Causes and Consequences of Fragmented Care Delivery: Theory, Evidence and Public Policy

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Abstract

The US Healthcare delivery system is famously inefficient, but the causes of the inefficiencies are poorly understood. In this paper, we analyze one widely discussed source of inefficiency, the "fragmentation hypothesis". According to this hypothesis healthcare is spread out across an excessively large number of poorly coordinated providers leading to low quality and high costs. The fragmentation hypothesis is widely discussed and has motivated important policy initiatives, but theoretical and evidentiary support are weak.

Our analysis of the fragmentation hypothesis is both theoretical and empirical. The theory examines how healthcare providers balance the gains from specialization against the higher coordination costs entailed by specialization and details the market failures that may support inefficiently high levels of fragmentation. It also identifies channels through which identical patients may experience different degrees of fragmentation depending on the region in which they are located. Empirically we find that regional variation in fragmentation is quite important. Not only are there marked regional differences in fragmentation, but Medicare members who move across regions immediately experience a change in fragmentation towards the level characteristic of their destination. Regional fragmentation also contributes powerfully to spending: a one standard deviation increase in fragmentation resulting from a move is associated with a 10% increase in annual spending. Much of the effect of regional fragmentation on utilization appears to involve the substitution of specialist care for primary care as well as more intense utilization of inpatient care, testing, and imaging. In spite of the important role of specialization, regional fragmentation effects are not influenced by market size or density. Regional fragmentation may also be an important channel for the well-documented regional variation in spending: we estimate fragmentation can account for at most 29% of the cross regional variation in spending.

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I. Introduction

The US Healthcare delivery system is famously inefficient, but the causes of its inefficiency are poorly understood. In this paper, we analyze one widely discussed potential source of inefficiency, fragmented care delivery.

To illustrate the economic and clinical issues raised by fragmentation, consider a patient with a complex chronic disease such as diabetes. The patient's primary care provider (PCP) manages the care of the patient 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 providers, it is easier to customize patient care more closely to the clinical conditions and preferences of individual patients. At the same time, the larger network of providers makes care coordination and care continuity more challenging. Efficient care delivery must balance the marginal benefits of increased specialization against the marginal costs of more difficult coordination (Becker and Murphy 1992; Meltzer 2001).

The fragmentation hypothesis asserts that delivery has not achieved this optimal balance. Instead care is spread out across an excessively large number of providers resulting in "too much" specialization and "too little" care coordination and continuity (Baicker and Chandra 2004, Cebul, et al. 2008, Hussey, et al. 2014). Concerns about the higher costs and lower quality resulting from fragmentation are widely discussed and have motivated important policy initiatives. [1] Some of these policy initiatives are aimed at improving the technology of care coordination, e.g. subsidized investments in health information technology. Others seek to improve provider incentives to offer integrated care, e.g. Patient Centered Medical Homes, Accountable Care Organizations (ACOs) and various types of bundled payment reforms.

In spite of its visibility and influence, the fragmentation hypothesis has relatively weak evidentiary and theoretical support. In this paper we propose a conceptual framework for analyzing the causes and consequences of care fragmentation and we use this framework to motivate and interpret a new set of empirical results based on an analysis of Medicare enrollees

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1 The rise in spending may result from that fact that in a smaller group of providers it is easier to establish reliable transfers of patient information and clarity about responsibility for on-going patient care as Milstein and Gilberston (2009) argue. Smaller groups may also enable the PCP to better monitor for redundant and unnecessary care. Along these lines Romano, Segal and Pollack (2015) report an association between measures of fragmented care delivery and the overuse of medical procedures

who move across regions. As we discuss below, our analysis also has implications for assessing the efficacy of anti-fragmentation policies.

From an economic perspective, perhaps the most important gaps in our understanding of fragmentation are empirical. Neither economists nor health services researchers have a clear sense of the drivers of care fragmentation. For example, we do not know how much of the variation in observed fragmentation is the result of the patient's specific clinical situation and how much is due to other factors that may be more amenable to policy interventions. In addition, the endogeneity of treatment decisions leading to more or less fragmented care greatly complicates estimates of the causal effect of fragmentation on resource utilization and quality. [2]

The endogeneity of treatment decisions raises similarly difficult challenges for public policy. Providers are powerfully motivated to deliver care that promotes each patient's welfare. Given this, it is unlikely that anti-fragmentation policies aimed at altering care patterns will improve overall patient welfare absent important market failures. What exactly are these market failures and, in a second best world, under what conditions will ameliorating the market failures improve patient welfare? Addressing these questions requires a model of the link between the purported market failures, the determinants of provider decision-making that drives fragmentation, and patient welfare.

Our analysis is presented in four parts. In Section 2 we introduce a simple conceptual framework to analyze provider treatment and referral decisions. In this model, providers balance each patient's gains from more specialized care against the costs of more challenging coordination. Critically for our analysis, provider decisions are influenced by spillover effects. Spillovers occur when treatment decisions made for one patient influence the efficiency of treatments others receive (Chandra and Staiger 2007). In terms of our prior motivating example, spillover effects imply that a primary care provider who keeps diabetic care "in house" gets more efficient at delivering this sort of care. Similarly, a PCP who relies more on referrals to cardiologists, endocrinologists and other

[2] A number of studies have reported that high levels of fragmentation are associated with higher spending and other outcomes. Frandsen, et. al. (2015)examine a sample of chronically ill, commercially insured patients. They find that high fragmentation is associated with significantly higher costs and lapses in care quality. Hussey et. al. (2014) study a sample of chronically ill Medicare patients and find that reduced care continuity (which is the obverse of measured fragmentation) is associated with higher costs, higher hospitalization rates, higher rates of emergency department visits, and higher rates of complications. Baicker et. al. (2004) report that regions with higher concentrations of specialists also experience higher costs and have more specialists involved in end of life care with little or no improvements in measured quality. In each of these studies, however, it is difficult to argue that the associations represent causal effects because of the presence of omitted patient and provider characteristics that likely exert an influence on both costs and patient treatment patterns.

specialists gets more efficient at delivering this sort of care. Spillovers matter because they can cause identical patients to receive different treatments depending on the regions in which they are located. This insight provides the basis for our empirical analysis of the causes and consequences of fragmentation.

Section 3 presents three sets of empirical results. The first set of findings establish that regional variation in fragmentation is quite important. Not only are there marked regional differences in fragmentation, but the style of care received by Medicare members who move across regions quite quickly resembles the prevalent style in their destination region. Almost immediately upon arrival in a new region, Medicare movers experience changes in fragmentation levels that are 63% of the difference in average fragmentation between destination and origin regions. Under reasonable assumptions, 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 that emerge in our model of spillover effects.

The second set of empirical findings concern the relationship between regional fragmentation and utilization. We find large effects: moving to a region with a one standard deviation higher level of fragmentation is associated with 10% greater annual resource utilization. Delving deeper into utilization patterns we find that higher levels of regional fragmentation increase in-patient costs, hospitalizations, and specialized physician services. In addition, moving to regions with higher levels of fragmentation reduces the mover's annual number of primary care visits while increasing the annual number of specialist visits across a wide variety of specialists. These results are consistent with our theoretical model in which fragmentation emerges as a result of substituting services delivered by specialists for services delivered by primary care providers.

The third set of empirical findings in Section 3 concern the interpretation of regional fragmentation effects. If regional patterns of fragmentation reflect regional differences in the use of specialists, then the economic dictum that specialization is supported by larger markets (Luis Garicano and Hubbard 2008) suggests that our regional fragmentation effects may reflect regional differences in market size. We find, however, that this is not the case.

A second interpretation of regional fragmentation effects concerns their role in explaining regional variations in Medicare spending. A rich literature in health economics documents that regions exert a powerful direct effect on spending, although the reasons for these regional effects are murky (Finkelstein, Gentzkow and Williams 2014). This raises the question of whether regional fragmentation is the channel through which regional cost variations influence individual costs of care. We estimate that *at most* 29% of the effect of regional practice style on spending can be attributed to variation in regional fragmentation levels. We interpret this result as suggesting that other place-based aspects of practice style also likely play an important role in explaining regional cost variations.

In Section 4 of the paper we consider the implications of our analysis for anti-fragmentation policies aimed at improving physician incentives. Many of these policies are premised on the assumption that in a fragmented care delivery system, the cost consequences of 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. When spillovers matter, however, this intuition need not hold because reducing excessive fragmentation can itself lead to losses in productive efficiency. We model the effects of improved provider incentives and 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.

We conclude the paper by discussing the limitations of our analysis as well as directions for future research.

II. A Model of Physician Decision Making

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 their patient.

Under treatment 1, the PCP delivers more services themselves and makes fewer specialist referrals than under treatment option 2. When making specialist referrals under treatment 1, the PCP also relies on a standard set of providers. Relying on a standard set of specialists enhances coordination between the PCP and specialists – in part by reducing the number of providers involved in patient handoffs.

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 cost effects of treatment T; the proportion of patients in a PCP's practice receive treatment T, P_T; and mean zero random variables, ε_T^q and ε_T^c that capture patient specific factors that influence both quality and cost outcomes[3]:

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

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

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). [4] Non-zero spillover parameters, α_T^q and α_T^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.[5] 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.

We allow fragmented care to differ in cost from well-coordinated care by some amount c:[6]

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

Much of the public policy concern about fragmentation is premised on the assumption that $c > 0$ because in this case the fragmented mode of care, $T = 2$, involves higher average cost but not higher average quality.

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3 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.

4 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.

5 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.

6 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.

We describe the social tradeoff between quality and costs by a parameter λ that represents the dollar value of quality. Social welfare 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 each patient's 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 their 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 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:

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

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 later when we return to our analysis of policies aimed at improving physician incentives.

Our model 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 strength of spillover effects (α). The third is through multiple equilibria. We discuss each of these channels in turn.

We illustrate the impact of regional differences in patient characteristics by considering regions with normally distributed patient characteristics, ε. We simplify the example by assuming that all regions have a mean value of $\varepsilon = 0$ but different standard deviations, σ. The higher the variance, the larger the proportion of patients for whom physicians will select more fragmented care, $T = 2$.

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, treatment is determined by: $1(T(\varepsilon) = 2; s) = 1\big(\varepsilon > -\alpha(\ 2\tilde{P}_{2,s}(\sigma) - 1)\ \ - \tilde{\beta}\big)$. Where the term involving α captures the effect of spillovers on treatment decisions. For any σ, the boundary (in ε) between fragmented and well-coordinated care is given by:

$$(9)\ H(\sigma) = -\alpha(\ 2\tilde{P}_{2,s}(\sigma) - 1)\ - \tilde{\beta}.$$

Two individuals with identical ε but in regions with different σ may have different treatment status. Figure 1 offers a visual illustration of this point - a patient with $\varepsilon = .62$ will receive well-coordinated care in regions with $\sigma < .8$ and more fragmented care should they move to regions with $\sigma > .8$.[7]

The second channel for regional differences in the treatment of identical individuals is via regional differences in spillover effects. Our Roy model is concerned with the consequences of spillover effects and so offers little detail on the determinants of parameter α. It may reflect

[7] The parameter values used to construct Figure 1 are: $\alpha^q = 0.1; \alpha^c = -0.1; \beta_1^q = 1; \beta_2^q = 1.2;\ \beta_1^c = 1;\ \beta_2^c = 1.7; \lambda = 1; \theta = 1$. The distribution of ε is normal with mean zero and variance according to the graphs.

learning-by-doing or it may be the result of prior investments in specialized knowledge that lie outside the bounds of the reduced form model we present. Common sense as well careful economic modeling suggests that investments in specialized knowledge are easier to sustain in larger markets (Gary S. Becker and Murphy 1992, Luis Garicano and Hubbard 2008) It is reasonable, then, to suppose that parameter α 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 more larger markets.

Even if regions have the same distribution of patient characteristics and identical spillover effects, it is still possible for identical individuals to receive different treatments in different regions. This third channel is the result of the multiple equilibria that emerge very naturally in the context of the Roy model. This possibility is easiest to see by examining the graphical representation of equation (8) in Figure 2. Equilibria occur wherever the complementary cumulative density function, $1 - F_\varepsilon\left(-\tilde{\beta} - \alpha\left(2\tilde{P}_2 - 1\right)\right)$, intersects the dotted 45 degree line. 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. [8] This means that in cases where there are multiple equilibria, there will always be multiple stable equilibria. 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.[9]

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.

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8 Stability requires $2\alpha < \frac{1}{f_\varepsilon}$ where f_ε is the density function of F_ε.

9 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.

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. [10] 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. More intensive relationships with a primary care physician for care coordination should reduce this measure of care fragmentation, if the patient intersperses visits to specialists with frequent visits to the primary care provider.

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 members 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.

[10] 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).

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.[11] 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.[12]

<u>Summary Graphs and Statistics</u>

Figure 3 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 two rows of the Table compare differences in fragmentation and average patient age across terciles. It is noteworthy that there are not meaningful differences in age across the fragmentation terciles because at the individual level fragmentation tends to be higher for older Medicare members – no doubt reflecting the increased use of specialized care as the patient becomes increasingly sick or frail.

Row 3 of Table 1 presents average annual utilization per year within each 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

[11] 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.

[12] 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. (2014) and adjust total spending to strip away variation that is due to regional price adjustments.

fragmentation and average regional spending is also evident in the scatter plot of HSA fragmentation and average utilization presented in Figure 4.

The remaining rows 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. Regions with greater care fragmentation also have patients seeing more unique providers on average, with patients in the lowest tercile seeing an average of 8.9 providers while those in most fragmented regions seeing 29% more providers. Despite the higher number of total visits, we find that patients in the most fragmented regions have 10% fewer primary care visits than patients in the least fragmented regions.[13] 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 three rows of Table 1 concern the use of hospital services. In contrast to total utilization measures, inpatient care appears to be quite similar across regions with different levels of fragmentation. Total hospitalizations per patient are 3% higher in the most fragmented regions, although ambulatory care sensitive hospitalizations are 9% lower.

These cross-regional variations in fragmentation and utilization may be driven by region 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.

<u>Medicare Movers</u>

Figure 5 shows a histogram of the regional fragmentation changes associated with patient moves. The histogram appears almost symmetric, suggesting that movers are roughly equally likely to move to regions with higher or lower levels of fragmentation. To ease interpretation, we normalize the data so that 1 indicates a move to a region with 1 SD higher fragmentation. It is clear from the Figure that moves frequently entail substantial changes in regional fragmentation.

Table 2 reports summary statistics for mover and non-mover patients. The care patterns of movers appear similar to non-movers, although movers have more fragmented care, are slightly older and have higher costs on average. Average annual utilization is $8,101 for movers, compared to $8,065 for non-movers; the standard deviation of costs is very high for both groups, because of the extreme skewness of the medical cost distribution. A finer grained look at utilization reveals that patients have, on average, 24 separate encounters in a year (i.e. unique provider-date service

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

pairs), spread across 10 providers and only 6 of these encounters are with primary care physicians. A quarter of movers are hospitalized in a given year. Hospitalizations for ambulatory care sensitive conditions are relatively unusual, with only 0.06 such hospitalizations per patient, on average.

Our conceptual framework as well as our regression strategy emphasizes the effect of regional fragmentation patterns on individual care patterns. Figure 5 presents a binned scatterplot of this relationship. 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 regional change in fragmentation along the x-axis, and the average change in individual fragmentation along the y-axis, for each vigintile. 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. [14]

Estimation Strategy

We adapt the event study methodology of Finkelstein et al. (2014) to study the effects of changes in regional fragmentation on movers. Our basic regression framework takes the following form:

$$(10) \quad y_{it} = \alpha_i + \beta post_{it} \Delta \widehat{fragmentation}_i + \tau_t + \rho_{r(i,t)} + x_{it}\gamma + \varepsilon_{it}$$

where y_{it} is the outcome variable (such as care fragmentation or utilization) for beneficiary i in year t. [15] 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 $\widehat{fragmentation}_i$, the change in average regional fragmentation comparing destination to 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 $\widehat{fragmentation}_i$ and $\rho_{r(i,t)}$ are normalized to zero for 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

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

[15] 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 25% 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.

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, but other time-varying factors no-doubt remain unaccounted for. Because the parameter β is identified solely by comparing movers to other movers, these omitted patient-level, time-varying 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 binary variable $post_{it}$ in equation (10) with a series of fixed effects for relative years $\theta_{r(i,t)}$

$$(11) \quad y_{it} = \alpha_i + \theta_{r(i,t)} \Delta \widehat{fragmentation_i} + \tau_t + \rho_{r(i,t)} + x_{it}\gamma + \varepsilon_{it}$$

This specification allows us to investigate any correlation between a patient's trends prior to a move and the change in fragmentation post-move. If we estimate (11) and find that our estimates of $\theta_{r(i,t)}$ are flat prior to the move, this lends strong support to our identifying assumption and increases our confidence that changes in regional fragmentation are exerting a causal effect on individual patient outcomes.

The Effect of Regional Factors on Care Fragmentation and Utilization

Figure 6 presents event study graphs for various individual outcomes. The points in each graph plot our estimates of $\theta_{r(i,t)}$ from equation (11). The point of these graphs is to establish 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 (10). These estimates are presented in Table 3.

We begin with an analysis of our measure of care fragmentation. In Panel A of Figure 6 we see that estimates of $\theta_{r(i,t)}$ from equation (11) 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. 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 preferences and needs of individual patients, the estimated effect of regional fragmentation on an individual's level of care fragmentation is strikingly large. One way to see of the magnitude of this coefficient is to assume, following Finkelstein, Gentzkow and Williams (2014), 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 care fragmentation.

A natural follow-on question is whether these regional effects are symmetric. Does a diabetic patient who, for example, moves to a region that relies on relatively few specialist visits experience the same decline in specialist visits as a patient who moves to a region that relies heavily on specialists? As indicated by the coefficients in columns 2 and 3 of Table 3, the regional effects are nearly symmetric across move types.

We now examine the effects of regional fragmentation on resource utilization. Panel B of Figure 6 plots estimates of $\theta_{r(i,t)}$ from equation (11) 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 (10) 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 individual care 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 other dimensions of utilization including the annual number of visits, the annual number of providers and the annual number of primary care visits. 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 6 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 providers visited is noteworthy. 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. Alternatively, 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.

Rows 6, 7 and 8 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' medical condition 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 hospitalization increase as patients move to more fragmented regions. We note, however, that this coefficient is imprecisely measured and the effect size is small. The 95% confidence interval around our estimate bounds the impact of one standard deviation increase in regional fragmentation at a 5% increase in ambulatory care sensitive hospitalizations.

<u>Specialist Care</u>

Having established in Table 3 that high fragmentation regions make use of fewer primary care visits, 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. This suggests a 13.4% increase in the propensity of primary care physicians to refer to a cardiologist. On both 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 1.9 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 and anesthesiologists may be consistent with this story as well if the increases in testing and imaging used by specialists requires radiology and anesthesia (as is true for some common diagnostic procedures such as 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 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 Table 3 and Table 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 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 comprised primarily of 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 & 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.

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 procedures 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. We find no increased spending on cancer care, which appears to be particularly insensitive to regional fragmentation.

Robustness checks

Our baseline results are based on a comparison of 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 7, 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 must 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 7 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.

Interpretations of the Results:

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 variations. 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 differences, but given the importance of specialization for fragmentation, other explanations are possible. Indeed, given the economic dictum that specialization is supported by larger markets (Luis Garicano and Hubbard 2008), regional differences might emerge from variation in market size even if there were no spill-over 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 area. 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.

In Panel C of Table 7, 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, Gentzkow and Williams 2014). 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 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 (10) 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. Indeed the ratio of our Table 3 estimate to the IV estimate provides a measure of 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.[16] 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 exerts a powerful effect on 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. 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 parameter θ closer to 1.

In the set-up 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 parameter $c > 0$. When

[16] Our reduced form regression follows that in Amy Finkelstein, Gentzkow and 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*posts* 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.

PCPs more full internalize the additional costs associated with Treatment 2, they will thus tend to shift some of their patients towards Treatment 1. Those patients who shift from T=2 to T= 1 as a result of the increase in $\theta$are now better off, 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 $\lambda c > \ (2\alpha - \frac{1}{f_\varepsilon(\alpha - 2\alpha\tilde{P}_2 - \tilde{\beta})})\frac{d\tilde{P}_2}{d\theta}$

As part of the proof of Proposition 1, we establish that both $\frac{d\tilde{P}_2}{d\theta}$ and $(2\alpha - \frac{1}{f_\varepsilon(\alpha - 2\alpha\tilde{P}_2 - \tilde{\beta})}) < 0$ 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

Excessive fragmentation of care delivery is a widely discussed source of inefficiency in the US Healthcare system, but theoretical and empirical support for this hypothesis has been weak. In this paper we propose a conceptual framework for analyzing the causes and consequences of care fragmentation as well as a new set of empirical results on the effects of fragmentation based on an analysis of Medicare enrollees who move across regions.

The theory examines how healthcare providers balance the gains from specialization against the higher coordination costs and details the market failures that may support inefficiently high levels of fragmentation. Importantly for our empirical work, the theory also identifies the ways in which provider spill-over effects can cause identical patients to experience different degrees of fragmentation depending on the region in which they are located.

Consistent with the presence of spill-overs, we find that regional variation in fragmentation is quite important. Not only are there marked regional differences in fragmentation, but Medicare members who move across regions immediately experience a dramatic change in fragmentation towards the level characteristic of their destination. Under reasonable assumptions, these regional practice styles account for roughly 60% of the cross-regional variation in care fragmentation. Regional fragmentation also exerts a powerful effect on the resources utilized by movers: a one standard deviation increase in regional fragmentation resulting from a move increases average annual Medicare spending by 11%. Much of the effect of regional fragmentation appears to involve the substitution of specialist care for primary care as well as more intense utilization of in-patient care and testing/imaging.

In spite of the effect of fragmentation on specialization, regional fragmentation effects do not appear to be influenced by market size or density. Regional fragmentation may also be an important channel for the well-documented effect of regions on costs: although we estimate that fragmentation can account for no more than 29% of the effect of regions on costs. We interpret this result as suggesting that other place-based aspects of practice style (such as physician beliefs in clinically unsupported treatment procedures as described in Cutler et al. 2013) also likely play an important role in explaining regional cost variations.

This paper has a number of limitations that are worth noting and that may inspire future research. The first limitation is the absence of good measures of care quality. Without such measures, it is impossible to know how much of the heightened costs associated with high regional fragmentation may be offset by improvements in outcomes or other determinants of patient welfare. The second 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. Much more, however, remains to be done to establish that the patterns we have uncovered in this paper apply beyond Medicare.

A final limitation of our analysis concerns public policy. 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. Frandsen and Rebitzer's (2014) simulation of incentives in Accountable Care

Organizations, for example, finds that free-riding problems pose a nearly fatal challenge unless ACOs are able to introduce additional to influence provider decisions. Exactly how organizations go about implementing such ancillary motivators is an important, but unresolved, question. Clearly much more remains to be learned about effective public policy responses to fragmented care delivery.

Appendix I: Proof of Proposition I

Preliminaries:

The equilibrium condition presented in equation (8) in the text is:

$$\tilde{P}_2 = 1 - F_\varepsilon\left(-\tilde{\beta} - \alpha\left(2\tilde{P}_2 - 1\right)\right) - \tilde{P}_2 = 0$$

Some of the resulting equilibria will be stable and others not. Stability requires that the effect of a change in $\tilde{P}_2$ on the proportion of people treated with treatment 2 be less than the initial change in $\tilde{P}_2$. Differentiating F above with respect to $\tilde{P}_2$ makes clear that stability requires $f_\varepsilon(\cdot)2\alpha - 1 < 0$.

We next use the implicit function theorem to derive an expression for $\frac{d\tilde{P}_2}{d\theta}$:

$$\frac{\partial F}{\partial \tilde{P}_2} = f_\varepsilon\left(-\tilde{\beta} - \alpha\left(2\tilde{P}_2 - 1\right)\right)2\alpha - 1 < 0$$

$$\frac{\partial F}{\partial \theta} = -f_\varepsilon\left(-\tilde{\beta} - \alpha\left(2\tilde{P}_2 - 1\right)\right)\lambda c < 0$$

$$\frac{d\tilde{P}_2}{d\theta} = \frac{-f_\varepsilon\left(-\tilde{\beta} - \alpha\left(2\tilde{P}_2 - 1\right)\right)\lambda c}{f_\varepsilon\left(-\tilde{\beta} - \alpha\left(2\tilde{P}_2 - 1\right)\right)2\alpha - 1} < 0$$

An analogous application of the implicit function theorem also yields

$$\frac{d\tilde{P}_2}{dc} = \frac{-f_\varepsilon\left(-\tilde{\beta} - \alpha\left(2\tilde{P}_2 - 1\right)\right)\lambda\theta}{f_\varepsilon\left(-\tilde{\beta} - \alpha\left(2\tilde{P}_2 - 1\right)\right)2\alpha - 1} < 0$$

for stable equilibrium.

Proof of Proposition 1:

Differentiating the expression for welfare (equation 4 in the text) with respect to θ and rearranging we get:

$$\frac{dW}{d\theta} = -\alpha\frac{d\tilde{P}_2}{d\theta}\left(1 - 2\tilde{P}_2\right) + \left(\mu\left(\tilde{K}\right) - \tilde{K}\right)\left(f_\varepsilon\left(\tilde{K}\right)\left(\lambda c - 2\alpha\frac{d\tilde{P}_2}{d\theta}\right) + \frac{d\tilde{P}_2}{d\theta}\right) - (1-\theta)\lambda c\frac{d\tilde{P}_2}{d\theta}$$

where $\tilde{K} \equiv -\tilde{\beta} - \alpha(2\tilde{P}_2 - 1)$. Since $\mu(x) - x > 0$ and $\frac{d\tilde{P}_2}{d\theta} < 0$, the sufficient conditions for $\frac{dW}{d\theta} \geq 0$ in Proposition1 follow immediately.

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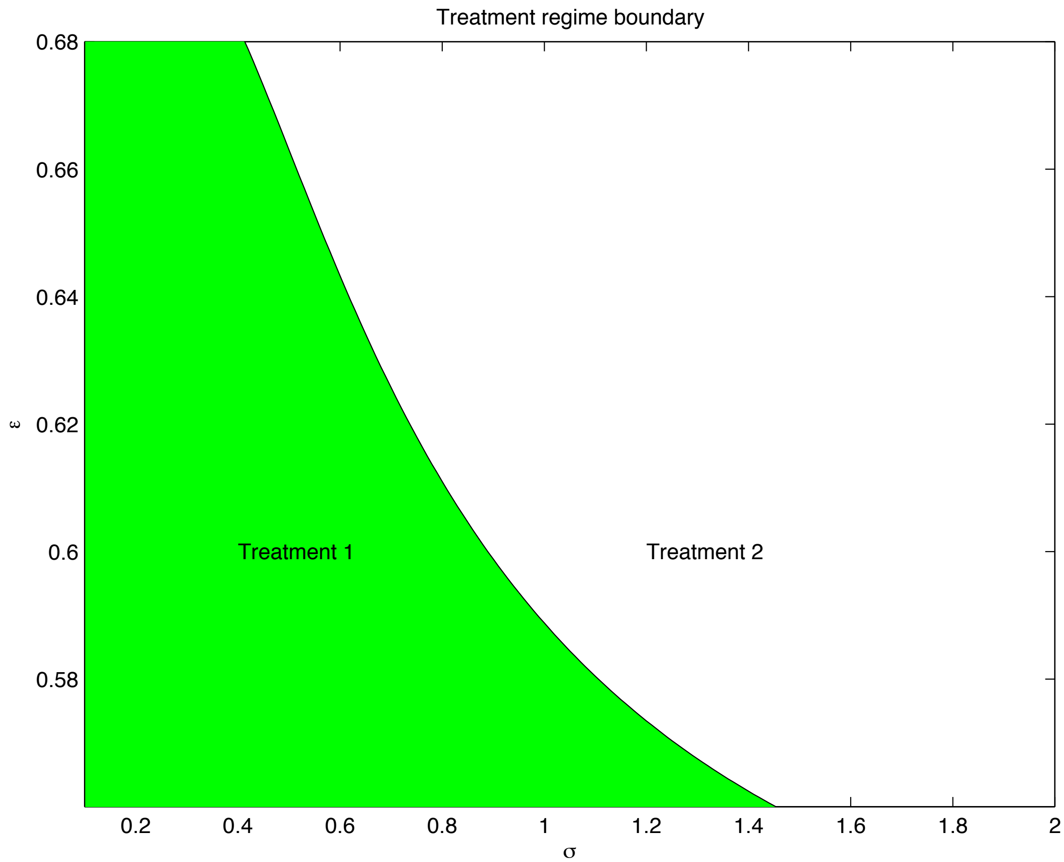
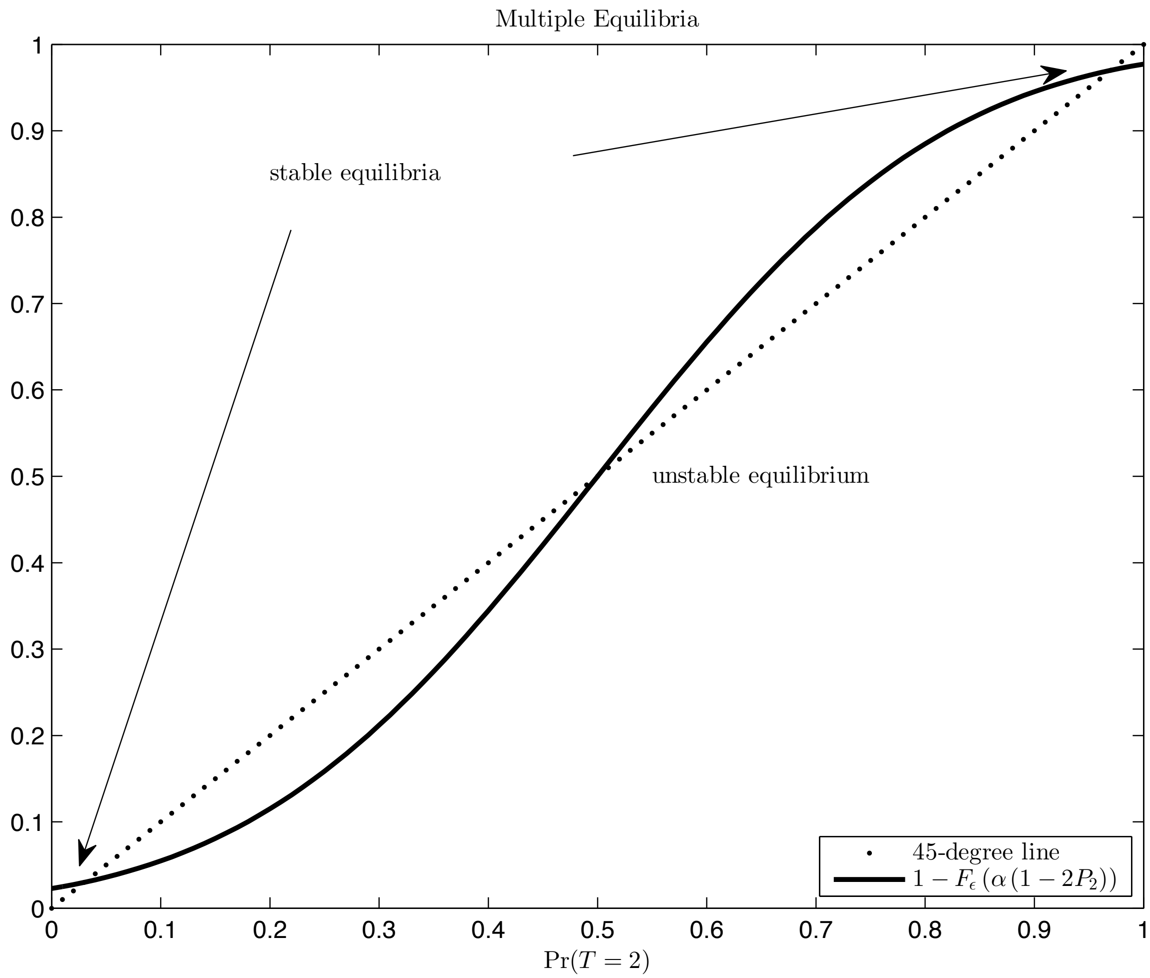
Figure 1: Equilibrium treatment mode



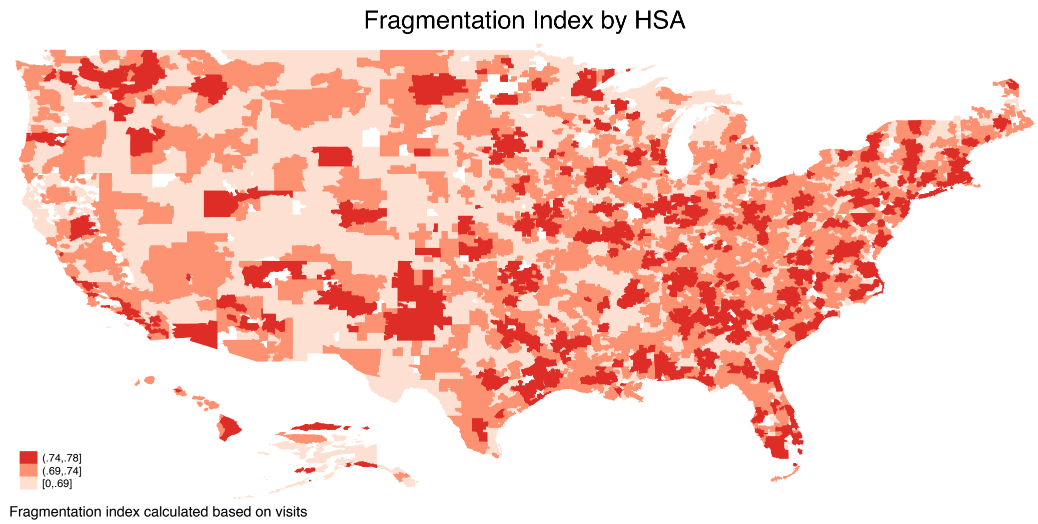
Notes: The shaded and white regions show the equilibrium treatment mode as a function of the population distributional parameter sigma (horizontal axis) and the individual heterogeneity parameter epsilon (vertical axis). The boundary is defined by equation (9) in the text, setting parameters θ= 1, λ= 1, $\beta_1^q = 1$, \$\beta_2^q = 1.2$, α_q= -α_c= .1, c = .7, assuming that εin the population is normally distributed with mean zero and standard deviation varying according to the figure, and P_2 is set according to equation (8) in the text.

Figure 2: Multiple equilibrium treatment modes with health care spillovers



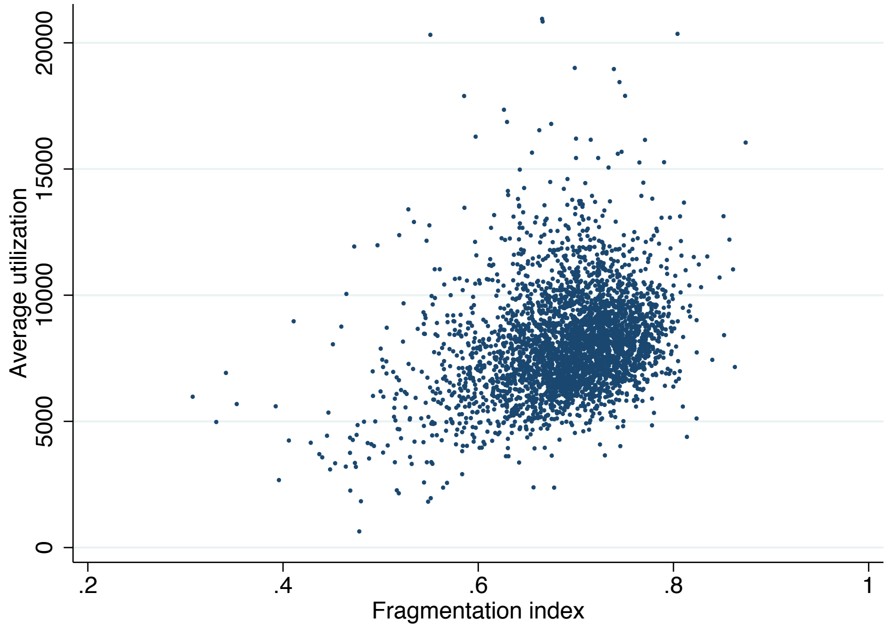
Notes: The solid curve plots the right-hand side of equation (8) in the text. Points of intersection with the 45-degree dotted line represent equilibrium solutions. Parameters values are \tilde{\beta} = 0 and \alpha = 2, and epsilon is assumed to be normally distributed with mean zero and standard deviation one.

Figure 3: Map of regional fragmentation levels



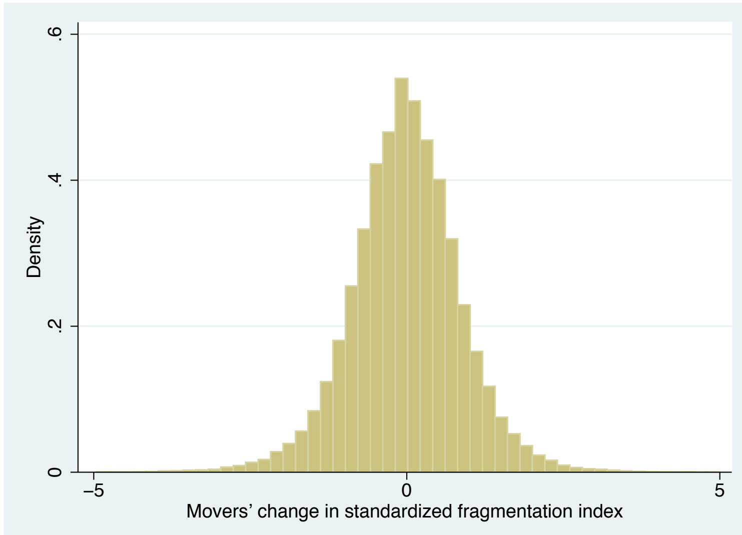
Notes: Each hospital service area (HSA) is shaded according to its tercile of the regional average care fragmentation index. Darker shaded regions have more fragmented care patterns.

Figure 4: Scatterplot of HSA fragmentation level and average utilization



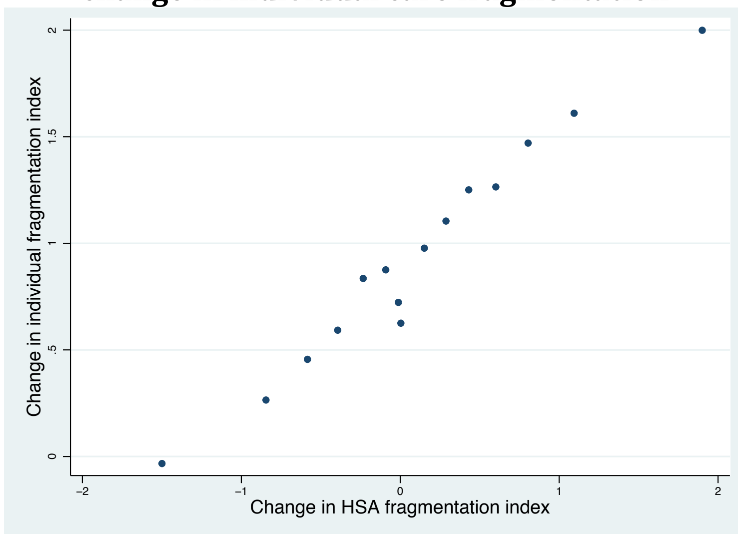
Notes: Scatterplot of average care fragmentation index and average care utilization in each hospital service area (HSA). Utilization is adjusted for regional differences in pricing patterns to describe utilization in standardized dollar units.

Figure 5: Histogram of move fragmentation changes



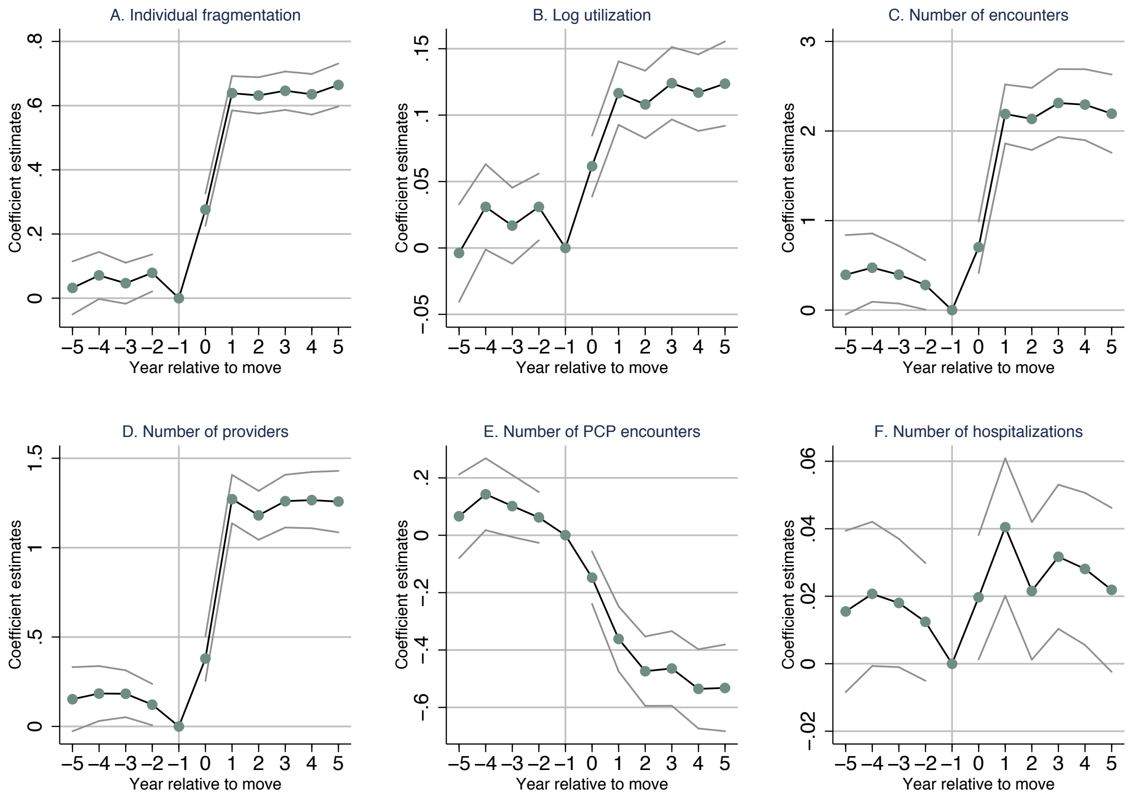
Notes: Histogram of regional care fragmentation change experienced by movers. Fragmentation measure is standardized so that a value of 1 indicates moving to a region with 1 standard deviation higher fragmentation.

Figure 6: Binned scatterplot of change in regional fragmentation index vs. change in individual care fragmentation



Notes: Movers are binned into 20 groups according to the size of the regional fragmentation change they experience. Average regional fragmentation change is plotted along the x-axis and average change in individual fragmentation is plotted along the y-axis. Individual fragmentation change is calculated over the two years post-move and compared to the two years pre-move.

Figure 7: 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 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.

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

	Low Fragmentation (1)	Medium Fragmentation (2)	High Fragmentation (3)
Visit-based fragmentation index	0.69	0.74	0.78
Age	76.18	76.14	76.54
Total utilization ($)	7606	7941	8604
Number of encounters	22.06	24.09	26.82
Number of providers	8.98	10.32	11.61
Number of primary care encounters	6.49	6.05	5.66
Any hospitalizations	0.24	0.24	0.24
Number of hospitalizations	0.48	0.48	0.50
Number ACSC hospitalizations	0.07	0.06	0.06
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.

Table 2: Summary statistics: Mean and Standard Deviations

	Moves to higher fragmentation	Moves to lower fragmentation	Non-movers
	(1)	(2)	(3)
Visit-based fragmentation index	0.73	0.73	0.68
	-0.23	-0.23	-0.24
Total costs	$8,897	$8,668	$8,065
	-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)
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
Age	77.9	77.9	76.3
	(7.6)	(7.7)	(7.6)
Number of 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. Column 3 includes only non-mover beneficiaries.

Table 3: Regression results describing care patterns after fragmentation change

	All moves (1)	Moves to higher fragmentation (2)	Moves to lower fragmentation (3)
Dependent variable:			
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)
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)
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 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 4: Specialist visits after fragmentation change

	Mean number of visits	Regression coefficient	Percent change
	(1)	(2)	(3)
Dependent variable:			
1 Cardiology	1.60	0.2134***	13.4%
		(0.0267)	
2 Radiology (diagnostic)	1.92	0.1396***	7.3%
		(0.0240)	
3 General surgery	1.08	0.0115	1.1%
		(0.0181)	
4 Ophthalmology	1.04	0.0353***	3.4%
		(0.0129)	
5 Podiatry	0.59	0.0552***	9.3%
		(0.0121)	
6 Emergency	0.58	0.0141	2.4%
		(0.0120)	
7 Urology	0.38	0.0439***	11.6%
		(0.0097)	
8 Dermatology	0.35	0.0642***	18.1%
		(0.0083)	
9 Gastroenterology	0.34	0.0755***	22.1%
		(0.0090)	
10 Pathology	0.28	0.0403***	14.3%
		(0.0064)	
11 Anesthesiology	0.28	0.0572***	20.2%
		(0.0091)	
12 OBGYN	0.17	0.0069	4.0%
		(0.0072)	
13 Neurology	0.21	0.0495***	23.4%
		(0.0090)	
Number of observations		4,716,739	

Notes: Column 1 reports the average number of annual visits to each specialist type. Each cell in column 2 reports the coefficient and standard error from a separate regression, where the dependent variable is the number of annual visits to the specialist type noted in row and the independent variable of interest is the change in the regional fragmentation index interacted with a post-move dummy. See notes to Table 3 for details. Column 3 calculates the corresponding percent change in specialist visits from the mean associated with a 1 standard deviation change in regional fragmentation. We report results for all specialties with at least 0.2 annual visits. * 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

	Mean of dependent var. (1)	Regression coefficient (2)	Percent change (3)
Dependent variable:			
Total utilization	8246.04	665.10***	8%
		(110.53)	
Carrier utilization	2837.30	416.00***	15%
		(32.17)	
Outpatient utilization	1177.00	-67.41***	-6%
		(21.58)	
Inpatient utilization	4231.73	316.51***	7%
		(86.76)	
Number of observations		4,716,739	

Notes: Column 1 reports the mean annual medical spending per beneficiary in dollars, adjusted for regional differences in pricing patterns to describe utilization in standardized dollar units. Each cell in column 2 reports the coefficient and standard error from a separate regression, where the dependent variable is the utilization type noted in row and the independent variable of interest is the change in the regional fragmentation index interacted with a post-move dummy. See notes to Table 3 for details. Column 3 calculates the corresponding percent change in utilization from the mean associated with a 1 standard deviation change in regional fragmentation. 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. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 6: Regression results describing carrier utilization after fragmentation change

	Mean of dependent variable (1)	Regression coefficient (2)	Percent change (3)
Dependent variable:			
Office evaluation & management	446.05	37.80***	8%
		(2.89)	
Hospital evaluation & management	271.63	43.75***	16%
		(7.21)	
Specialist & consultation evaluation	261.30	44.94***	17%
		(3.06)	
Emergency dept. evaluation & management	66.03	3.89***	6%
		(0.96)	
Home or nursing home evaluation & management	68.62	18.31***	27%
		(2.37)	
Imaging & endoscopy	433.93	90.76***	21%
		(4.99)	
Testing	193.45	57.64***	30%
		(2.28)	
Major procedures & anesthesia	235.03	20.51***	9%
		(5.06)	
Other procedures & dialysis	419.44	59.66***	14%
		(6.92)	
Cancer claims	150.55	8.34	6%
		(12.22)	
Vaccines	11.29	0.64***	6%
		(0.12)	
Durable medical equipment	2.40	2.15	90%
		(2.41)	
Other	304.01	26.34**	9%
		(12.06)	
Undefined	9.03	1.24	14%
		(0.85)	
Number of observations		4,716,739	

Notes: Column 1 reports the mean annual dollars of medical spending per beneficiary, adjusted for regional differences in pricing patterns to describe utilization in standardized dollar units. Mean is calculated only over movers. Each cell in column 2 reports the coefficient and standard error from a separate regression, where the dependent variable is the utilization type noted in row and the independent variable of interest is the change in the regional fragmentation index interacted with a post-move dummy. See notes to Table 3 for details. Column 3 calculates the corresponding percent change in utilization from the mean associated with a 1 standard deviation change in regional fragmentation. Outcome variable is calculated as total spending within the Carrier (noninstitutional) claims on these categories of service. Service categories are defined by BETOS codes. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 7: Alternative Specifications and Robustness

	N	Fragmentation	Log(utilization)
		Dependent variable:	
	(1)	(2)	(3)
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: Column 1 reports the number of observations. Each cell in columns 2 and 3 reports the coefficient and standard error from a separate regression, where the dependent variable is noted in the column header and the 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.

Appendix I: Proof of Proposition I

<u>Preliminaries:</u>

The equilibrium condition presented in equation (8) in the text is:

$$\tilde{P}_2 = 1 - F_\varepsilon\left(-\tilde{\beta} - \alpha\left(2\tilde{P}_2 - 1\right)\right) - \tilde{P}_2 = 0$$

Some of the resulting equilibria will be stable and others not. Stability requires that the effect of a change in $\tilde{P}_2$ on the proportion of people treated with treatment 2 be less than the initial change in $\tilde{P}_2$. Differentiating F above with respect to $\tilde{P}_2$ makes clear that stability requires $f_\varepsilon(\cdot)2\alpha - 1 < 0$.

We next use the implicit function theorem to derive an expression for $\frac{d\tilde{P}_2}{d\theta}$:

$$\frac{\partial F}{\partial \tilde{P}_2} = f_\varepsilon\left(-\tilde{\beta} - \alpha\left(2\tilde{P}_2 - 1\right)\right)2\alpha - 1 < 0$$

$$\frac{\partial F}{\partial \theta} = -f_\varepsilon\left(-\tilde{\beta} - \alpha\left(2\tilde{P}_2 - 1\right)\right)\lambda c < 0$$

$$\frac{d\tilde{P}_2}{d\theta} = \frac{-f_\varepsilon\left(-\tilde{\beta} - \alpha\left(2\tilde{P}_2 - 1\right)\right)\lambda c}{f_\varepsilon\left(-\tilde{\beta} - \alpha\left(2\tilde{P}_2 - 1\right)\right)2\alpha - 1} < 0$$

An analogous application of the implicit function theorem also yields

$$\frac{d\tilde{P}_2}{dc} = \frac{-f_\varepsilon\left(-\tilde{\beta} - \alpha\left(2\tilde{P}_2 - 1\right)\right)\lambda\theta}{f_\varepsilon\left(-\tilde{\beta} - \alpha\left(2\tilde{P}_2 - 1\right)\right)2\alpha - 1} < 0$$

for stable equilibrium.

<u>Proof of Proposition 1</u>:

Differentiating the expression for welfare (equation 4 in the text) with respect to θ and rearranging we get:

$$\frac{dW}{d\theta} = -\alpha\frac{d\tilde{P}_2}{d\theta}\left(1 - 2\tilde{P}_2\right) + \left(\mu(\tilde{K}) - \tilde{K}\right)\left(f_\varepsilon(\tilde{K})\left(\lambda c - 2\alpha\frac{d\tilde{P}_2}{d\theta}\right) + \frac{d\tilde{P}_2}{d\theta}\right) - (1-\theta)\lambda c\frac{d\tilde{P}_2}{d\theta}$$

where $\tilde{K} \equiv -\tilde{\beta} - \alpha(2\tilde{P}_2 - 1)$. Since $\mu(x) - x > 0$ and $\frac{d\tilde{P}_2}{d\theta} < 0$, the sufficient conditions for $\frac{dW}{d\theta} \geq 0$ in Proposition1 follow immediately.