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ABSTRACT

Fragmented health care occurs when care is spread out across a large number of poorly coordinated providers. We analyze care fragmentation, an important source of inefficiency in the US healthcare system, by combining an economic model of regional practice styles with an empirical study of Medicare enrollees who move across regions. Roughly sixty percent of cross-regional variation in care fragmentation is independent of patients' clinical needs or preferences for care. A one standard deviation increase in regional fragmentation is associated with a 10% increase in utilization. Our analysis also identifies conditions under which anti-fragmentation policies can improve efficiency.

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I. Introduction

When healthcare delivery is spread out across an excessively large number of poorly coordinated providers, the result is fragmented care. Care fragmentation is considered an important source of inefficiency in the US healthcare system and concern about the problem motivates public policy initiatives, but its causes and consequences are only dimly understood.

To illustrate the economic and clinical tradeoffs raised by fragmentation, consider a patient with a complex chronic disease such as diabetes. The patient's primary care provider (PCP) manages the patient's care in part by the direct provision of services and in part via referrals to specialists and other providers. If the PCP operates with a larger network of specialized providers, it is easier to customize care more closely to the clinical conditions of individual patients. At the same time, when care involves a larger network of providers, the PCP may find it harder to establish reliable transfers of patient information and clarity about responsibility for ongoing patient care (Milstein and Gibertson 2009). Involving more doctors in care may also make it difficult for the PCP to monitor for redundant and unnecessary care.[1]

From an economic perspective, efficient healthcare delivery balances the marginal benefits of increased specialization against the marginal costs of more difficult coordination (Becker and Murphy 1992, Meltzer 2001). When this optimal balance is not achieved, the result can be that care is spread across an excessively large number of providers who offer "too much" specialization, and "too little" care coordination and continuity (Baicker and Chandra 2004, Cebul et al. 2008, Hussey et al. 2014).

Concern about the inefficiencies resulting from excessively fragmented practice styles has motivated important policy initiatives and debates. Some of these policy initiatives are aimed at improving the technology of care coordination, e.g. subsidized investments in health

[1] For a striking qualitative depiction of the problems of coordination see Matthew J. Press. 2014 . Along these same lines Romano, Segal and Pollack (2015) report an association between measures of fragmented care delivery and the overuse of medical procedures.

information technology. Others seek to strengthen provider incentives to improve care coordination and continuity, e.g., Patient Centered Medical Homes, Accountable Care Organizations (ACOs) and various types of bundled payment reforms. In spite of these long standing concerns and significant policy initiatives, many fundamental questions about care fragmentation remain unanswered.

In this paper we examine three questions concerning care fragmentation: (1) to what extent are observed patterns of fragmentation the result of physician practice styles that are independent of a patient's clinical conditions and preferences? (2) are fragmented practice styles associated with increased resource utilization independent of a patient's clinical condition and preferences? and (3) can public policy interventions that discourage fragmented practice styles produce more efficient healthcare delivery? The answers to these three questions turn out to be closely connected.

We approach the first question by developing a Roy model of care fragmentation that builds on two assumptions. The first is that providers are motivated to deliver care that promotes each patient's welfare. The second is that providers' care decisions are also shaped by spillover effects. In our example of a patient with diabetes, spillover effects arise when a PCP who keeps diabetic care "in house" gets more efficient at delivering this sort of care. Spillovers will similarly cause a PCP who relies more on referrals to endocrinologists, cardiologists, and other specialists to become more proficient at delivering this sort of care. From these two assumptions, our model identifies channels through which equilibrium levels of fragmentation can vary across regions independently of individual patient's clinical conditions or preferences. Our theory provides new insight into the emergence of local practice styles as an outcome of physicians optimizing tradeoffs between specialization and coordination.

We find strong empirical support for such regional variations in fragmentation style when we examine the experience of Medicare enrollees who move across regions. Adapting the econometric approach pioneered by Finkelstein, Gentzkow and Williams (2016), we find that upon arrival in a new region, these Medicare movers experience changes in fragmentation levels that are on average 63% of the difference in average fragmentation between destination and origin regions. Under conventional assumptions (cf. Finkelstein et al. 2016), this estimate suggests that more than sixty percent of the variation in fragmentation across regions is due to the place-specific differences in practice styles.

The quantitative importance of regional fragmentation styles enables us to address our second question concerning the association between fragmentation and care utilization. A number of prior studies have reported a high cross-sectional correlation between higher fragmentation and higher costs (cf. Frandsen et al. 2015, Hussey et al. 2014, Baicker and Chandra 2004), but it is difficult to assess how much of this association is driven by unobserved patient characteristics. By exploiting variation in fragmentation experienced by beneficiaries who move across regions, we isolate the impact of fragmentation from the contaminating effects of patient-level unobservables that may have confounded prior studies. We find that moving to a region with a one standard deviation higher level of fragmentation leads to 10% higher annual care utilization for the mover. Higher regional fragmentation also leads to more encounters, but fewer with primary care providers, more hospitalizations, and more prescription drugs.

In our more fine-grained analysis, we distinguish between two sources of care fragmentation: primary care fragmentation, where a patient's care is split across many general practitioners, and specialty fragmentation, where a patient's care is split across many distinct types of specialists. While both types of fragmentation are associated with higher total utilization, more total visits, and fewer visits with primary care providers, primary care fragmentation also leads to significant increases in hospitalizations. This suggests that when primary care becomes more fragmented, either patients' health deteriorates or patients substitute inpatient treatment for conditions that may otherwise have been addressed in an outpatient setting. These findings shed some light on the consequences of fragmentation for care quality as well as on the trade-off between specialization and coordination in care delivery.

Our findings that fragmentation is powerfully determined by practice styles and that these styles have a large and positive association with costs immediately raises the central issue of concern in question 3: can public policies aimed at discouraging fragmentation improve efficiency? In our model of fragmentation, the primary source of inefficiency is that the cost consequences of treatment and referral decisions are externalities to the primary care doctors making these choices. Intuitively it would seem that policies aimed at improving incentives so that PCPs have to internalize more of these external costs ought to both reduce expensive fragmentation and also improve welfare. When spillovers matter, however, this intuition need not hold because reducing excessive fragmentation can itself lead to losses in productive efficiency. We find that better incentives *can* improve patient welfare - but only if the extra spending entailed by fragmented care is sufficiently large. From this perspective, our empirical results suggesting that fragmentation has a powerful positive effect on utilization creates the possibility that anti-fragmentation policies aimed at improving physician incentives may be welfare improving.

The paper proceeds in four parts. In Section 2 we introduce a simple economic model of provider treatment and referral decisions when there are spillovers. Section 3 presents our empirical results. In Section 4 of the paper we analyze the 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.

II. Physician Decisions and Fragmented Practice Styles

We analyze a setting in which PCPs manage the trade-off between coordination and specialization for patients with complicated, perhaps chronic, conditions that require a team of providers to deliver care. In our set-up, the PCP must decide which of two treatment options to offer her patient.

Under treatment 1, the PCP delivers more services herself and makes fewer specialist referrals than under treatment option 2. In treatment 2 the PCP substitutes specialist visits for services she provides. In addition the PCP sends patients to specialists outside of the standard set. The advantage to the more fragmented treatment 2 is that the expanded use of specialists and the larger set of specialist providers allows care to be more finely calibrated to a patient's specific clinical condition or preferences. The disadvantage is that care coordination is more difficult.

We capture these tradeoffs in the following Roy model which is adapted from Chandra and Staiger (2007). Let $T = 1$ correspond to well-coordinated care within the standard set of providers and $T = 2$ correspond to fragmented care involving the larger set of providers. Quality and cost outcomes depend on constant terms, β_T^q and β_T^c, reflecting average quality and costs of treatment T; the proportion of patients in a PCP's practice who receive treatment T is denoted P_T; and mean zero random variables, ε_T^q and ε_T^c capture patient-specific factors that influence both quality and cost outcomes: [2]

(1) $\quad Quality_T = \beta_T^q + \alpha^q P_T + \varepsilon_T^q$

(2) $\quad Cost_T = \beta_T^c + \alpha^c P_T + \varepsilon_T^c.$

The inclusion of P_T as a determinant of quality and cost reflects the influence of treatment spillovers of the sort highlighted by Chandra and Staiger (2007).[3] Non-zero spillover parameters, α^q and α^c, allow for the possibility that physicians who chose treatment T for more of their patients get better at it and experience higher quality and/or lower costs when delivering treatment T.[4] As we demonstrate below, these spillovers are important because they lead to equilibria in which patients with identical clinical conditions and preferences may receive different treatments depending on the regions in which they are being treated.

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2 Throughout we will assume that the random variables are characterized by log-concave distributions. This is a large class of distributions that includes many common probability distributions including the normal, uniform, logistic and extreme value.

3 Chandra and Staiger (2007) treat these spillovers as occurring across physician practices within a region. As we demonstrate below, however, even in the absence of cross physician spillovers, within practice spillovers can generate region specific care styles.

4 In this set-up, we have allowed the net effect of spillovers on individual patients to be identical across treatment options. Relaxing this assumption complicates the analysis without adding any insights.

We allow fragmented care to differ in cost from well-coordinated care by an amount c:[5]

(3) $$\beta_2^c = \beta_1^c + c.$$

If $c > 0$, the fragmented mode of care, $T = 2$, involves higher average cost but it may also offer higher quality. We describe the social tradeoff between quality and costs by a parameter λ that represents the dollar value of quality. Social welfare under treatment mode T is:

(4) $$W_T = Quality_T - \lambda Cost_T = \beta_T + \alpha P_T + \varepsilon_T$$

where $\beta_T \equiv \beta_T^q - \lambda\beta_T^c$ and $\alpha \equiv \alpha^q - \lambda\alpha^c$.

In our model, physicians are assumed to be altruistic in the sense that they care about the cost and quality outcomes that determine social welfare. If the PCPs fully internalize both cost and quality outcomes, they will make choices that maximize social welfare. If, on the other hand, they do not fully internalize the cost consequences of their actions, their decisions will tend to favor $T = 2$ when $c > 0$. We allow for the possibility of cost externalities by introducing parameter θ into the following equations describing the preferences of PCPs:

(5) $$U_T = \tilde{\beta}_T + \alpha P_T + \varepsilon_T,$$

(6) $$\tilde{\beta}_T = \beta_T^q - \lambda\theta\beta_T^c$$

where $0 < \theta < 1$ reflects the strength of cost externalities. As θ increases, the PCP internalizes more of the cost consequences of her choice of treatment.

The physician selects treatment option 2 when the perceived net benefit to a specific patient exceeds the net benefit offered under treatment option 1. Thus treatment 2 is chosen when:

(7) $$(T = 2) = (U_2 > U_1) = \tilde{\beta} + \varepsilon + \alpha(2P_2 - 1) > 0;$$

where: $\tilde{\beta} = \beta_2^q - \beta_1^q - \lambda\theta c$ describes the PCP's assessment of the net benefit of treatment 2 for the average patient without spillover effects; $\varepsilon = \varepsilon_2 - \varepsilon_1$ captures the influence of individual patient

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[5] Parameter c focuses on cost differentials of the sort that are measured in billing records from Medicare and private payers. It does *not* include the costs of investments in care processes, information technology or relationships that may improve care coordination. These costs are instead captured in the α^c parameter. We assume PCPs fully internalize these costs.

characteristics that make them more or less suitable for treatment method 2; and $\alpha(2P_2-1)$ reflects the effect of treatment spillovers. Spillover effects differ from the other factors in (7) in that they are not a characteristic of the treatment method per se. Rather they are determined by the physician's treatment choices with their specific population of patients. For this reason, we define a treatment method as efficacious if the perceived net benefits independent of spillover effects are positive, i.e. if $\tilde{\beta}+\varepsilon>0$. One undesirable implication of equation (7) is that if spillover effects are powerful enough, physicians will prescribe treatment 2 even when it is not an efficacious treatment for the patients who receive it. To rule out this possibility, we will restrict our analysis to parameter values where the equilibrium value of $P_2<\frac{1}{2}$.

The equilibrium use of treatment method 2 by a physician occurs when the equilibrium fraction of patients receiving treatment option 2, $\tilde{P}_2$, equals the proportion who would be assigned this treatment by doctors using the decision rule in (7). More formally, equilibrium is defined by a fixed point of the following relation:

(8) $$\tilde{P}_2 = Pr\,(\tilde{\beta}+\alpha\,(2\tilde{P}_2-1)\ +\varepsilon>0)\ = 1-F_{\varepsilon}(-\tilde{\beta}-\alpha(2\tilde{P}_2-1)).$$

The key feature of this equilibrium condition is that two individuals with identical characteristics may receive different treatments depending on their physician's practice style. To highlight that this result is driven by spillovers rather than imperfect incentives, we adopt the assumption that $\theta=1$ for the remainder of this section. We relax this assumption in Section 4 when we return to our analysis of policies aimed at improving physician incentives.

The equilibrium in (8) highlights three channels through which regions may influence treatment choices. The first is through regional differences in the distribution of patient characteristics in regions (F_{ε}). The second is through regional differences in the relative efficacy of method 2, $\tilde{\beta}$. The third is through multiple stable equilibria. We discuss each of these channels in turn.

We illustrate the impact of regional differences by considering regions with normally distributed patient characteristics, ε. We simplify the example further by assuming that all regions have a mean value of $\varepsilon = 0$ but different standard deviations, σ. In this case , if $\tilde{\beta} < 0$ the average patient in the region benefits more from treatment 1 than treatment 2, but some fraction of patients will still benefit from treatment 2 and this fraction increases with σ.

Let region s be characterized by a distribution of ε and an equilibrium probability of treatment option 2, $\{F_{\varepsilon,s}, \tilde{P}_{2,s}\}$. Fixing an individual's characteristics at ε, the individual patient's treatment is determined by: $1(T(\varepsilon) = 2; s) = 1(\varepsilon > -\alpha(2\tilde{P}_{2,s}(\sigma) - 1) - \tilde{\beta})$. The term involving α captures the effect of spillovers on treatment decisions. It is clear from this that two individuals with identical ε but in regions with different σ may therefore receive different treatments.

The second channel for regional differences in the treatment of identical individuals is via regional differences in the relative efficacy of treatment 2, the fragmented style of care. In terms of our model, we capture these regional differences by regional differences in the parameter $\tilde{\beta}$. A fragmented style of care is most likely to be beneficial for the average patient (that is, $\tilde{\beta}$ is higher) when a specialist's expertise can be closely matched with a patient's particular set of conditions. The ability to match in turns depends on the degree of specialization in the market. Common sense as well careful economic modeling suggests that investments in specialized knowledge are easier to sustain in larger markets (Becker and Murphy 1992, Garicano and Hubbard 2008). It is reasonable, then, to suppose that the parameter $\tilde{\beta}$ will be greater in larger markets and, from equation (8) this will lead to greater use of treatment 2, fragmented care delivery, in regions having larger markets.

Even if regions have the same distribution of patient characteristics and identical efficacy of treatment 2, there is still a third channel for identical individuals to receive different treatments in different regions. This third channel is the result of the multiple equilibria that emerge naturally in the context of the Roy model. To see this, consider the graphical representation of equation (8) in Figure 1. Equilibria occur wherever the complementary cumulative density function, $1 - F_{\varepsilon}(-\tilde{\beta} - \alpha(2\tilde{P}_2 - 1))$, intersects the dotted 45 degree line; the Figure depicts two stable equilibria.[6] Economics does not offer a generally accepted theory of equilibrium selection, so we cannot identify conditions under which a region might settle on one equilibrium or another. Nevertheless the likelihood of multiple stable equilibria creates another conduit through which spillover effects will lead to regional variations in the treatment of identical individuals.[7]

III. Empirical Analysis of Fragmentation

Data and Fragmentation Measures

The empirical analysis is conducted using a 20% sample of Medicare fee-for-service beneficiaries from 2000-2010, 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 patient moves.

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.[8]

6 Stability requires $2\alpha < 1/f_{\varepsilon}$ where f_{ε} is the density function of F_{ε}. We show, in an unpublished appendix available from the authors that as long as parameters are such that the equilibrium is not at a corner solution, there is always an odd number of equilibria in this model which alternate between stable and unstable as you move from low to high values of P_2. This means that in cases where there are multiple equilibria, there will always be multiple stable equilibria.

7 In an unpublished appendix available from the authors, we also prove that multiple equilibria are more likely to emerge when the cost and quality differences between the two modes of care are small relative to the spillover effect.

8 Analysis is based on the 2012 HEDIS NDC list for high risk drugs in the elderly (DAE), which was the earliest year available.

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.[9] 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:

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

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 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

[9] 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).

with a single primary care physician should enable improved care coordination and will also reduce this measure of care fragmentation.

Regional levels of care fragmentation are calculated by averaging these individual concentration measures within hospital service areas. For ease of interpretation, we normalize the units of our fragmentation measure by dividing by the standard deviation of average 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.[10] As we report below, our results are not sensitive to using these larger regional definitions.

We are interested in understanding both the causes and consequences of fragmentation. In pursuit of this latter goal 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.[11]

[10] To ensure that reported addresses reflect the likely residence of Medicare beneficiaries, we check that claim locations match the reported address. Both movers and non-movers are required to have at least 75% of their claims each year for services provided in the same HRR as their recorded address. (For movers, we do not impose this requirement during the year of the move.) Further, we exclude moves that involve an address change but no change in the associated HRR; this restriction helps to exclude local movers who may be unlikely to change their care providers.

[11] 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.

Summary Graphs and Statistics

Figure 2 presents the variation in care fragmentation across regions by shading Hospital Service Areas (HSAs) according to which third 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 fragmentation tercile. We note that average annual utilization in the highest fragmentation regions is over $1,000 greater than for 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 3.

The remaining rows of Panel 1 of Table 1 delve more deeply into resource utilization. Total encounters in a year are higher in high fragmentation regions by over 4.5 visits per patient, from a mean of 22.1 annual encounters in the lowest tercile regions. Regions with greater care fragmentation also have patients seeing more unique providers on average, with patients in the lowest tercile seeing an average of 8.98 providers while those in most fragmented regions see 29% more providers. Despite the higher number of total visits, we find that patients in the most fragmented regions have 10% fewer primary care encounters than patients in the least fragmented regions.[12] This pattern raises the possibility that specialized care is acting as a substitute for primary care in these regions - an issue we explore in more detail below.

The next panel of Table 1 concerns the use of hospital services. In contrast to total utilization measures, hospitalization rates and rates of hospitalizations due to ambulatory care sensitive conditions (ACSC) appear to be quite similar across regions with different levels of fragmentation. Total hospitalizations per patient are slightly higher in the most fragmented regions, although ACSC hospitalizations are a bit lower.

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

The third panel of Table 1 summarizes our prescription drug use measures. Patients in highly fragmented region are prescribed more unique drugs within a year - a difference of 0.76 additional drugs per patient-year in the highest tercile relative to the bottom tercile. Despite the increase in overall use of prescription drugs, there is no evident increase in the use of high risk medications for elderly patients.

The final panel of Table 1 presents average patient age and number of unique patients. Average age appears to be quite similar across regions.

These cross-regional patterns of fragmentation and utilization may be driven by regional practice styles of the sort we modeled in Section 2 or they may be the result of variation in patient characteristics. To investigate this issue, we turn to an analysis of Medicare members who move between regions with different average levels of care fragmentation.

Medicare Movers

Table 2 reports summary statistics for mover and non-mover patients. Anticipating our statistical analysis below, we divide the movers into two groups, those who move to HSAs with higher levels of fragmentation than their origin HSA and those who move HSAs with lower fragmentation. The averages and standard deviations we report combine pre- and post-move data.

There are three noteworthy relationships in the table. The first is that in terms of fragmentation and utilization, hospitalizations, prescription drug use and age, the movers who enter HSAs with higher levels of fragmentation than their origin region are quite similar to those entering HSAs with lower levels of fragmentation. The second is that there are large numbers of movers in both groups: roughly 266,000 movers went to regions with higher fragmentation and 214,000 went to regions with lower fragmentation. The third result is that movers appear similar to non-movers, although movers have more fragmented care, are slightly older and have higher annual average utilization levels. These differences between movers and non-movers, it is worth noting, are not important for our estimation strategy because our regressions include individual fixed effects and allow movers to be on differential time trends. Our regression strategy requires that regional fragmentation patterns influence individual care patterns. Figure 4 visualizes this influence using binned scatterplot. Specifically, we divide Medicare movers 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 ventile. 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 members. Patients moving to more fragmented regions clearly experience larger increases in their own fragmentation than patients moving to less fragmented regions, as evidenced by the strongly upward sloping pattern displayed in the plot. [13]

Estimation Strategy

We adapt the event study methodology of Finkelstein et al. (2016) to study the effects of changes in regional fragmentation on movers. Our basic regression framework takes the following form:

(9) $$y_{it} = \alpha_i + \beta post_{it} \Delta fragmentation_i + \tau_t + \rho_{r(i,t)} + x_{it}\gamma + \varepsilon_{it}$$

where y_{it} is the outcome variable (such as care fragmentation or utilization) for beneficiary i in year t. [14] The key coefficient of interest is β, 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

[13] 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.

[14] 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.

difference between destination and origin regions. The regression also controls for individual fixed effects α_i, calendar year effects τ_t, one-year bins for patient age x_{it}, and a vector of fixed effects for relative years $\rho_{r(i,t)}$. Note that $\Delta fragmentation_i$ and $\rho_{r(i,t)}$ are normalized to zero for non-movers.

Coefficient β 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. Because the parameter β is identified solely by comparing movers to other movers, omitted time-varying patient factors only introduce a bias if they are correlated to 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 (10) with a series of fixed effects for relative years $\theta_{r(i,t)}$

(10) $y_{it} = \alpha_i + \theta_{r(i,t)} \Delta fragmentation_i + \tau_t + \rho_{r(i,t)} + x_{it}\gamma + \varepsilon_{it}$

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. If we estimate (11) and find that our estimates of $\theta_{r(i,t)}$ are flat prior to the move, this supports our identifying assumption that pre-move trends are uncorrelated with ultimate changes in regional fragmentation.

In the next section we use parameter β from various versions of equation (9) as our estimate of the magnitude of the effect of changes in regional care fragmentation. In addition, we use plots of estimates of $\theta_{r(i,t)}$ from equation (10) to investigate the validity of the identifying assumption we rely on in interpreting β as being independent of omitted, time-varying, patient characteristics.

<u>The Effect of Regional Fragmentation</u>

Figure 5 plots estimates of $\theta_{r(i,t)}$ from the event study specification in equation (10) for various individual outcomes. The purpose of these event study graphs is to probe the validity of our identifying assumption for each outcome measure. We then estimate the magnitude of region effects on care patterns and utilization using equation (9). These estimates are presented in Table 3.

We begin with an analysis of changes in regional fragmentation influence the fragmentation of care that individual patients receive. In Panel A of Figure 5 we see that estimates of $\theta_{r(i,t)}$ from equation (10) 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 3, we present estimates of the magnitude of the region effects from equation (10). We find that moving to a region that has one standard deviation greater care fragmentation increases the mover's individual care fragmentation by 0.63 standard deviations.

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, following 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 0.63 suggests that 63% of the cross-regional variation in care fragmentation is due to region effects of the sort we model in

Section 2. To our knowledge this is the first estimate of the importance of regional effects in determining a patient's level of care fragmentation.

Our results in column 1 of Table 3 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 obscures the types of behaviors that may be driving these regional 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 that a diabetic who is exposed to lots of specialty care comes to demand such care 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 Table 3 columns (2) and (3) we present disaggregated estimates for these two types of movers and we find that the effects of changes in regional fragmentation on individual fragmentation are nearly identical. This symmetrical response indicates that regional effects are not the result of patients getting "locked into" highly fragmented care patterns. Rather individual patterns of care conform to styles prevailing in the region.

We now examine the effects of regional fragmentation on resource utilization. Panel B of Figure 5 plots estimates of $\theta_{r(i,t)}$ from the event study specification in equation (10) estimated 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. Increasing fragmentation leads to an increase in log spending and decreasing fragmentation leads to a decrease in spending. Estimates of equation (9) presented in row 2 of Table 3, reveal that moving to a region with 1 standard deviation higher care fragmentation is associated with a 10.7% increase in utilization. The estimates in columns 2 and

3 indicate that these changes are symmetric across moves to higher or lower fragmentation regions.

Regional fragmentation influences aspects of individual patient care other than overall utilization. Row 3 of Table 1 reports that moving to a region with a 1 standard deviation higher level of fragmentation is associated with 2.2 more encounters each year, 1.3 additional distinct providers, and 0.5 *fewer* encounters with a primary care physician. Panels C, D and E in Figure 5 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 greater use of specialists. In theory, 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.

The estimates in panel B of Table 3 analyze hospitalizations. We find evidence that patients are slightly more likely to be hospitalized in highly fragmented regions, with an estimated 0.8 percentage point increase in the probability of having any hospitalization and 0.3 total additional hospitalizations after a move to a region with 1 standard deviation higher fragmentation. We cannot distinguish whether these increases in hospitalization rates are due to deterioration of the patients' health in more fragmented regions or due to a style of care that relies more heavily on hospital use for a given disease state. Our point estimate of the effect of ambulatory care sensitive hospitalizations is positive, suggesting that these hospitalizations increase as patients move to more fragmented regions. We note, however, that this coefficient is imprecisely measured and the effect size is small.

Panel C of Table 3 reports that moving to more highly fragmented regions is associated with greater use of prescription drugs. A one standard deviation increase in regional fragmentation is associated with 0.50 additional unique drugs each year, significant at the 1% level. Although overall drug use increases, there is no consistent evidence that fragmentation is associated with greater use of high risk drugs. In most specifications, we find a positive, though statistically insignificant effect on the use of high risk drugs. Restricting only to moves to higher fragmentation levels, patients are prescribed 0.08 additional high risk drugs each year (p=0.012), suggesting that discontinuing high risk drugs when moving to a lower fragmentation region may be less likely to occur, relative to adding high risk drugs when moving to a higher fragmentation region.

Specialist Care

The results in Table 3 indicate that high fragmentation regions make use of fewer primary care visits and point towards greater reliance on specialists. We use the results in Table 4 to probe more deeply into the effect of regional fragmentation on referrals to specialists. We find that a one standard deviation increase in regional fragmentation increases the number of cardiologist visits by 0.21 on a mean of 1.60 visits per year, or a 13.4% increase. On an absolute basis, cardiologists seem to be the specialty most responsive to changes in regional fragmentation.

The second most responsive specialty group is diagnostic radiologists. A one standard deviation increase in regional fragmentation is associated with 0.14 additional visits per patient with a diagnostic radiologist, from a mean of 1.99 visits annually. The more intensive use of diagnostic imaging may be an important channel through which regional fragmentation leads to higher costs.

Other specialties also experience a statistically significant increase in visits as regional fragmentation increases. These include ophthalmology, urology, podiatry, dermatology, gastroenterology, pathology, anesthesiology, neurology, and psychiatry. For each of these areas, specialty visits increase between 0.035 and 0.076 per patient after moving to a region with 1 standard deviation greater care fragmentation.

With the notable exception of anesthesiology and pathology, most of the specialties experiencing an increase in visits are those where there may be significant overlap in the scope of practice between primary care providers and specialists. After all, primary care physicians can monitor their patient's use of statins just as cardiologists can. The increased encounters with pathologists, radiologists and anesthesiologists may be consistent with this story as well if the increases in testing and imaging ordered by specialists may necessitate the use of these services (as is true for some common diagnostic procedures such as biopsies, imaging studies, and colonoscopies). On this basis it appears that regional fragmentation influences specialist use most for common medical conditions where the skills of primary care providers and specialists overlap or where the skills of the specialist are required to support higher levels of testing and imaging.

Interestingly, not all specialties appear to be substitutes for primary care providers in more fragmented regions. We find regional fragmentation has a small, insignificant effect on encounters with specialists in general surgery, emergency medicine, and radiation oncology. There may be little possibility for substitution between specialists and general practitioners in the radiological treatment of cancer or in surgery. Substitution may also be less feasible in emergency departments because the primary care provider may have little influence over events leading a patient to visit the emergency department.

Taken together, the results in Tables 3 and 4 suggest that regional fragmentation effects influence the decision to substitute the care of a specialized provider for that of a primary care provider. The large regional effects suggest that the degree of substitutability between many specialists and primary care doctors is substantial.

Utilization in more detail

Table 5 offers a more detailed analysis of regional fragmentation effects on utilization. It breaks utilization into three type of Medicare bills: provider-submitted "Carrier" bills, hospital outpatient bills, and hospital inpatient bills. Total utilization across all types of bills increases by $665 after a patient moves to a region with 1 SD higher care fragmentation. The largest source of this increase is from the $416 rise in provider-submitted carrier bills, which are largely bills for physician services. This likely reflects the increase in specialist visits analyzed above. We also find greater fragmentation is associated with a significant, $316 per patient per year increase in inpatient costs - consistent with the higher reported number of hospitalizations.

Finally, we find a small but significant decrease in hospital outpatient utilization of $67 per patient, slightly offsetting the increases in carrier and inpatient utilization. It is not clear what drives this decrease, as many of the same outpatient services can be billed either to the carrier claims or the outpatient claims depending on the location of services and the organizational arrangement between the providers and the hospital. One possibility is that regions with greater fragmentation tend to rely more on independent physician practices rather than integrated hospital-based delivery systems.

Table 6 examines the increase in carrier claims in more detail. Specifically we categorize provider-submitted carrier claims using Berenson-Eggers Type of Service (BETOS) codes. Here we find increases in all types of evaluation and management claims, with the largest absolute increases coming in the specialist and consultation evaluation and hospital evaluation categories, both of which increased by almost $45 (roughly 16%). The percent increase in hospital-based physician evaluation claims is higher than the relative increase in hospital-submitted inpatient bills or number of inpatient stays, suggesting that regions with more fragmented care styles may be engaging more physicians to evaluate patients during each hospital stay. These results are consistent with the results in Table 4 documenting greater reliance on specialists in regions with more fragmented care styles as well as with the findings of more intensive hospital use in highly fragmented regions.

Regions with more fragmented care patterns also utilize more testing and imaging services; these services are among the most responsive to changes in care fragmentation. Moving to a region with 1 SD higher average fragmentation increases utilization of testing by $58 per beneficiary (30%), and utilization of imaging and endoscopy increases by $91 (21%). As more specialists become involved in evaluating the patient, they may be increasingly likely to order additional diagnostic tests, further increasing the total costs of care.

Patients' use of procedures, anesthesia, and dialysis all increase with a move to a more fragmented region. One possible channel for this result is that specialists are more likely to recommend tests and procedures than primary care providers. Another possibility is that the greater use of tests and procedures in highly fragmented regions increases the detection of medical conditions that require additional specialists for treatment.

Taken as a whole, the empirical patterns suggest that a potential mechanism for utilization increases in fragmented regions is additional evaluations by more specialized doctors, increased testing and imaging, and higher levels of inpatient resource utilization. A notable exception is cancer care.

Distinguishing between specialization and fragmentation

The main empirical findings in Table 3 are that when patients move to regions with more fragmented patterns of care, their care becomes more costly, they see more providers (but fewer primary care providers), and they are hospitalized more frequently. Our measure of fragmentation, however, increases with the range of specialists involved in care. This raises the possibility that the higher costs and more challenging coordination associated with fragmented care may be offset by gains from involving a broader set of specialists in treatment.

To address these issues, we introduce in this section two new 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 unpublished Appendix for the categories). The across-specialty fragmentation measure is constructed using the same rescaled Herfindahl-Hirschman concept as before, but it 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. The primary care fragmentation measure is constructed in the same way as our main fragmentation measure, but the variable is restricted to encounters with providers 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 providers.

As a first step in this analysis, we proceed as before and verify that movers who experience regional changes in each fragmentation measure also experience a change in the corresponding individual fragmentation measures. We modify equation 9 to replace the interaction of the aggregate fragmentation measure and the post-move dummy with two variables equaling the change in each type of fragmentation (across specialty and primary care), each interacted with the post-move dummy. The first row of Table 7 shows that individual-level primary care fragmentation responds strongly to post-move changes in regional primary care fragmentation, but that across-specialty type fragmentation is not influenced by these same regional changes. The second row shows individual-level across-specialty fragmentation responds strongly to post-move changes in regional across-specialty fragmentation, but that it is much less responsive to changes in regional primary care fragmentation. That each individual level measure responds to regional changes in its own type of fragmentation gives confidence that these regional measures are capturing distinct dimensions of practice style.

Second, we regress our battery of health care volume, hospitalization, and prescription drug outcomes on primary care and across-specialty fragmentation measures. The remaining rows of Table 7 report coefficients on the fine-grained fragmentation measures from regressions of log utilization, number of encounters, number of providers, number of primary care visits, hospitalizations, and prescription drug outcomes. For the health care volume, hospitalization, and total prescription drug outcomes, within-primary care fragmentation has a statistically and economically significant effect, even when controlling for across-specialty fragmentation. Measures of the use of high-risk drugs do not generally appear to be affected by either fragmentation component.

Specifically, the results in column 1 show that a one standard deviation increase in regional primary care fragmentation as a result of a move increases utilization by 3.4%, increases number of encounters by 0.50, and increases number of providers by 0.19, all statistically significant at the 1% level. Remarkably, increases in regional primary care fragmentation significantly *decrease* the moving beneficiary's number of annual primary care visits by 0.899.

Regional changes in within-primary care fragmentation also increase hospitalization. The probability of hospitalization and the number of hospitalizations are both significantly increased. The last row provides suggestive evidence that within-primary care fragmentation may also increase ambulatory care sensitive hospitalizations (P=0.045), an effect that was not evident in estimates using the aggregate fragmentation index in Table 3.

The bottom of column (1) of Table 7 shows that a one standard deviation increase in primary care fragmentation leads to an estimated 0.33 additional drug prescriptions (s.e.=0.15). The effects on high-risk drug indicators are very close to zero and precisely estimated, however. Fragmentation across specialty groups (second column) does not have a significant effect on drug outcomes.

Taken together, the results in column (1) suggest that the relationship between measured fragmentation and utilization is not solely the result of involving a broader array of specialists in care delivery. This suggests that fragmentation induced increases in utilization may not simply reflect a (possibly efficient) tradeoff between higher costs and the benefits of involving more types of specialists in care delivery.

Comparing columns (1) and (2) in Table 7 it is noteworthy that volume of care outcomes (log utilization, visits, number of providers) increase with both measures of fragmentation. In contrast hospitalization effects appear to be entirely the result of changes in primary care fragmentation, not across-specialty fragmentation. These increased hospitalizations may be a signal of deteriorated health status, or perhaps of using the hospital as a substitute for outpatient primary care in a setting where patient relationships with their primary care providers may be particularly weak.

Robustness checks

In this section, we probe the robustness of our results to a number of alternative specifications. First, our baseline results compare Medicare movers up to three years before and 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.

In Panel A of Table 8, we report that our results are not sensitive to varying the window of years around the move date. Using only one year of pre and post move data leads to a slightly stronger estimated relationship between regional fragmentation and individual care fragmentation and utilization, although differences between the estimates are not statistically significant. Broadening the window to 5 years before or after the move also yields consistent results.

In addition to the width of the window of analysis, one may be concerned with selection into or out of the sample. Specifications restricting to patients who do not die during our study window yield similar results to those reported above. Our results become even stronger if we restrict our analysis to a balanced sample of patients who survive and retain fee-for-service Medicare coverage for the entire 7-year period centered on their move date. This estimate, however, necessarily conditions on a selected group of older patients who have been Medicare eligible for at least 3 years before moving, and excludes all observations from patients who die or switch to a Medicare Advantage plan. This stringent sample exclusion criterion also leads to noticeably larger standard errors.

In Panel B of Table 8 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 more aggregate 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 mover sample. Note that the scale of these numbers are 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 1 SD increase in fragmentation on total utilization is to be expected.

<u>Interpretations of the Results:</u>

In this section of the paper we consider two alternative interpretations of our empirical results. The first alternative considers the role of market size and density in explaining the presence of regional variation in fragmentation. The second considers the importance of regional fragmentation as a mechanism for explaining the well-established effect of regions on utilization and costs.

Market Size and Density

Our model in Section 2 highlights the role of spillover effects in shaping regional variation in fragmentation styles that are independent of individual patient characteristics. It is possible, however, that regional differences are the result of variations in market size. Indeed, given the economic dictum that specialization is supported by larger markets (Garicano and Hubbard 2008), regional differences might emerge from variation in market size even if there were no spillover effects at all.

We assess the role of market size and density by examining the importance of urbanicity as a driver of regional effects. We determine the urbanicity of each HSA in our data set by linking zipcodes to the Census Bureau definitions of urbanized areas. We construct a continuous measure of urban status by measuring the fraction of the population within an HSA that lives in a Census-designated urban area zip code.

In Panel C of Table 8, we re-run our estimates of equation (10) controlling for the region's urbanicity. If the care fragmentation measure were primarily capturing differences in market size and density resulting from urbanization, we would expect to find a diminished role of fragmentation once we control for this variable. Notably, the coefficient on regional fragmentation remains virtually unchanged from our baseline specification. Moving to a region with 1 SD higher fragmentation is associated with 0.61 SD increase in an individual's fragmentation level and an 11% increase in utilization.

As an alternative approach, we run a series of regressions where we restrict only to moves within a specific urbanicity tercile. For example, in the low urbanicity regression, we include only non-movers residing in low-urbanicity regions and movers who move from one low-urbanicity region to another. If all of our previous findings were being driven by moves from very rural areas to urban ones (and vice versa), then we would expect to find a diminished effect of fragmentation when restricting to moves within an urbanicity tercile.

We find very consistent results in all three sub-samples. Point estimates on the impact of a 1 SD increase in regional fragmentation range from a 0.54 to 0.63 SD increase in individual fragmentation; these results are not statistically distinguishable. Thus, the local effect of an increase in regional care fragmentation appears remarkably stable across rural and urban environments. The estimated relationship between fragmentation and utilization is also consistent. The impact of a 1 SD increase in fragmentation ranges from 8% to 13% higher utilization.

Taken together, these findings establish that there is ample regional variation in fragmentation conditional on a region's urban status, and this variation is linked to individual care fragmentation and outcomes regardless of whether the area is urban or rural.

Fragmentation as a Channel for Regional Cost Differentials.

A rich literature in health economics documents that regions exert a powerful direct effect on costs and utilization, although the reasons for these regional effects are murky (Finkelstein et al. 2016). In this section we use the machinery of instrumental variables to assess how important regional fragmentation is as a channel for regional effects on costs.

Our approach is to estimate an upper bound on the degree to which care fragmentation mediates the connection between individual and regional variation in health care costs. To maximize the mediating role of regional fragmentation, we want to estimate a model in which we assume temporarily that the *only* channel by which regional utilization influences individual utilization is through regional care fragmentation. This approach is equivalent to imposing the "exclusion restriction" that needs to hold if regional costs were to be a valid instrument for regional fragmentation. By estimating equation (9) while instrumenting regional fragmentation with regional average costs we are, in fact, maximizing the importance of regional fragmentation as a channel for the effect of regional costs.

In conventional IV applications the "exclusion restriction" is assumed to be correct. Our purposes, however, do not require this assumption. Rather, we want to understand the extent to which the exclusion restriction is violated, i.e. the extent that regional and individual costs are related through channels other than regional fragmentation. If the additional channels are, for example, positively correlated with fragmentation, then the IV estimates obtained by imposing the exclusion restriction will be larger than the 11% effect of fragmentation on costs presented in row 2 of Table 3. The ratio of our Table 3 estimate to the IV estimate measures the degree to which the connection between regional and individual costs is mediated by fragmentation.

Carrying out this IV exercise by instrumenting average regional fragmentation with average regional costs, we find that a 1 SD increase in regional fragmentation is associated with a 37% increase in individual care utilization.[15] This IV estimate is considerably larger than our baseline estimate of 11%. The discrepancy implies that there are other channels by which regional costs influence individual costs besides regional fragmentation, and those channels are positively correlated with fragmentation. Taking the ratio of the two estimates suggests that *at most* 29% of the effect of regional costs on individual costs is explained by fragmentation. We interpret this result as suggesting that other place-based aspects of practice style are also likely play an important role in explaining regional cost variations. An example of these might be physician beliefs in clinically unsupported treatment procedures as described in Cutler et al. (2013).

IV. Policies Aimed at Improving Physician Incentives

We have so far established that regional fragmentation is strongly related to care patterns and resource utilization. Our results are consistent with the spillover effects modeled in Section 2. In this section we consider the implications of these findings for anti-fragmentation policies aimed at improving physician incentives.

Many of these anti-fragmentation policies are premised on the assumption that in a fragmented care delivery system, the cost consequences of more fragmented treatment and referral decisions are externalities to the primary care doctors making these decisions. It seems but a short logical step to argue that improving incentives so that PCPs have to internalize more of these external costs ought to both reduce expensive fragmentation and also improve welfare.

[15] Our reduced form regression follows that in Amy Finkelstein, Matthew Gentzkow and Heidi Williams. 2014 except that it replaces *change in regional fragmentation* with *change in regional costs*. Our estimate of the coefficient on *change in regional costs*post* is 0.54, which is very close to theirs. Our first stage regression of *change in regional fragmentation*post* on *change in regional cost*post* is 1.46. This yields a pseudo IV estimate of 0.37.

When spillovers matter, however, this intuition need not hold because reducing excessive fragmentation can itself lead to losses in productive efficiency. We apply the model from Section 2 to identify conditions under which better incentives can improve patient welfare.

We introduce externalities into or model by setting θ to a value between 0 and 1. In the extreme case of $\theta = 0$, PCPs do not internalize any costs. In the other extreme case of $\theta = 1$, the cost externalities disappear altogether and the preferences that guide physician decisions are identical to those that promote social welfare, W, as defined in equation (4). Improving incentives in our model is represented by moving the parameter θ closer to 1.

In the setup in Section 2, physicians are deciding between choosing more fragmented care, Treatment 2, and less fragmented care, Treatment 1. On the basis of our empirical results, we adopt the assumption that Treatment 2 is more costly than Treatment 1 so that the parameter $c > 0.$ When PCPs more fully internalize the additional costs associated with Treatment 2, they will thus tend to shift some of their patients towards Treatment 1. The social welfare of patients who shift from T=2 to T= 1 increases, but the marginal gain might be small. Offsetting this gain is the loss of productivity benefits from spillovers for patients who still are receiving T =2. The question for policy is thus under what conditions is $\frac{dW}{d\theta} > 0$. It turns out that the sign of this derivative depends critically on the magnitude of parameter c, the added spending associated with adopting more fragmented treatments.

In an appendix to the paper, we prove the following proposition.

Proposition 1 : $\frac{dW}{d\theta} \geq 0$ provided that $\lambda c > \left(2\alpha - \frac{1}{f_\varepsilon(\alpha - 2\alpha\tilde{P}_2 - \tilde{\beta})}\right)\frac{d\tilde{P}_2}{d\theta}$

As part of the proof of Proposition 1, we establish that both $\frac{d\tilde{P}_2}{d\theta}$ and $\left(2\alpha - \frac{1}{f_\varepsilon(\alpha - 2\alpha\tilde{P}_2 - \tilde{\beta})}\right)$ are negative for any stable equilibrium. Thus, under Proposition 1, reducing the cost externality by increasing θ improves welfare provided that c is not "too small".

Put somewhat differently, our empirical finding that c is substantial creates the possibility that altering incentives so that physicians internalize more of the costs of fragmented care delivery may improve social welfare – even in a second-best delivery system characterized by meaningful spillover effects.

V. Conclusion

The fragmentation of care delivery is widely discussed as a potential source of inefficiency in the US healthcare system, but the causes and consequences of the phenomenon are only dimly understood.

In this paper we have examined three interrelated questions concerning care fragmentation: (1) to what extent are observed patterns of fragmentation the result of physician practice styles that are independent of a patient's clinical condition and preferences? (2) are fragmented practice styles associated with increased resource utilization independent of a patient's clinical condition and preferences? and (3) can public policy interventions that discourage fragmented practice styles produce more efficient healthcare delivery?

We addressed these questions by combining an economic model of regional fragmentation with an empirical study of Medicare enrollees who move across regions. We find strong evidence for regional variations in fragmentation style and we find that these styles are associated with higher utilization levels. Roughly sixty percent of cross-regional variation was independent of patient characteristics and a one standard deviation increase in regional fragmentation was associated with a 10 percent increase in utilization of resources by Medicare enrollees when they move across regions.

Our primary measure of fragmentation increases with the range of specialists involved in care. This raises the possibility that part of the higher costs and more challenging coordination associated with fragmented care may be offset by gains involving a broader set of specialists in treatments. In more fine-grained analyses, we explore the consequences of two distinct types of fragmentation. The first involves the dispersal of care across many specialty types while the second involves the dispersal of care across many primary care physicians. We find that both types of fragmentation are distinct and both are associated with greater utilization of physician services and higher costs, but only dispersal across primary care providers is associated with higher rates of hospitalization. These increased hospitalizations may be a signal of deteriorated health status, or perhaps of using the hospital as a substitute for outpatient primary care in a setting where patient relationships with their primary care providers may be particularly weak.

An important limitation of our analysis is that we cannot identify how much regional variations in fragmentation contribute to the well-documented effect of regions on costs. We are, however, able to calculate an upper bound estimate and we find that regional fragmentation can account for no more than 29% of the effect of regions on costs. It is therefore likely that other place-based aspects of practice style also play an important role in explaining regional cost variations.

This paper has a number of additional limitations that are worth noting and that may inspire future research. One important limitation is that our estimates of regional fragmentation are constructed from a population of Medicare enrollees. In prior work, we have found a positive association between costs and fragmentation for a population of chronically ill commercial insureds (Frandsen, et al., 2015) and in unpublished work, we have documented a positive correlation between regional Medicare fragmentation and the fragmentation of care received by this same group of commercial patients.

Our research design also gives only limited insights into what it is about fragmented care styles that leads to cost increases. We find that on average, fragmentation appears to involve the substitution of specialists for primary care providers. The overall empirical patterns suggest that care fragmentation is associated with additional evaluations by more specialized doctors, increased testing and imaging, and higher levels of inpatient resource utilization. One possible channel for this result is that specialists are more likely to recommend tests and procedures than primary care providers. Another possibility is that the greater use of tests and procedures in highly fragmented regions increases the detection of medical conditions that require additional procedures for treatment. Yet a third possibility is that the higher utilization is the result of less effective coordination between providers, with greater duplication and provision of low-value services. Our finding that concentrating care within a smaller number of PCPs directly reduces utilization and hospitalization offers suggestive support for this third channel, but much more remains to be done.

A final limitation of our analysis concerns public policy implications. Many notable anti-fragmentation initiatives such as Accountable Care Organizations seek to improve provider incentives to offer care that is less fragmented and more integrated. Our model identifies conditions under which improved physician incentives may increase welfare in a second best world characterized by spillovers. Our analysis does not, however, consider the challenges of improving physician incentives. McWilliams (2016) argues that programs designed to enhance care coordination have shown minimal savings. Frandsen and Rebitzer's (2014) simulation of incentives in Accountable Care Organizations, similarly finds that free-riding problems pose a nearly fatal challenge unless ACOs are able to supplement financial incentives with ancillary motivators that influence provider decisions. Unfortunately neither health policy nor health economics has much to say about how organizations go about introducing such ancillary motivators. Clearly much more remains to be learned about effective public policy responses to fragmented care delivery.

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Tables

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

	Low Fragmentation	Medium Fragmentation	High Fragmentation
	(1)	(2)	(3)
Fragmentation & utilization			
Visit-based fragmentation index	0.69	0.74	0.78
Total utilization ($)	7606	7941	8604
Number of encounters	22.06	24.09	26.82
Number of unique providers	8.98	10.32	11.61
Number of primary care encounters	6.49	6.05	5.66
Hospitalizations			
Any hospitalizations	0.24	0.24	0.24
Number of hospitalizations	0.48	0.48	0.5
Number ACSC hospitalizations	0	0	0.06
Prescription drugs			
Number of prescription drugs †	11.34	11.85	12.10
Any high risk drugs †	0.27	0.28	0.26
Number of high risk drugs †	0.36	0.38	0.35
Patient characteristics			
Patient age	76.18	76.14	76.54
Number of unique patients	1,423,026	1,463,173	1,473,757

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 and are normalized by the standard deviation across regions. ACSC hospitalizations are ambulatory care sensitive hospitalizations. † indicates that sample sizes are smaller for prescription drug outcomes. (Medicare Part D data are only available from 2006-2010 after the implementation of the program, and not all patients enroll in Part D.) The bottom fragmentation tercile contains prescription drug data for 96,454 unique patients; the middle tercile conatains 93,809 patients, the top tercile contains 94,912 patients.

Table 2: Summary statistics: Mean and Standard Deviations

	Moves to higher fragmentation	Moves to lower fragmentation	Non-movers
	(1)	(2)	(3)
Fragmentation & utilization			
Visit-based fragmentation index	0.73	0.73	0.68
	(0.23)	(0.23)	(0.24)
Total costs	$8,897	$8,668	$8,056
	(17,152)	(16,268)	(16,125)
Number of encounters	26.1	25.6	24.4
	(25.7)	(24.9)	(24.1)
Number of providers	11.2	10.9	10.3
	(10.1)	(9.8)	(9.2)
Number of primary care encounters	6.5	6.5	6.1
	(7.7)	(7.9)	(7.4)
Hospitalizations			
Any hospitalizations in 1 year	0.27	0.26	0.24
	(0.44)	(0.44)	(0.43)
Number of hospitalizations per year	0.57	0.55	0.48
	(1.28)	(1.26)	(1.17)
Number of ACSC hospitalizations	0.07	0.07	0.06
	(0.38)	(0.37)	(0.36)
Prescription drugs			
Number of prescription drugs †	10.9	11.0	11.8
	(7.6)	(7.9)	(8.2)
Any high risk drugs †	0.27	0.27	0.27
	(0.44)	(0.45)	(0.44)
Number of high risk drugs †	0.37	0.36	0.36
	(0.70)	(0.68)	(0.69)
Patient characteristics			
Age	77.9	77.9	76.3
	(7.6)	(7.7)	(7.6)
Number of patient-year observations	266,008	214,106	4,359,956
Number of unique patients	40,476	32,638	841,333

Notes: Reported means of variables over all in sample patients and years. Standard deviations reported in parentheses. Column 1 includes only patients who move to higher fragmentation HSAs during the study period. Column 2 includes only patients who move to lower fragmentation HSAs. The results in columns 1 and 2 combine pre and post move data. Column 3 includes only non-mover beneficiaries. † indicates that sample sizes are smaller for prescription drug outcomes. We observe prescription drug outcomes for 4,520 patient-year observations and 2596 unique patients moving to higher fragmentation; 4303 patient-year observations and 2416 unique patients moving to lower fragmentation; 886,592 patient-year observations and 282,626 unique patients who do not move.

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

Dependent variable	All moves (1)	Moves to higher fragmentation (2)	Moves to lower fragmentation (3)
A. Fragmentation and utilization			
Fragmentation index	0.6333***	0.5688***	0.6065***
	(0.0244)	(0.0518)	(0.0552)
Log of total utilization	0.1073***	0.0876***	0.0874***
	(0.0107)	(0.0219)	(0.0243)
Number of encounters	2.2451***	1.3705***	2.8108***
	(0.1565)	(0.3069)	(0.3573)
Number of providers	1.2849***	0.7950***	1.5256***
	(0.0609)	(0.1239)	(0.1339)
Number of primary care visits	-0.4557***	-0.2883***	-0.4205***
	(0.0573)	(0.1092)	(0.1354)
B. Hospitalizations			
Any hospitalizations	0.0079***	0.0015	0.0046
	(0.0028)	(0.0055)	(0.0066)
Number of hospitalizations	0.0314***	0.0243	0.0062
	(0.0087)	(0.0177)	(0.0195)
Number ACSC hospitalizations	0.0008	-0.0064	0.001
	(0.0014)	(0.0052)	(0.0057)
C. Prescription drugs			
Number of prescription drugs †	0.4991***	0.6718**	0.5569
	(0.1639)	(0.3121)	(0.3587)
Any high risk drugs †	0.0132	0.0331	0.0039
	(0.0101)	(0.0202)	(0.0217)
Number of high risk drugs †	0.0262	0.0766**	-0.0123
	(0.0162)	(0.0304)	(0.0375)
Number of observations	4,716,739	4,501,312	4,640,394

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 index is 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 in column 1 include all movers, within 3 years before or after the move, excluding the year of the move itself. Regressions in column 2 include only movers where average fragmentation is higher in the destination HSA than the origin HSA. Regressions in column 3 include only movers where average fragmentation is lower in the destination HSA than the origin HSA. 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.

† indicates that sample sizes are smaller for prescription drug outcomes. We have 949,412 total observations; 909,502 in the moves to higher fragmentation; 906,301 in the moves to lower fragmentation.

Table 4: Regression results describing effects on number of specialist visits after regional fragmentation change

Specialty:	Mean number of visits	All moves (1)	Moves to higher frag. (2)	Moves to lower frag. (3)
1 Cardiology	1.56	0.2134***	0.0712	0.3324***
		(0.0267)	(0.0484)	(0.0650)
2 Radiology (diagnostic)	1.99	0.1396***	0.0579	0.1410***
		(0.0240)	(0.0472)	(0.0538)
3 General surgery	1.02	0.0115	0.0399	0.0086
		(0.0181)	(0.0347)	(0.0436)
4 Ophthalmology	1.03	0.0353***	-0.0088	0.0803***
		(0.0129)	(0.0255)	(0.0296)
5 Emergency	0.66	0.0141	0.0078	0.0518*
		(0.0120)	(0.0230)	(0.0296)
6 Urology	0.34	0.0439***	0.0418**	0.0796***
		(0.0097)	(0.0187)	(0.0237)
7 Podiatry	0.63	0.0552***	0.0084	0.1128***
		(0.0121)	(0.0221)	(0.0320)
8 Dermatology	0.35	0.0642***	0.0713***	0.0526***
		(0.0083)	(0.0152)	(0.0198)
9 Gastroenterology	0.33	0.0755***	0.0535***	0.0913***
		(0.0090)	(0.0187)	(0.0195)
10 Pathology	0.27	0.0403***	0.0423***	0.0422***
		(0.0064)	(0.0129)	(0.0148)
11 Anesthesiology	0.28	0.0572***	0.0315**	0.0562**
		(0.0091)	(0.0144)	(0.0221)
12 OBGYN	0.14	0.0069	0.0220*	0.0221
		(0.0072)	(0.0121)	(0.0182)
13 Neurology	0.24	0.0495***	0.0531***	0.0495***
		(0.0090)	(0.0175)	(0.0189)
14 Otolaryngology	0.18	0.0077	-0.0183	0.0296
		(0.0106)	(0.0248)	(0.0257)
15 Psychiatry	0.19	0.0417***	-0.0079	0.0704***
		(0.0100)	(0.0215)	(0.0223)
16 Radiation Oncology	0.12	0.0159	0.0160	0.0109
		(0.0099)	(0.0211)	(0.0205)
17 Immunology	0.06	0.0090	0.0180	-0.0201
		(0.0089)	(0.0153)	(0.0200)
Number of observations		4,716,739	4,501,312	4,475,333

Notes: Each cell reports the coefficient from a separate regression, where the dependent variable is the number of visits to specialist of the type 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 index is 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 in column 1 include all movers, within 3 years before or after the move, excluding the year of the move itself. Regressions in column 2 include only movers where average fragmentation is higher in the destination HSA than the origin HSA. Regressions in column 3 include only movers where average fragmentation is lower in the destination HSA than the origin HSA. 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 5: Regression results describing cost outcomes after fragmentation change

	Dependent Variable	
	Total utilization ($)	*Carrier utilization ($)*
Individual fragmentation	665.10***	416.00***
	(110.53)	(32.17)
Mean of dependent variable	8246.04	2837.30
Percent change	8%	15%
	Outpatient utilization ($)	*Inpatient utilization ($)*
Individual fragmentation	-67.41***	316.51***
	(21.58)	(86.76)
Mean of dependent variable	1177.00	4231.73
Percent change	-6%	7%

Notes: Each cell reports the coefficient from a separate regression, where the dependent variable is noted in the header and the independent variable of interest is the change in the regional fragmentation index interacted with a post-move dummy. Regressions includes full sample of movers and nonmovers. Outcomes are expressed in dollars of medical spending, adjusted for regional differences in pricing patterns to describe utilization in standardized units. Carrier utilization is comprised of bills submitted from non-institutional providers (e.g. physicians). Outpatient utilization includes bills from institutional outpatient providers. Inpatient utilization includes bills from inpatient hospitals for facility costs. See notes to Table 3 for more details. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 6: Regression results describing carrier utilization after regional fragmentation change

	Dependent variable			
	Office evaluation & management	*Hospital evaluation & management*	*Specialist & consultation evaluation*	*Emergency dept. evaluation & management*
Fragmentation change	37.80***	43.75***	44.94***	3.89***
	(2.89)	(7.21)	(3.06)	(0.96)
Mean of dependent variable ($)	446.05	271.63	261.30	66.03
Percentage change	8%	16%	17%	6%
	Imaging & endoscopy	*Testing*	*Major procedures & anesthesia*	*Other procedures & dialysis*
Fragmentation change	90.76***	57.64***	20.51***	59.66***
	(4.99)	(2.28)	(5.06)	(6.92)
Mean of dependent variable ($)	433.93	193.45	235.03	419.44
Percentage change	21%	30%	9%	14%
	Home or nursing home evaluation & management	*Cancer claims*	*Vaccines*	*Durable medical equipment*
Fragmentation change	18.31***	8.34	0.64***	2.15
	(2.37)	(12.22)	(0.12)	(2.41)
Mean of dependent variable ($)	68.62	150.55	11.29	2.40
Percentage change	27%	6%	6%	90%

Notes: Each cell reports the coefficient from a separate regression, where the dependent variable is noted in the header and the independent variable of interest is the change in the regional fragmentation index interacted with a post-move dummy. Regressions includes full sample of movers and nonmovers. Outcomes are expressed in dollars of medical spending, adjusted for regional differences in pricing patterns to describe utilization in standardized units. Outcome variable is calculated as total spending within the Carrier (noninstitutional) claims on these categories of service. Service categories are defined by BETOS codes. Mean of dependent variable is calculated only over movers. See notes to Table 3 for more details. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 7: Regression results distinguishing between effects of regional within-PCP fragmentation and across-specialty fragmentation

Dependent variable	Regional Primary Care Fragmentation index (1)	Regional Across-specialty Fragmentation Index (2)
Fragmentation and utilization		
Individual PCP Fragmentation Index	0.7826***	0.0411
	(0.0286)	(0.0346)
Individual Across Specialty Fragmentation Index	0.0882***	0.6630***
	(0.0311)	(0.0386)
Log of total utilization	0.0344***	0.0659***
	(0.0092)	(0.0116)
Number of encounters	0.4972***	1.4409***
	(0.1390)	(0.1677)
Number of providers	0.1887***	0.9314***
	(0.0543)	(0.0656)
Number of primary care visits	-0.8987***	-0.2844***
	(0.0458)	(0.0576)
Hospitalizations		
Any hospitalizations	0.0111***	0.004
	(0.0025)	(0.0031)
Number of hospitalizations	0.0318***	0.0158*
	(0.0076)	(0.0093)
Number ACSC hospitalizations	0.0046**	-0.0007
	(0.0023)	(0.0027)
Prescription drugs		
Number of prescription drugs †	0.3296**	0.2676
	(0.1541)	(0.1773)
Any high risk drug †	0.0047	-0.0003
	(0.0090)	(0.0111)
Number of high risk drugs †	0.0026	0.0003
	(0.0135)	(0.0169)
Number of observations	4,716,739	

Notes: Each row reports the coefficients from a single regression, where the dependent variable is noted at left and the independent variables of interest are the changes in the regional fragmentation index labeled at the top of the column, interacted with a post-move dummy. The fragmentation index is 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 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. 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.

† indicates that sample sizes are smaller for prescription drug outcomes, for which we have 949,412 observations.

Table 8: Alternative Specifications and Robustness

	N	Dependent variable: Fragmentation	Log(utilization)
		(1)	(2)
A. Alternative sample frames:			
Baseline (within 3 years of move)	4,716,739	0.6333***	0.1073***
		(0.0244)	(0.0107)
Within 1 year of move	4,495,783	0.6837***	0.1313***
		(0.0305)	(0.0139)
Within 5 years of move	4,855,979	0.6255***	0.1047***
		(0.0231)	(0.0100)
Patients who never die	3,701,817	0.6362***	0.1131***
		(0.0287)	(0.0121)
Balanced panel (within 3 years of move)	4,366,717	0.8374***	0.1558**
		(0.1437)	(0.0632)
B. Alternative definition of regional fragmentation			
HRR fragmentation (rather than HSA)	4,716,739	0.7084***	0.0768***
		(0.0329)	(0.0075)
C. Alternative coding of regions:			
Controlling for urban status	4,431,616	0.6098***	0.1108***
		(0.0267)	(0.0122)
Moves within low urbanicity	1,395,118	0.6305***	0.1109***
		(0.0706)	(0.0326)
Moves within medium urbanicity	1,397,135	0.5365***	0.0824**
		(0.0790)	(0.0361)
Moves within high urbanicity	1,385,802	0.5968***	0.1340***
		(0.0738)	(0.0342)

Notes: 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. Panel C explores the role of urban status, first by controlling for the percent of the HSA that is urban, and then by partitioning results to include only moves within the same tercile of regional urbanicity and non-movers residing in that category of region. 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.

Figures

Figure 1: Illustrative example depicting equilibrium conditions for the physician practice style model

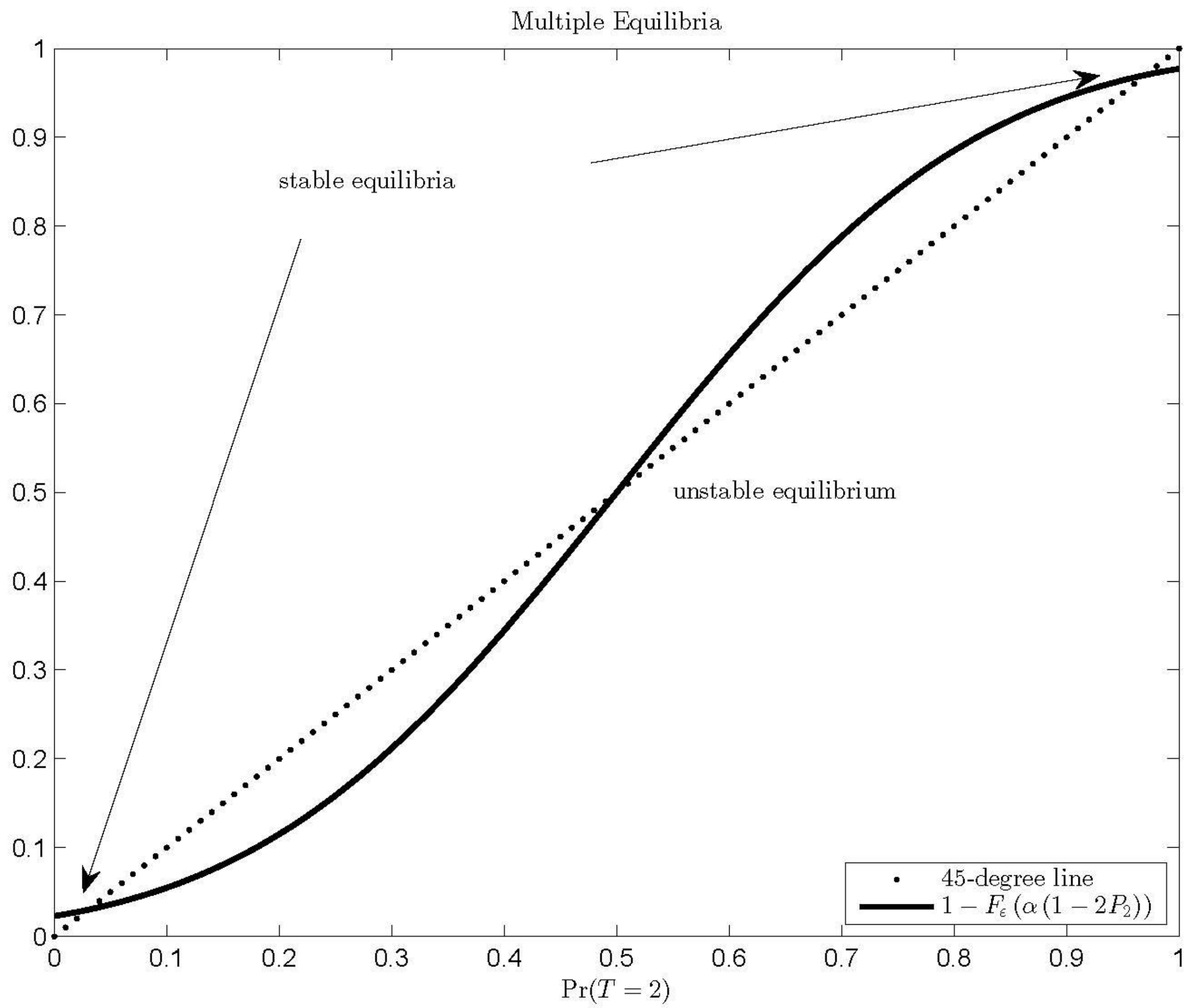


Figure 2: Fragmentation Index by Hospital Service Area

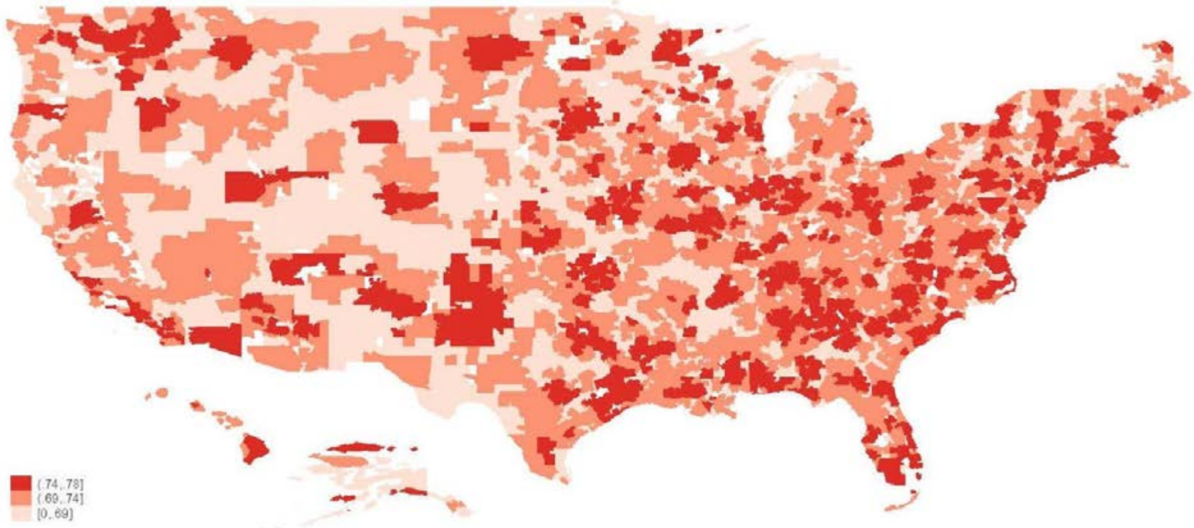


Figure 3: Scatterplot of HSA average utilization by HSA average fragmentation index

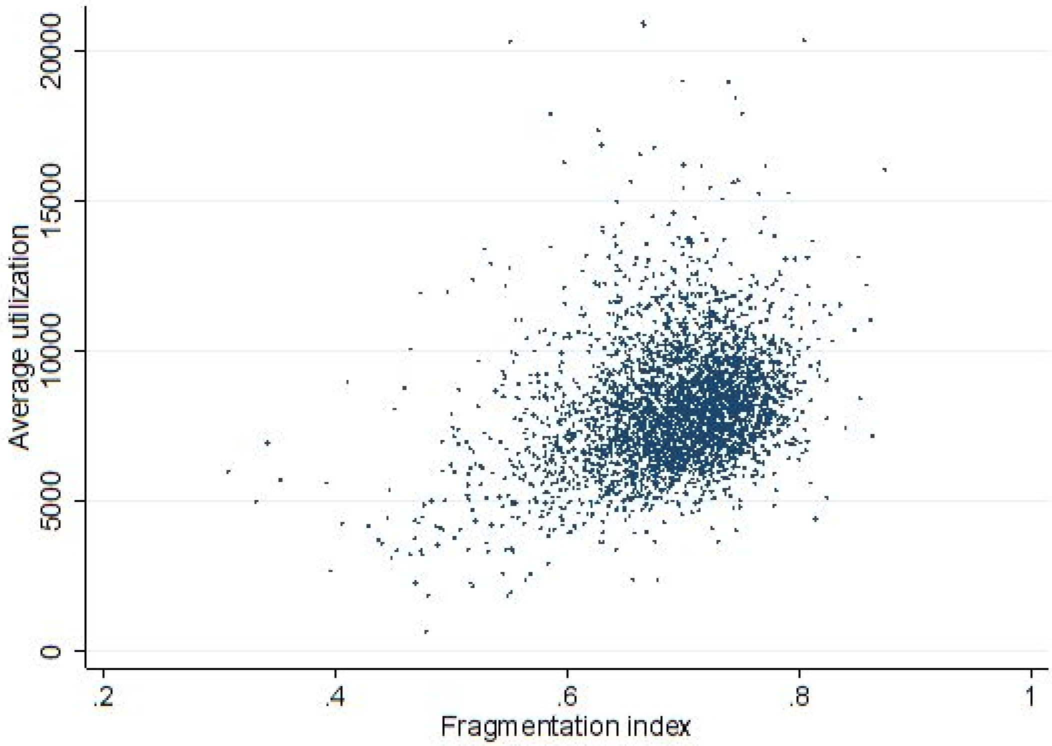


Figure 4: Binned scatterplot of change in regional fragmentation index vs. change in individual care fragmentation

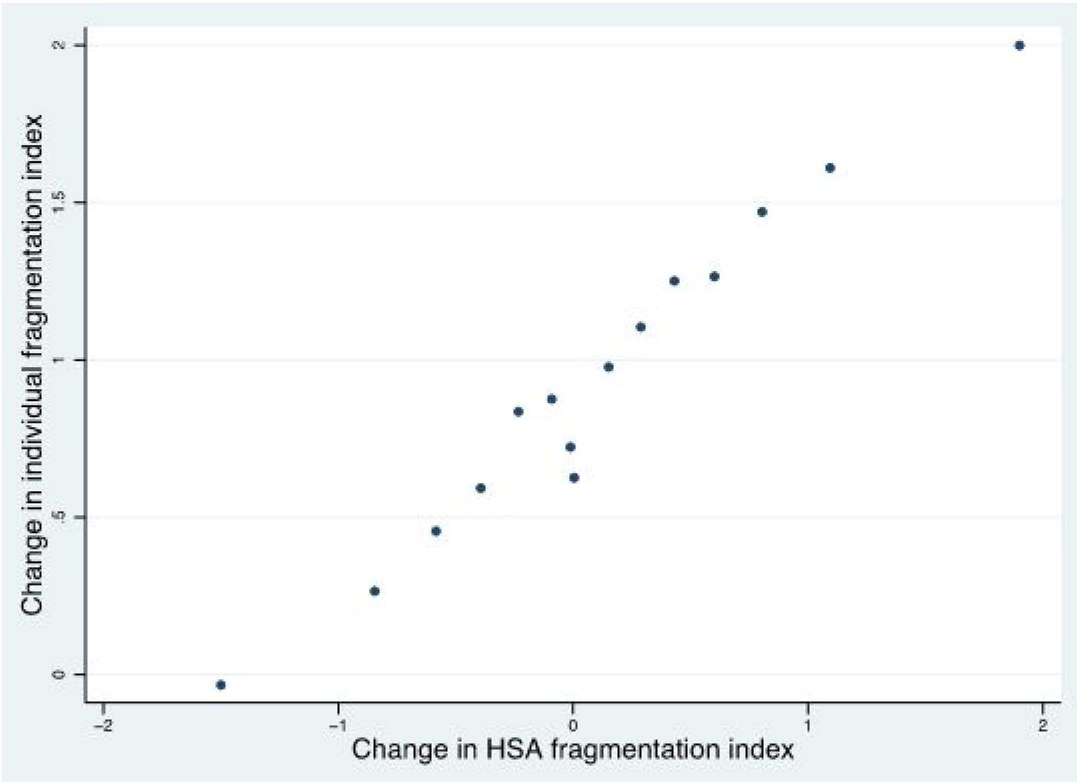
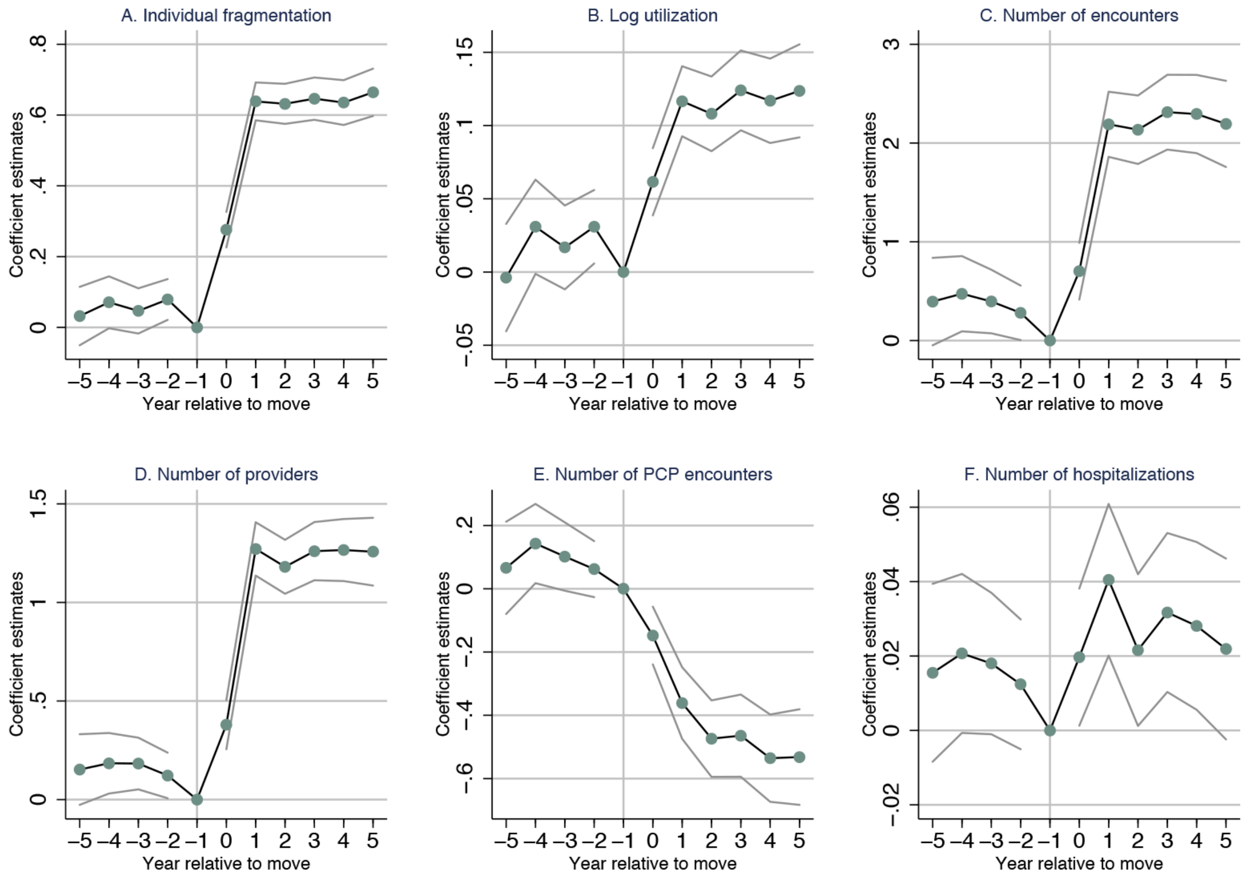


Figure 5: Event study graphs



Notes: Each graph reports the coefficients and 95% confidence interval 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 5,053,165 beneficiary-year observations.