it} - Y_{it-1} | R_{it-1} = r_0, R_{it} = r, T_i = t] \\ = \quad & E[Y_{it}(r) - Y_{it}(r_0) | R_{it-1} = r_0, R_{it} = r, T_i = t] + E[Y_{it}(r_0) - Y_{it-1}(r_0) | R_{it-1} = r_0, R_{it} = r, T_i = t]. \end{aligned}$$

Parallel trends among movers implies the second term on the right hand side of this equality is invariant to the destination region, and thus similarly adding and subtracting $Y_{it}(r_0)$ in the second term of the theorem's conclusion and simplifying yields

$$\begin{aligned} & E[Y_{it} - Y_{it-1} | R_{it-1} = r_0, R_{it} = r, T_i = t] - E[Y_{it} - Y_{it-1} | R_{it-1} = r_0, R_{it} = r', T_i = t] \\ = \quad & E[Y_{it}(r) - Y_{it}(r_0) | R_{it-1} = r_0, R_{it} = r, T_i = t] - E[Y_{it}(r') - Y_{it}(r_0) | R_{it-1} = r_0, R_{it} = r', T_i = t]. \end{aligned}$$

No Selection on Gains implies these two conditional expectations can be expressed as conditional on $M_i = 1$ only, which means the right hand side simplifies to

$$E[Y_{iT_i}(r) - Y_{iT_i}(r') | M_i = 1] =: \Delta(r, r').$$

■