Dangerous Prescribing and Healthcare Fragmentation: Evidence from Opioids*

Keith Marzilli Ericson
Boston University's Questrom School of Business and NBER

Adam Sacarny
Columbia University and NBER

Annetta Zhou
RAND Corporation

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Abstract

Fragmented healthcare received from many different physicians results in higher costs and lower quality, but does it contribute to dangerous opioid prescribing? The effect is theoretically ambiguous because fragmentation can trigger costly coordination failures but also permits greater specialization. We examine dangerous opioid prescribing, defined as receiving high dosages, long prescription durations, or harmfully interacting medications. Cross-sectionally, regions with higher fragmentation have lower levels of dangerous opioid prescribing. This relationship is associational and may result from unobserved patient-level confounders. Identifying the impact of healthcare fragmentation by examining patients who move across regions, we find a relatively precise null effect of regional fragmentation on dangerous opioid prescribing. These results cast doubt on the role of fragmentation in this phenomenon and highlight the potential role of other forces in driving it.

Keywords: Healthcare productivity, coordination failures, healthcare fragmentation, opioid prescribing, regional variation

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1. Introduction

The opioid crisis is a major public policy problem, and physician prescribing decisions play a central role in patients' long-term exposure to opioids and their risk of opioid use disorder (Barnett, Olenski, and Jena 2017; Eichmeyer and Zhang 2021). Concerns that opioid-related harms were partly driven by poor cross-provider coordination have motivated policies such as prescription drug monitoring programs (PDMPs) and drug utilization review programs. Indeed, many opioid overdose deaths involve patients who receive concurrent prescriptions that interact harmfully with opioids (Carey, Jena, and Barnett 2018; Sun et al. 2017). While the overdose death rate for older adults from prescribed opioids grew fourfold from 2002-2019, deaths from opioids taken alongside medications with dangerous interactions grew at least 11-fold and accounted for an average of 23% of opioid overdose deaths each year (Appendix Figure A1).

Our paper examines whether healthcare fragmentation—patients receiving care from many different providers or organizations—leads physicians to make more dangerous opioid-related prescription decisions. Healthcare fragmentation has been hypothesized as a source of dangerous prescribing (Coleman 2019; Guy et al. 2019), and has been shown to lead to lower value of care (Frandsen et al. 2015; Agha, Frandsen, and Rebitzer 2019; Agha et al. 2021; Agha, Ericson, and Zhao forthcoming; Hussey et al. 2014; Cebul et al. 2008). However, there is little causal evidence linking fragmentation to dangerous opioid prescribing. Finkelstein, Gentzkow, and Williams (2016) find substantial geographic variation in healthcare use due to place effects, and Finkelstein et al. (2022) show a large role for place effects in the level of and transitions into risky opioid use. Yet the causal effect of fragmented delivery systems on the quantity and quality of opioid prescribing remains uncertain.

Fragmented healthcare might raise the risk of inappropriate prescribing of opioids because a larger and disorganized care team could inadvertently prescribe medications with dangerous opioids interactions or unnecessarily prescribe extra opioids. Providers could fail to coordinate because they may not be in the same organization, may not know each other, and may not have interoperable information technology. On the other hand, fragmentation could permit greater specialization and provide more opportunities to catch errors, reducing the risk of dangerous prescribing.

We examine whether physicians are more likely to make dangerous opioid prescribing decisions when healthcare delivery is more fragmented. Our key results are twofold. First, we show that in the cross-section, regions with more fragmentation prescribe fewer opioids and are less likely to engage in risky opioid prescribing. For instance, compared to the least fragmented tercile of regions, patients living in regions in the highest tercile of fragmentation have 8.8 fewer days of opioid prescriptions and a 2.6 percentage point lower probability of having any overlap between opioids and other interacting drugs. The pattern of results persists with some attenuation in cross-sectional regressions that add controls for rich patient observables. These findings are surprising because previous research has established—both in correlational and causal analysis—that more fragmented regions use more healthcare and do not have better outcomes (e.g. Agha, Ericson, and Zhao forthcoming).

Second, we show that the negative cross-sectional association is likely driven by patient unobservables; when we control for time-invariant patient unobservables with a "mover" design, we find a precise zero effect of regional fragmentation on opioid prescribing. Our research design exploits patients who move across areas with differing levels of fragmented care delivery. This approach allows us to separate out the effect of regional fragmentation from other measures of health status (Agha, Frandsen, and Rebitzer 2019). This design compares people who move to more fragmented regions to those who move to less fragmented regions, and thus does not use non-movers for identification. While individuals who move to relatively more fragmented regions experience an increase in their own

experienced healthcare fragmentation, we find no increase in dangerous opioid prescribing or most measures of opioid prescribing. Stated concisely, under our identification assumptions, the additional healthcare fragmentation induced by moving to a more fragmented region does not increase dangerous opioid prescribing.

To examine the link between healthcare fragmentation and dangerous opioid prescribing, we first calculate each patient's provider fragmentation, which measures the spread of a patients' healthcare across providers, and organizational fragmentation, which measures the spread of a patients' healthcare across organizations. These measures have been used in previous literature and shown to be linked to healthcare spending (Agha, Ericson, and Zhao forthcoming). We then aggregate these fragmentation measures up to the regional level, providing the key independent variables in our cross-sectional and "mover" analyses.

Our analyses focus on several measures of dangerous opioid prescribing (Appendix Table A1).[2] Importantly, we examine dangerous opioid *prescribing,* not the entire breadth of opioid misuse (e.g. taking illicitly acquired opioids).[3] We use measures of dangerous opioid prescribing that are well-observed in Medicare prescription drug data. Our measures include multiple overlapping opioid prescription fills, since these patients are much more likely to experience overdose and death (Carey, Jena, and Barnett 2018); receiving opioids alongside central nervous system depressants (sleep aids, muscle relaxants, and antipsychotics), following FDA warnings that taking these drugs exacerbates respiratory depression and risk of overdose (U.S. Food and Drug Administration 2016); and receiving

[2] There are two notable exclusions from this table. First, we omit overlapping opioids and benzodiazepines even though they featured prominently in the FDA guidance. Benzodiazepines were not covered by Medicare, and thus not observed in our data, until 2013. Second, we omit overlapping receipt of opioids and gabapentinoids. Taking these drugs together can also be risky for patients, but the FDA warning for combining the two was issued in 2019, well after our sample period (U.S. Food and Drug Administration 2019).

[3] Our question is thus distinct from the effect of "provider shopping" or the role of "pill mills", which also might be important contributors to the opioid overdose epidemic.

high daily opioid doses or long-duration opioid prescriptions, given CDC guidelines that urge prescribers to limit dosages (Dowell, Haegerich, and Chou 2016).

We consider the impact of fragmentation on opioid prescribing because it provides a unique and timely opportunity to observe low-quality and dangerous forms of health care. We note four key reasons for this focus. First, there is ample evidence that improper prescribing of opioids can have severe consequences for patients, including overdose and death. Second, the potential harms from opioids are a priori linked to fragmentation of healthcare: they often involve taking the drugs from multiple prescribers or taking them alongside other interacting medications, which may have come from other prescribers. Third, there is significant consensus on the riskiest forms of opioid prescribing, allowing us to consult major guidelines and government warnings to track such prescribing in healthcare data. Fourth, harms from opioids are a central issue in public health, and research to understand their determinants is sorely needed to address the opioid epidemic.

Our findings—no clear impacts of fragmentation on risky prescribing— matter because concerns about fragmentation across physicians leading to dangerous opioid prescribing have partially motivated major policy initiatives. PDMPs aim to reduce patient opioid misuse by improving physicians' awareness of a patient's prescriptions from other providers. Mandatory use of PDMPs may reduce opioid misuse (Buchmueller and Carey 2018; Grecu, Dave, and Saffer 2019; though also see Horwitz et al. 2018). Moreover, beginning in 2019, CMS has introduced drug utilization review policies for Medicare beneficiaries that aim at increasing coordination between prescribers, pharmacists, and patients (Centers for Medicare and Medicaid Services 2018). These drug utilization review initiatives post-date our data, and their components to improve coordination may not be effective, given our null result fragmentation to dangerous opioid prescribing.

Our findings also address a substantial gap in the literature on how healthcare fragmentation affects the quality of prescribing, particularly prescribing of opioids. The sign of this relationship is

not *a priori* obvious because fragmentation could imply coordination failures and result in risky prescribing, or it could imply more contact with highly specialized professionals and result in higher-quality prescribing.

Among the most relevant work is Agha, Frandsen, and Rebitzer (2019), which uses a movers design closely related to ours and estimates that moving to a more fragmented region leads to more prescribing overall and more high-risk prescribing, though each effect is only significant in a different specification. However, this study does not directly evaluate any measure of opioid prescribing. Conversely, Finkelstein et al. (2022) study place effects on risky opioid prescribing with a movers design, but they do not consider the role of fragmentation.

Some research speaks to the connection between opioid prescribing and fragmentation. Baker, Bundorf, and Kessler (2020) find that enrollment in a Medicare Advantage plan (which integrates drug coverage with other medical coverage) significantly reduces beneficiaries' likelihood of filling an opioid prescription, as compared to enrollment in a stand-alone drug plan. Ong et al. (2017) show that in the cross-section, receiving care from providers that work more closely together (i.e. tend to share patients) is associated with lower rates of multiple providers prescribing interacting drugs.

Other literature looks at overdose conditional on prescribing behavior. For instance, conditional on being prescribed opioids with benzodiazepines, a class of anti-anxiety medications that synergistically interacts with opioids and raises the risk of overdose, patients are more likely to overdose if those prescriptions came from multiple prescribers (Chua et al. 2021). Moreover, filling opioid prescriptions using different insurers (e.g. Medicare and Veteran's Affairs) is also linked to higher overdose probabilities (Moyo et al. 2019). Our results cast doubt that the existing observational literature has uncovered a *causal* relationship between risk of overdose and healthcare delivery system fragmentation, at least as typically measured.

2. Data

2.1 Source Data and Sample Selection

Our main data source is the universe of inpatient, outpatient, professional and pharmacy (Part D) claims for 20% of Medicare fee-for-service beneficiaries from 2008 to 2016. Patient demographics (age, sex, zip code) come from Medicare enrollment data, and we draw on indicators for chronic conditions produced by CMS that use standard diagnosis code-based algorithms. Our data includes spending for each service, and we remove regional price adjustments by instead using the national median price for each service within each calendar year.[4] To identify opioids (and to exclude opioid use disorder medications) we use data published by the CDC and derived from IBM Micromedex RED BOOK.[5] To identify interacting drugs, we use data sourced directly from RED BOOK.

Sample restrictions defined here generally follow the construction process outlined in Agha, Frandsen, and Rebitzer (2019) with amendments to account for our focus on prescribing. We include a patient-year observation in the sample if the patient is fully enrolled in Original Medicare (fee-for-service Parts A and B) and the Medicare prescription drug benefit (Part D) for the full year, allowing us to observe their healthcare service use during this time. This restriction omits patients with incomplete coverage as well as those in a private Medicare Advantage plan, for whom we cannot reliably observe care. We further restrict our sample to patients who had at least one professional encounter with a healthcare provider in the sample period. To focus on older adults, for whom Medicare coverage is close to universal, we then limit the sample to only those aged 66-99.

Our analysis sample consists of two groups of patients: movers and non-movers. To define a patient's location and whether they move, we assign each patient to a hospital service area (HSA) on

[4] Specifically, we use the national median allowed charge for the given service in the given year. As units, we use diagnosis-related groups for inpatient stays, procedure code x status indicator code x first procedure modifier code interactions for outpatient visits, and procedure code x first procedure modifier code interactions for professional encounters. We scale the inpatient, outpatient, and professional prices so that total payments priced under these values sum to actual payments for the given set of services.

[5] This data is available on request from the CDC at https://www.cdc.gov/opioids/data-resources/index.html

an annual basis using their ZIP code on file with Medicare at the end of the year. We also track the patient's hospital referral region (HRR) in the same way; HRRs are collections of HSAs. To be included as a non-mover, the patient must only ever be observed at one HSA in our data. We use 100% of the non-movers to create HSA-level fragmentation indices. However, because these patients are so numerous and do not meaningfully contribute to identification in the mover research design, for tractability our regression analyses use a 20% random sample of them. These restrictions result in 4,071,248 such non-mover patients in our analysis sample.

To be included as a mover, the patient's HSA must have changed once in our 9-year period, and this change must have involved crossing HRRs. To omit patients with changes in addresses on file with Medicare that do not actually represent moves, we follow Finkelstein, Gentzkow, and Williams (2016) and require that that patient's share of claims in the destination HRR go up by at least 75 percentage points.[6] Further, the patient must be continuously in the sample from one year before their move to one year after. Finally, to ensure that we can measure the patient's change in fragmentation, we restrict to movers whose source and destination HSAs both have fragmentation measures. After applying these restrictions, our analysis sample contains 619,220 mover patients.

2.2 Construction of Fragmentation Measures

We define fragmentation at both the provider and organization levels. Provider fragmentation measures the extent to which patients receive their care from many providers (Agha, Frandsen, and Rebitzer 2019). It is modeled on a Herfindahl-Hirschman concentration index, and ranges from 0 to 1. A value of 0 means the patient experienced no fragmentation of care (visited a single provider), while a value approaching 1 indicates more fragmentation of care (visited many providers, each with a low share of the patient's visits). The share of the patient's visits that involved the provider is defined

[6] For patients with no post-move claims, we require that the share of their claims in the destination HRR is 5% or lower during the pre-move period. For patients with no pre-move claims, we require that after the move, their share of claims in the destination HRR is over 95%.

as $share_{itd} = visits_{itd} / \sum_{d' \in D_{it}} visits_{itd'}$ where i indexes patients, t indexes years, d indexes providers, and D_{it} is the set of providers who the patient saw in the year. The provider fragmentation index is 1 minus the sum of the squared shares: $1 - \sum_{d \in D_{it}} share_{itd}^2$.

Organizational fragmentation measures the extent the providers a patient sees are associated with the same organization or with different organizations (Agha, Ericson, and Zhou forthcoming). Like provider fragmentation, organization fragmentation is also modeled on a Herfindahl-Hirschman concentration index, and ranges from 0 (all providers visited by a patient are in the same organization) to 1 (as it approaches 1, a patient received care from many organizations, each with a low share of patient visits). We define the share of the patient's visits that involved the organization as $share_{ito} = visits_{ito} / \sum_{o' \in O_{it}} visits_{ito'}$, where o indexes organizations, and O_{it} is the set of organizations that the patient saw in the year. The organizational fragmentation index is 1 minus the sum of the squared shares: $1 - \sum_{o \in O_{it}} share_{ito}^2$.

To measure visits, we use Medicare professional claims of physicians. A visit is defined as a patient encounter with a physician on a day. If a patient has multiple encounters with a physician on the same day, these encounters are rolled into one. When measuring organizational fragmentation, we still count visits with different physicians in the same organization on the same day separately.

We identify organizations via Tax Identification Numbers (TINs) and define physicians that bill under the same TIN as belonging to the same organization. An extensive array of prior work has relied on this approach to measuring organizations (e.g. Capps, Dranove, and Ody 2018; Baker, Bundorf, and Kessler 2020b). While this method does have some risk of mismeasurement because practice groups often have multiple TINs, Agha, Ericson, and Zhao (forthcoming) show that it maps closely to an alternative based on Medicare group practice identifiers. Since the alternative is not available for the bulk of our analyses period, that research is reassuring for the validity of our TIN-based approach.

We construct our measures of healthcare fragmentation for all individuals in our analysis sample at the patient-year level. We then average patient-year observations to the regional (HSA) level using the non-movers in the sample. For our regressions, we rescale both measures so that a 1 unit change equals the standard deviation in fragmentation across HSAs. That is, we divide provider fragmentation by its standard deviation, 0.0656, and divide organizational fragmentation by 0.0746.

2.3 Descriptive Statistics

We now characterize fragmentation and prescribing across regions visually and quantitatively. Figure 1 presents maps of geographic variation in fragmentation and opioid prescribing. Panel A depicts provider fragmentation, and like Agha, Frandsen, and Rebitzer (2019), we find that the Northeast and Southeast are relatively heavily fragmented. Panel B splits regions by rates of dangerous opioid overlap, while Panel C splits regions by measures of dangerous opioid receipt (defined as receiving long duration or high dose opioids).

Appendix Table A2 divides regions into terciles of regional provider fragmentation and presents summary statistics. The first row shows that the highest tercile has, on average, a fragmentation index that is 0.10 units (or 1.5 standard deviations) higher than the lowest tercile. The next row shows that provider and organizational fragmentation are correlated across regions; organizational fragmentation is also lower than provider fragmentation. Consistent with previous work, compared to low fragmentation regions, high fragmentation regions have higher total health spending but similar patient characteristics as measured by age and rates of chronic conditions.

Regions that are more fragmented have lower levels of dangerous opioid receipt. Appendix Table A2 shows that relative to low-fragmentation areas, patients in high-fragmentation regions are less likely to experience dangerous opioid overlaps each year (9% for the most fragmented versus 12% for the least) and have lower rates of receiving long duration or high dose opioids (7% versus 9%). Panel E of the table shows that this result may reflect lower rates of overall prescribing in high-fragmentation

areas. These regions have lower numbers of total prescriptions (5 fewer fills and 30 fewer days of all prescription drugs per year). They also have a lower opioid prescribing volume: each year, the average patient receives 8.8 fewer days of opioids and has a 4 percentage point lower probability of receiving any opioid.

3. Identification

Our starting point is to study the *association* between regional fragmentation and prescribing. The association is already strongly suggested by the summary statistics we just presented. To quantify the relationship, we run the following associational regression:

$$y_{it} = \alpha + \beta * frag_{r(i,t)} + \gamma X_{it} + \varepsilon_{it}, \quad (1)$$

where i indexes patients, r indexes regions, and t indexes years. y_{it} is an outcome of interest, such as a prescribing quality measure; $frag_{r(i,t)}$ measures average fragmentation in the patient's region, X_{it} is a set of control variables (the patient's demographics and chronic conditions at the end of previous calendar year), and ε_{it} is the regression error term. β provides the association between regional fragmentation and the outcome.

This regression is unlikely to provide a causal estimate of the effect of fragmentation on prescribing outcomes, as unobserved patient characteristics may vary by region and be associated with both regional fragmentation and prescribing outcomes. For example, patients who live in higher fragmentation regions may also tend to have greater needs or preferences for opioids.

Our identification strategy examines patients as they move across regions of varying care fragmentation, which eliminates time-constant unobserved patient factors as potential confounders. We control for these factors with a patient fixed effect. We run the following regression:[7]

[7] Equation 2 is algebraically equivalent to another form in which these mover regressions are frequently presented (eg. Agha, Ericson, and Zhao 2021): $y_{it} = \alpha_i + \beta \Delta frag_{r(i,t)} \times Post_{it} + \gamma X_{it} + \tau_t + \theta_{m(i,t)} + \varepsilon_{it}$, where $\Delta frag_{r(i,t)}$ is the change in fragmentation from source to destination region, and $Post_{it} = 1$ in years after the move and 0 before.

$$y_{it} = \beta * frag_{r(i,t)} + X_{it} + \kappa_i + \tau_t + \theta_{m(i,t)} + \varepsilon_{it}, \quad (2)$$

where κ_i are the patient fixed effects; τ_t is a year fixed effect; $m(i,t)$ is the years since the patient's move, i.e. 0 when t is the year of the move, it is -1 in the year before, and 1 in the year after; and θ_m are relative move year effects, allowing outcomes to change systematically when patients move. Here, X_{it} includes only fixed effects for age in integer years; we omit controls for chronic conditions because they may develop endogenously due to changes in fragmentation induced by moves.

Previous work by Agha, Frandsen, and Rebitzer (2019) has laid out the set of assumptions under which β in this regression gives the causal effect of regional fragmentation on the outcome: *no selection on gains* (among movers, the treatment effect of moving on the outcome, e.g. opioid receipt, is independent of the time of move and the origin-destination pair of move), *parallel trends among movers* (movers' potential outcomes evolve on parallel trends with those of other movers), and *fragmentation selection on observables* (after controlling for observables, other factors that influence a region's effect on the outcome are uncorrelated with its fragmentation level). Note that these assumptions still allow moves to occur non-randomly in many ways. For instance, the decision to move may be correlated with time-constant patient unobservables, as may the fragmentation of the move destination.

While we cannot directly test these assumptions, they do suggest falsification exercises. Violations of no selection on gains would require that older adults select their move destination based on individual-level heterogeneity in how different regions would affect their opioid receipt. For instance, movers to Kentucky would need to disproportionately represent people for whom Kentucky uniquely increases (or decreases) their opioid receipt. While we cannot rule this violation out, it is not readily clear why adults would move in this way. Moreover, we alleviate some of this concern by showing that our results are similar for the subset of patients who move in the direction of higher area fragmentation as well as patients who moved to lower fragmentation.

Figure 2 presents event study graphs to support our parallel trends among movers assumption, as it shows small or absent pre-trends in both fragmentation (consistent with previous literature) and dangerous opioid prescribing. Finally, fragmentation selection on observables requires that factors other than fragmentation that influence dangerous opioid prescriptions are not correlated with fragmentation. Previous research by Agha, Frandsen and Rebitzer (2018), and Agha, Ericson, and Zhao (forthcoming) shows that the addition of detailed controls about the region did not change the estimated effect of fragmentation on other healthcare service use. Here, we weaken the assumption by including a richer set of controls, specifically state-year effects to account for opioid policies such as PDMPs. Encouragingly, our results are little changed under this approach.

4. Results

4.1 Cross-Sectional Regressions

Table 1 examines the relationship between dangerous opioid prescribing and both provider and organization fragmentation measures using cross-sectional regressions as specified in Equation 1. The first column for each fragmentation measure includes patient age, race, and sex as basic controls. The second column adds indicators for prior chronic conditions to control for patient health status. The third column adds HRR fixed effects, and so the association is identified by residual between-HSA variation in fragmentation within HRRs. This table confirms what we see in the descriptive statistics: regions with higher fragmentation have more spending, lower volumes of risky opioid prescribing, and lower measures of prescribing intensity. In our most controlled specification, an increase of 1 standard deviation of provider fragmentation predicts a 0.5 percentage point decline in the probability of having any dangerous opioid overlap and a 0.3 percentage point decline in having a long duration or high dose opioid, with both associations statistically significant. We find that associations with organizational fragmentation tend to have the same sign, but are smaller in magnitude and sometimes not statistically significant.

This analysis shows that fragmentation is generally associated with lower levels of dangerous opioid prescriptions. However, omitted factors about patients that vary across regions could obscure a true positive relationship between fragmentation and dangerous prescribing—with these results, it is possible that fragmentation does lead to lower quality prescribing, but that regions with fragmented care delivery also have patients who are less likely to seek or fill prescriptions. To address these concerns, we turn to our identification strategy using movers.

4.2 Regressions Using Movers Identification Strategy

Table 2 shows the results of our mover regressions as specified in Equation 2. In contrast to the previous results, we find no statistically significant effect of fragmentation on any measure of dangerous prescribing. Our effects are relatively tightly estimated and the 95% confidence intervals can rule out reasonably-sized effects. Column 1 uses provider fragmentation as the measure of fragmentation, while Column 2 uses organizational fragmentation as the measure of fragmentation. Both display similar patterns, so we discuss them together. Figure 3 summarizes the findings for measures of prescribing graphically, rescaling the estimates by the non-mover means for comparability. Across all the different outcomes and fragmentation measures, the average effect of a 1 standard deviation increase in regional fragmentation is a 0.2% decrease in the outcome.

Panels A and B of Table 2 examine individually-experienced fragmentation and spending, respectively. They replicate previous research that finds that moving to higher fragmentation regions increases the fragmentation that the patient experiences. Using normalized individual-experienced provider fragmentation as the outcome, the coefficient of 0.61 in column 1 shows that when moving to a one standard deviation higher provider fragmentation area, 61% of this area fragmentation increase is expected to pass through to the patient's individually-experienced fragmentation. The organizational fragmentation pass-through, reported in column 2, is 89%. We also reaffirm that moving to a higher fragmentation area increases spending.

In Panel C of Table 2 (and Panel A of Figure 3), we examine several measures of dangerous opioid overlaps. In each case, we find no statistically significant result, with 95% confidence intervals ruling out small impacts on days of overlap. For instance, the average patient receives 2 days of opioid-muscle relaxant overlap each year, and the 95% confidence interval for the impact of a 1 standard deviation increase in provider fragmentation ranges from ±0.1 days of overlap. Looking at the probability of having any overlap of opioids with the 4 classes of interacting medications, 12% of patients have an overlap in a given year. Moving to a 1 standard deviation higher provider fragmentation region lowers the probability of having such an overlap by 0.28 percentage points (95% CI: -0.40 to -0.00 percentage points), while a 1 standard deviation increase in organizational fragmentation region lowers that probability by 0.09 percentage points (95% CI lowered by 0.19 to raised by 0.09 percentage points).

In the next panel of the table and figure, we show that we can rule out small impacts of fragmentation on measures of dangerous opioid receipt. In a given year, about 8% of patients have either a long-duration opioid prescription or at least one day with a high opioid dose. Our estimates imply that when a patient moves to a region with 1 standard deviation higher provider fragmentation, the probability they receive long-duration or high doses rises 0.04 percentage points, with a 95% CI ranging from -0.06 to 0.24 percentage points. For organizational fragmentation, the corresponding estimate is a decline by 0.12 percentage points, with a 95% CI ranging from -0.20 to 0.04 percentage points.

Finally, in the last panel of the table and figure, we examine the impact of fragmentation on general measures of prescribing intensity. Recall that the cross-sectional regressions found a relatively robust pattern of higher fragmentation being associated with fewer opioids and less prescribing of medications overall. In contrast, the movers regressions show no systematic pattern: the point

estimates are smaller, most are not significantly different from zero, and they are relatively precisely estimated.

Figure 2 shows event study graphs for fragmentation and three key measures of opioid prescribing. The results are consistent with the point estimates we have already discussed. Panel A shows that after moving to an area with 1 standard deviation higher provider fragmentation corresponds to an immediate and persistent jump in individually-experienced fragmentation. Panels B and C plot measures of dangerous opioid prescribing. Panel B shows the effect of fragmentation on receiving any dangerous opioid prescription and depicts a small decline over time, consistent with the small and negative point estimate in Table 2. Panel C shows that the likelihood of receiving any long-duration or high-dose opioid prescription is clearly flat. Panel D, which looks at total opioid prescribing volume in days, shows a small and statistically insignificant decline over time, much like the point estimate for this outcome in the table. Crucially, across these outcomes, there is no evidence that more fragmentation *increases* these measures of opioid prescribing.

4.3 Robustness Checks

We conduct variety of robustness checks. They corroborate the results of our baseline analyses. First, we examine whether the effect of fragmentation on measures of dangerous prescribing differs by whether individuals move to regions with higher versus lower fragmentation; if patients endogenously select their destination region based on their expected need for prescription drugs, we might see different results depending on the direction of the move. Moreover, there may be an asymmetry in initiating new prescriptions versus stopping old prescriptions, or an asymmetry in how regional fragmentation translates into individual fragmentation. Appendix Table A3 reports the analyses restricting to movers whose moves increased (columns 1 and 3) or decreased (columns 2 and 4) the fragmentation of their area. Encouragingly, the estimated effects of fragmentation on dangerous prescribing remain quantitatively small and relatively precisely estimated in both directions.

Second, we investigated whether our findings were similar when focusing on movers who were opioid naïve or non-naïve immediately prior to the move. Finkelstein et al. (2022) show that risky opioid use is much more responsive to area effects among previous opioid users. However, Appendix Table A4 continues to show few signs that area *fragmentation* increases use or risky use in this group. Taken together, the results suggest that area effects matter, but not via a fragmentation channel.

Third, we note that our main results consider separate regressions for provider and organizational fragmentation. It is possible that conditional on each other, these two types of fragmentation could have opposite effects. Because they are positively correlated, simply putting one in the regression might give a misleading null result. We address this possibility using a specification in Appendix Table A5 that controls both for changes in provider fragmentation and changes in organizational fragmentation simultaneously. Accounting for fragmentation in this way returns results that are similar to the main findings with point estimates that are quantitatively small and generally not statistically significant.

We next show that our results are robust to alternative measures of fragmentation. Appendix Table A6 shows that our findings are essentially unchanged when calculating provider and organizational fragmentation *conditional* on patient covariates. Appendix Table A7 uses another measure of organizational fragmentation: the share of physicians in health systems. Areas with strong physician-health system ties may have more capacity to coordinate services across providers. We identify physicians' affiliations with health systems using the Health System and Provider Database (HSPD) at the National Bureau of Economic Research (Beaulieu et al. 2023). A health system is defined as groups of commonly owned or managed provider organizations and facilities containing at least one general short-term acute care hospital, ten primary care physicians, and 50 total physicians co-located within a single HRR. This definition aims to capture health systems that have the capability to coordinate healthcare delivery for a broad range of services, including primary care and specialty

care in the inpatient and outpatient settings. HSPD mapped physicians to health systems annually from 2012 to 2016. For our analysis, we generated an HSA-level measure of fragmentation that equals the share of all active physicians working in the HSA who are part of a health system averaged over those years. Given potential concerns about mismeasurement of provider organizations in claims data, these results provide further support that organizational concentration does not have meaningful effects on dangerous prescribing.

Fifth, our assumption of fragmentation selection on observables requires that factors other than fragmentation that influence dangerous opioid prescribing are not correlated with fragmentation. It is possible, for instance, that states with fragmented healthcare systems were more likely to introduce PDMPs, which aim to improve communication between prescribers. These PDMPs may then reduce dangerous opioid prescribing in areas with high fragmentation. To address these concerns, in the next column of Appendix Table A7 we run a specification that includes state-year fixed effects. This approach controls for essentially all state-level variation in policies, including the introduction of PDMPs.[8] Encouragingly, these results are quite similar to our baseline specification.

Sixth, one might be concerned that we identify a null effect of health fragmentation on dangerous opioid prescribing because PDMPs have already mitigated the effect of fragmentation. To address this concern, we retain state-year fixed effects and limit the sample to patients who never live in a state with must-access PDMPs, the type of PDMP that has been shown to be effective at reducing indicators of opioid misuse (Buchmueller and Carey 2018). The final column of Appendix Table A7 shows that results are similar to those in our main specification even in the absence of must-access PDMPs.

[8] Time invariant state effects are already largely controlled for in our main results, which include HRR fixed effects; HRRs are not always nested in states but are generally a finer level of geography than states.

Seventh, we rule out the possibility that the difference between our cross-sectional regressions and the regressions exploiting our movers identification strategy is due to a difference in the sample of observations. For instance, the difference between these two findings could have occurred because movers are different from non-movers in some way that generates a null result. To that end, Appendix Table A8 presents cross-sectional regressions on the movers sample. We find results that are very similar to the cross-sectional regressions originally presented in Table 1.

Finally, our results also hold when examining disabled individuals of any age with Medicare. In Appendix Table A9 we define our sample as Medicare beneficiaries who originally gained coverage due to disability, similar to Finkelstein et al. (2022), and find similar results as in our main analysis.

5. Conclusion

Fragmentation has been blamed for many of the healthcare system's ills. However, fragmentation's effect on dangerous opioid prescribing is theoretically ambiguous. Less coordination could lead to risky prescriptions of opioids alongside interacting medications, but more providers treating a patient could increase the probability that one catches an inappropriate prescription. To address concerns about unobserved patient-level factors, our identification strategy examined individuals who experienced variation in fragmentation as a result of a move across regions. We find that the effect of fragmentation on opioid prescribing is small in magnitude and statistically insignificant. We can rule out moderately-sized positive or negative impacts of fragmentation (measured in a variety of ways) on dangerous prescribing.

Our results are identified by Medicare recipients who move and may not generalize to non-movers. For instance, fragmentation may have heterogenous effects that happen to be small for movers, but act to increase dangerous opioid prescriptions for non-movers. However, movers and non-movers appear similar in many aspects (Appendix Table A10), and the cross-sectional comparisons do not suggest a greater degree of association between fragmentation and dangerous opioid prescribing. Our

primary results focus on older adults, but we show they also hold for disabled individuals of any age with Medicare. However, it is unclear how our results generalize to other populations. Working adults might, for instance, experience fragmentation when receiving care for a jobsite injury covered by workers' compensation and increase their receipt of risky opioids. Finally, like previous literature using a movers design, we are unable to account for unmeasured local characteristics that happen to be correlated with fragmentation. However, for these factors to cause us to miss a causal effect of fragmentation, they would have to just exactly offset that causal effect.

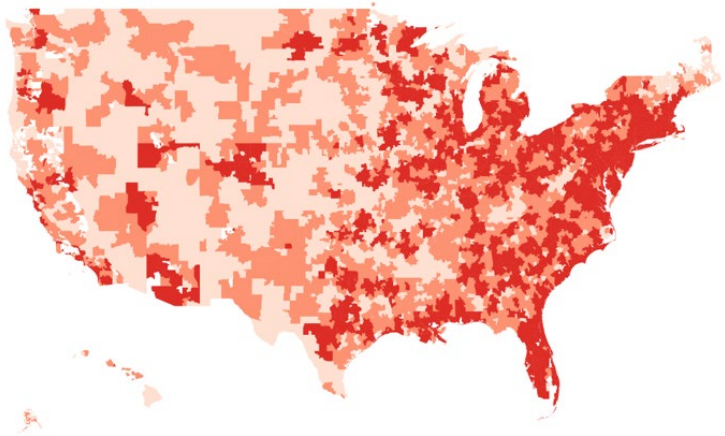
Our results indicate that correlations with regional variation in healthcare practices should be interpreted with caution. Areas with higher fragmentation do indeed have lower measures of dangerous opioid prescribing. Previous work implementing a movers design found that this approach attenuates the positive effects of fragmentation on another outcome, spending, estimated from cross-sectional regressions, but the effect is not reversed or eliminated (Finkelstein, Gentzkow, and Williams 2016; Agha, Frandsen, and Rebitzer 2019; Agha, Ericson, and Zhao forthcoming). Those results might have given us confidence to interpret regional correlations as slightly inflated estimates of true causal effects. However, here, the correlations taken from cross-sectional regressions and the causally identified effects from patient-mover regressions are quite different.

Nonetheless, our results highlight that there is substantial regional variation in dangerous opioid prescribing. Having cast doubt on the role of healthcare fragmentation in driving that variation, future investigations could examine other ways in which individual patient preferences interact with prescribers, how they vary by region, and the resulting impacts on risky prescribing of opioids and other medications.

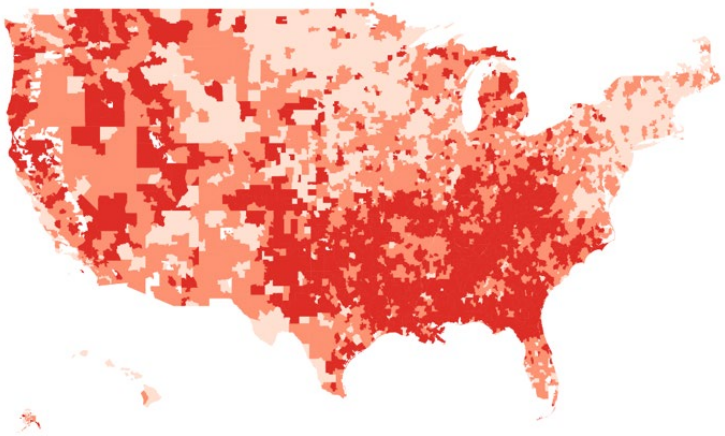
Tables And Figures

Figure 1 – Geographic Variation in Fragmentation and Dangerous Opioid Prescribing

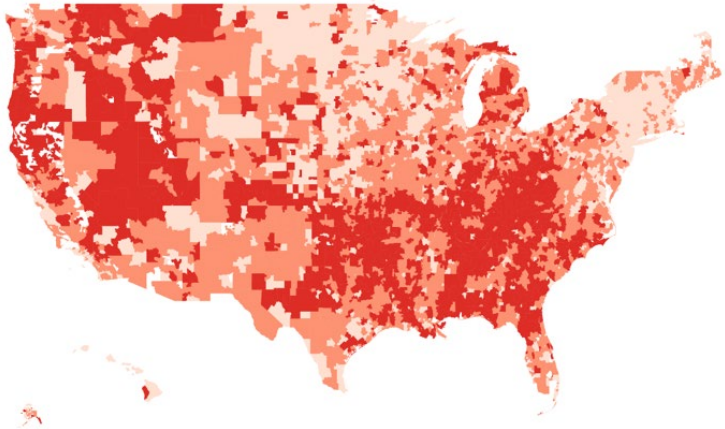
A. HSA Average Provider Fragmentation

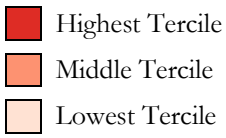


B. Share with Dangerous Opioid Overlap



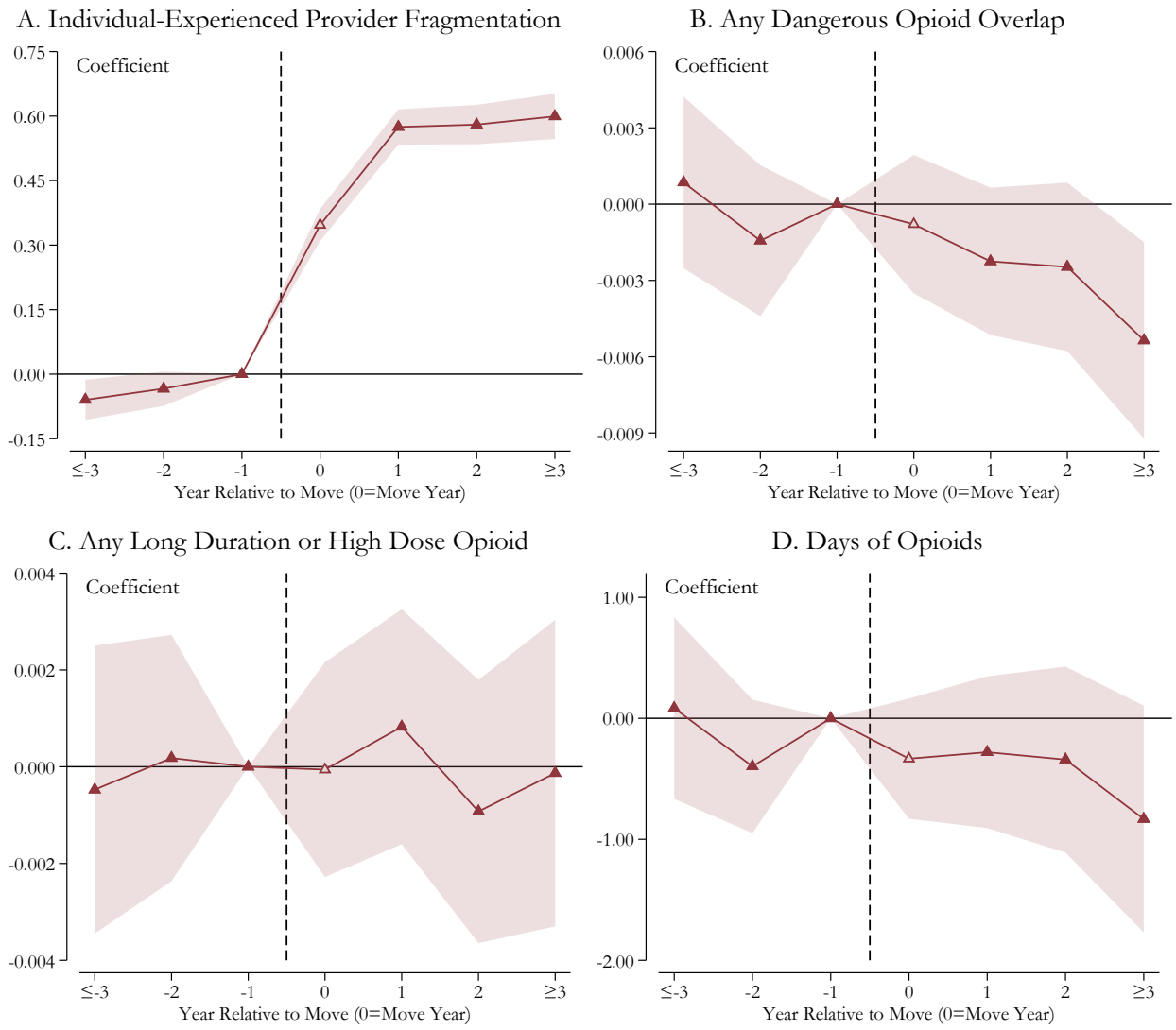
C. Share with Long Duration or High Dose Opioid





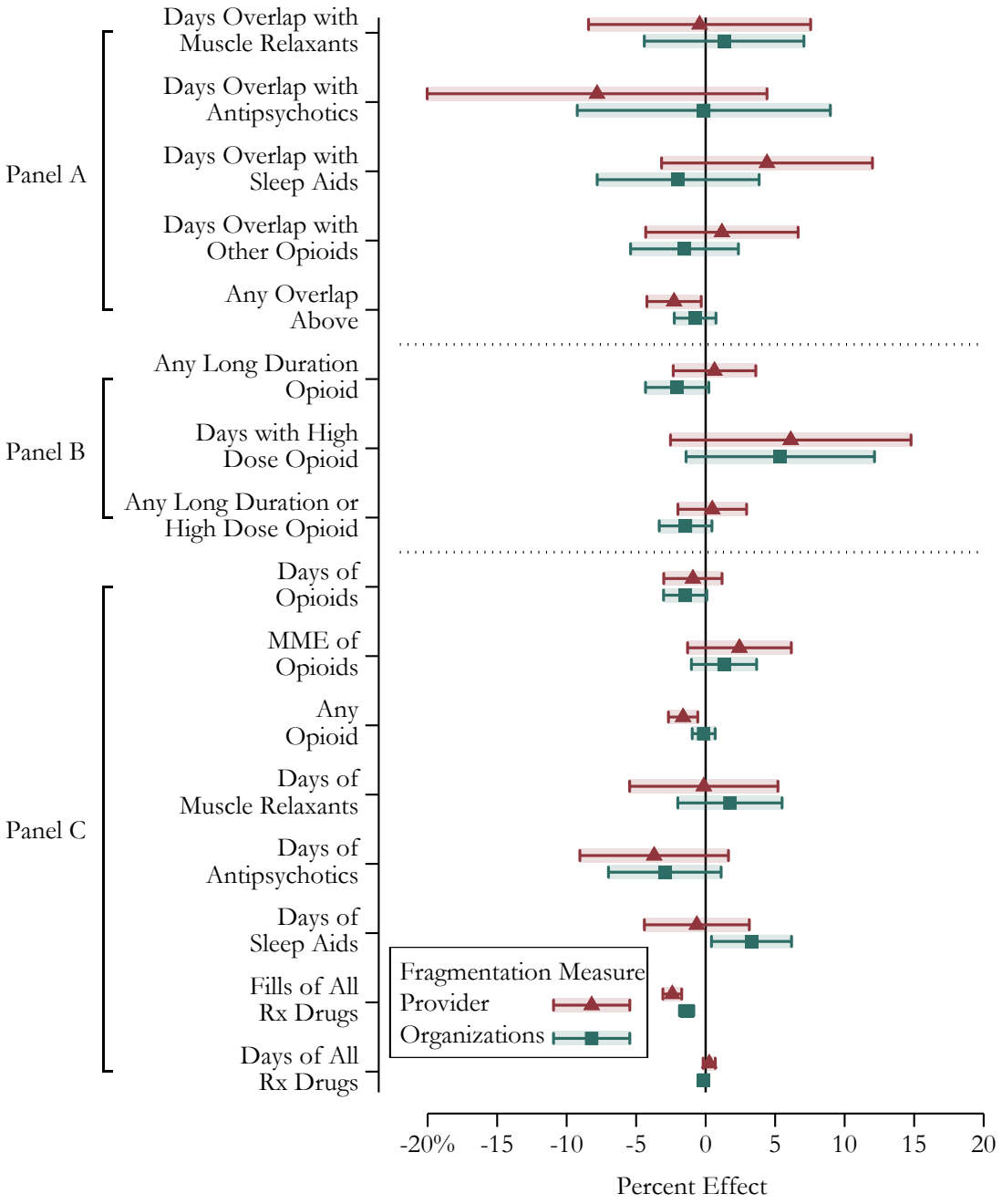
Notes: Panel A divides regions into terciles by average provider fragmentation of patients residing in the area, with higher indicating more fragmentation. Panel B divides regions by the share of patients in the area receiving a dangerous opioid overlap, as defined in Appendix Table A1. Panel C divides regions by the share of patients receiving opioids for a long duration (more than 210 days) or at a high dose (over 90 MME for at least 1 day) in a given year. Data: Panel A: All non-mover patients. Panels B-C: Non-mover patients in our analysis sample.

Figure 2 – Event Studies of Effect of 1 SD Increase in Area Provider Fragmentation



Notes: Panels plot regression coefficients for a version of Equation 2, where the impact of fragmentation is interacted with indicator variables for years relative to move. Panel A plots the individual-level experienced provider fragmentation in standard deviation units, while Panels B-D plot measures of dangerous opioid prescribing. Sample and regression specification follows that in Table 2. Robust standard errors clustered at the patient level in parentheses.

Figure 3 – Percent Effect of 1 SD Increase in Fragmentation on Prescribing



Notes: Plots percent effect: the point estimate from the movers analysis (see Table 2) divided by the average outcome among all non-movers in the sample (see Appendix Table A2). For each outcome, two effects are shown: those using normed provider fragmentation (triangles) and normed organizational fragmentation (squares). Each error bar indicates the 95% confidence interval of the estimate.

Table 1 – Cross-Sectional Regressions Relating Area Fragmentation to Spending and Prescribing

	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Fragmentation:	Provider			Organizational		
A. Spending	723.85	626.62	508.13	598.85	367.67	203.12
	(34.69)	(22.19)	(22.66)	(37.62)	(23.71)	(27.20)
B. Measures of Dangerous Opioid Overlap						
Days Overlap with Muscle Relaxants	-0.37	-0.39	-0.14	0.03	-0.04	-0.08
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Days Overlap with Antipsychotics	-0.22	-0.22	-0.11	-0.09	-0.13	-0.03
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Days Overlap with Sleep Aids	-0.18	-0.20	-0.04	0.14	0.08	-0.02
	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)
Days Overlap with Other Opioids	-0.53	-0.53	-0.16	-0.18	-0.30	-0.10
	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)	(0.06)
1[Any Overlap Above]	-0.0131	-0.0141	-0.0043	-0.0009	-0.0041	-0.0019
	(0.0010)	(0.0011)	(0.0008)	(0.0010)	(0.0011)	(0.0008)
C. Measures of Dangerous Opioid Receipt						
1[Long Duration] (>210 Days)	-0.0102	-0.0105	-0.0053	-0.0027	-0.0046	-0.0027
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0007)
Days with High Dose (>90 MME)	-0.28	-0.16	-0.01	-0.10	-0.13	-0.07
	(0.09)	(0.09)	(0.11)	(0.09)	(0.09)	(0.11)
1[Long Duration or High Dose]	-0.0101	-0.0106	-0.0026	-0.0019	-0.0041	-0.0006
	(0.0009)	(0.0009)	(0.0007)	(0.0009)	(0.0009)	(0.0007)
D. Measures of Prescribing Intensity						
Days of Opioids	-4.83	-5.03	-2.49	-1.16	-2.12	-1.25
	(0.33)	(0.34)	(0.29)	(0.35)	(0.38)	(0.29)
MME of Opioids	-124.11	-123.30	-45.79	-13.26	-42.27	-29.85
	(12.69)	(13.52)	(13.86)	(12.84)	(14.22)	(15.74)
1[Any Opioid]	-0.0193	-0.0219	-0.0033	-0.0010	-0.0063	-0.0004
	(0.0018)	(0.0019)	(0.0011)	(0.0017)	(0.0020)	(0.0011)
Days of Muscle Relaxant	-0.58	-0.65	-0.18	0.09	-0.06	-0.13
	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.08)
Days of Antipsychotics	0.22	0.35	0.01	0.12	-0.02	-0.20
	(0.14)	(0.13)	(0.13)	(0.18)	(0.13)	(0.14)
Days of Sleep Aids	0.94	0.88	1.16	1.37	1.24	0.43
	(0.13)	(0.14)	(0.14)	(0.14)	(0.13)	(0.14)
Fills of All Prescription Drugs	-2.52	-2.97	-2.20	-0.56	-1.54	-1.22
	(0.19)	(0.18)	(0.14)	(0.23)	(0.18)	(0.16)
Days of All Prescription Drugs	-16.27	-31.85	-8.45	3.27	-33.55	-11.01
	(4.09)	(3.66)	(3.21)	(4.51)	(3.09)	(3.13)
Controls						
Age, Race, Sex, Year	Y	Y	Y	Y	Y	Y
Prior Chronic Conditions	N	Y	Y	N	Y	Y
Hospital Referral Region FE	N	N	Y	N	N	Y

Notes: Each cell reports a point estimate and standard error for the coefficient on normed fragmentation from a separate regression given by equation 1. The sample is non-mover patients from the analysis sample. The number of patient-year observations is 4,071,248 in Columns 1 and 4. In the other columns, there are 3,678,787 observations (the number is smaller due to missing chronic conditions data). Robust standard errors clustered at the HSA level in parentheses. Age is controlled for as age in year fixed effects, and race is an indicator for white versus non-white.

Table 2 –Estimates of Effect of Area Fragmentation Using Movers Identification Strategy

Measure of Fragmentation:	(1) Provider	(2) Organizational
A. Individually-Experienced Fragmentation (Normalized)	0.61	0.89
	(0.02)	(0.01)
B. Spending	653.15	400.68
	(56.96)	(43.70)
C. Measures of Dangerous Opioid Overlap		
Days Overlap with Muscle Relaxants	-0.01	0.03
	(0.08)	(0.06)
Days Overlap with Antipsychotics	-0.10	0.00
	(0.08)	(0.06)
Days Overlap with Sleep Aids	0.09	-0.04
	(0.08)	(0.06)
Days Overlap with Other Opioids	0.04	-0.05
	(0.10)	(0.07)
1[Any Overlap Above]	-0.0028	-0.0009
	(0.0012)	(0.0009)
D. Measures of Dangerous Opioid Receipt		
1[Long Duration] (>210 Days)	0.0004	-0.0012
	(0.0009)	(0.0007)
Days with High Dose (>90 MME)	0.34	0.29
	(0.24)	(0.19)
1[Long Duration or High Dose]	0.0004	-0.0012
	(0.0010)	(0.0008)
E. Measures of Prescribing Intensity		
Days of Opioids	-0.28	-0.45
	(0.33)	(0.24)
MME of Opioids	24.70	13.41
	(19.34)	(12.16)
1[Any Opioid]	-0.0050	-0.0004
	(0.0017)	(0.0013)
Days of Muscle Relaxant	-0.01	0.09
	(0.14)	(0.10)
Days of Antipsychotics	-0.39	-0.31
	(0.29)	(0.22)
Days of Sleep Aids	-0.07	0.35
	(0.20)	(0.16)
Fills of All Prescription Drugs	-0.84	-0.48
	(0.12)	(0.09)
Days of All Prescription Drugs	3.53	-1.97
	(3.09)	(2.42)

Notes: Each cell reports a point estimate and standard error for the coefficient on normed fragmentation from a separate regression given by Equation 2. These regressions use the main analysis sample. *N*=4,459,556 patient-years in each regression. Robust standard errors clustered at the patient level in parentheses.

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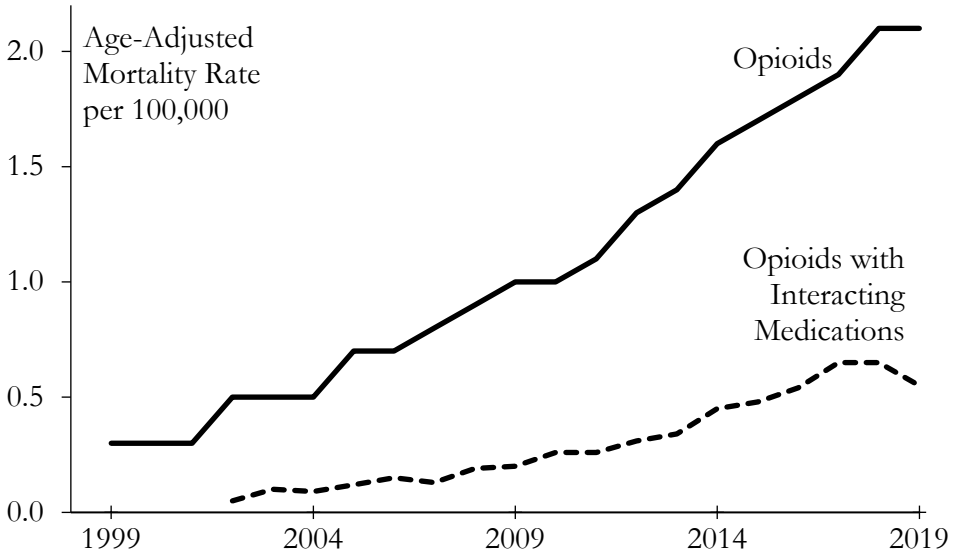
Online Appendix for

"Dangerous Prescribing and Healthcare Fragmentation: Evidence from Opioids"

Appendix Figure A1 – Prescription Opioid Overdose Mortality Rate, Age 65+, 1999-2019



Notes: Authors' calculations from CDC WONDER (https://wonder.cdc.gov) data. Plots age-adjusted mortality rate per 100,000 people for opioid prescription overdoses (solid line) and the subset of those overdoses that also involved an interacting medication (dashed line) for people age 65 and older. Interacting medication classes are those mentioned in the 2016 FDA warning on prescribing opioids with central nervous system depressants and are defined as benzodiazepines, sleep aids, antipsychotics, and muscle relaxants. Due to low rates of overdose, this series is not available before 2002. Opioid overdoses are defined as records with underlying cause ICD-10 codes X40-X44, X60-X64, X85, or Y10-Y14 and multiple cause codes T40.2-T40.3. Opioid overdoses with interacting medications must also have one of the following multiple cause codes: T42.4, T42.7, T43.3-T43.5 or T48.1.

Appendix Table A1: Measures of Opioid-Related Dangerous Prescribing

Measure	Definition	Rationale
Measures of Dangerous Opioid Overlap:		
Opioid-Muscle Relaxant Overlap Opioid-Antipsychotic Overlap Opioid-Sleep Aid Overlap	Number of days the patient took an opioid together with a drug in the given class.	FDA warning (2016) that taking these medications together can cause respiratory depression and overdose.
Opioid-Opioid Overlap	Number of days the patient took opioids from two or more opioid prescriptions	Carey, Jena, and Barnett (2018) study showing strong association with overdose and death.
Measures of Dangerous Opioid Receipt:		
High Dose Opioid Rx	Number of days the patient took a dose above 90 morphine milligram equivalents (MME).	CDC guidelines (2016) advise prescribers to avoid daily dosages over 90 MME.
Long Duration Opioid Rx	Indicator for taking opioids more than 210 days in the year.	CDC guidelines (2016) suggest short duration prescriptions and frequent reviews to consider discontinuation; Carey, Jena, and Barnett (2018) use a 210 day threshold for long duration.

Notes: To construct these measures, patients are assumed to start taking each medication on the day they fill the prescription and continue for as many days as the prescription supplies.

Appendix Table A2 – Summary Statistics

	Tercile of Provider Fragmentation			
	Low	Medium	High	All
A. Indices of Fragmentation				
Provider Fragmentation	0.57	0.63	0.67	0.63
Organizational Fragmentation	0.21	0.25	0.27	0.24
Share of Providers in Health Systems	0.36	0.45	0.48	0.43
B. Spending	7,934	8,635	8,910	8,493
C. Measures of Dangerous Opioid Overlap				
Days Overlap with Muscle Relaxants	2.21	2.23	1.46	1.96
Days Overlap with Antipsychotics	1.38	1.37	0.96	1.23
Days Overlap with Sleep Aids	2.23	2.31	1.78	2.11
Days Overlap with Other Opioids	3.82	3.71	2.97	3.50
Share with Any Overlap Above	0.12	0.12	0.09	0.12
D. Measures of Dangerous Opioid Receipt				
Share Long Duration (>210 Days)	0.06	0.06	0.05	0.06
Days with High Dose (>90 MME)	5.58	5.69	5.17	5.48
Share with Long Duration or High Dose	0.09	0.09	0.07	0.08
E. Measures of Prescribing Intensity				
Days of Opioids	34.1	32.5	25.3	30.6
MME of Opioids	1,096	1,081	871	1,016
Share Any Opioid	0.32	0.32	0.28	0.31
Days of Muscle Relaxants	5.58	5.73	4.32	5.21
Days of Antipsychotics	10.1	11.3	10.1	10.5
Days of Sleep Aids	9.8	11.0	11.0	10.6
Fills of All Prescription Drugs	36.8	35.8	31.8	34.8
Days of All Prescription Drugs	1,379	1,409	1,349	1,379
F. Patient Characteristics				
Age	75.7	75.7	75.8	75.7
Asthma	0.04	0.04	0.04	0.04
Depression	0.11	0.12	0.11	0.11
Alzheimer's or Dementia	0.08	0.09	0.08	0.09
Diabetes	0.28	0.28	0.26	0.27
Heart Condition	0.32	0.33	0.33	0.32
Any Cancer	0.07	0.07	0.08	0.07
Stroke or Hypertension	0.54	0.55	0.55	0.54
N Areas (HSAs)	2,102	779	555	3,436
N Patients	292,351	309,791	314,500	916,642
N Observations (Patient-Years)	1,357,837	1,357,549	1,355,862	4,071,248

Notes: Non-mover patients from the analysis sample. Patient-year observations are split into terciles by the provider fragmentation of the area where the patient resides, defined as their hospital service area (HSA). Fragmentation is not normalized here, and ranges from 0 to 1 as defined in Section 2.2. For the share of providers in health systems, physicians are allocated to HSAs by their plurality amount of claims.

Appendix Table A3 – Estimates of Effect of Area Fragmentation Using Movers Identification Strategy, by Direction of Move

	(1)	(2)	(3)	(4)
Measure of Fragmentation:	Provider		Organizational	
Direction of Move	To Higher	To Lower	To Higher	To Lower
A. Individually-Experienced	0.67	0.69	0.85	0.99
Fragmentation (Normalized)	(0.03)	(0.04)	(0.03)	(0.03)
B. Spending	425.04	1081.95	30.95	436.05
	(114.78)	(127.81)	(86.79)	(87.63)
C. Measures of Dangerous Opioid Overlap				
Days Overlap with Muscle Relaxants	0.22	-0.09	-0.02	-0.02
	(0.17)	(0.18)	(0.11)	(0.12)
Days Overlap with Antipsychotics	-0.19	0.07	0.05	-0.11
	(0.15)	(0.20)	(0.11)	(0.12)
Days Overlap with Sleep Aids	0.17	0.34	0.12	-0.02
	(0.16)	(0.21)	(0.11)	(0.14)
Days Overlap with Other Opioids	0.00	-0.10	-0.19	-0.08
	(0.21)	(0.21)	(0.14)	(0.14)
1[Any Overlap Above]	-0.0006	-0.0020	-0.0021	-0.0004
	(0.0023)	(0.0029)	(0.0018)	(0.0019)
D. Measures of Dangerous Opioid Receipt				
1[Long Duration] (>210 Days)	0.0012	-0.0002	-0.0009	-0.0026
	(0.0017)	(0.0021)	(0.0013)	(0.0014)
Days with High Dose (>90 MME)	-0.23	0.49	-0.11	0.19
	(0.50)	(0.51)	(0.37)	(0.37)
1[Long Duration or High Dose]	0.0002	-0.0016	0.0007	-0.0024
	(0.0020)	(0.0025)	(0.0016)	(0.0017)
E. Measures of Prescribing Intensity				
Days of Opioids	-0.33	-0.27	-0.63	-0.54
	(0.67)	(0.77)	(0.47)	(0.52)
MME of Opioids	54.74	-5.07	-5.84	-15.90
	(48.49)	(32.72)	(25.35)	(22.62)
1[Any Opioid]	-0.0010	-0.0013	0.0015	0.0046
	(0.0032)	(0.0039)	(0.0026)	(0.0026)
Days of Muscle Relaxant	0.16	-0.29	0.01	0.03
	(0.27)	(0.36)	(0.20)	(0.22)
Days of Antipsychotics	-0.90	0.01	-0.66	-0.05
	(0.54)	(0.75)	(0.42)	(0.45)
Days of Sleep Aids	0.01	-0.26	0.36	0.52
	(0.39)	(0.49)	(0.30)	(0.32)
Fills of All Prescription Drugs	-0.75	-0.55	-0.83	0.28
	(0.23)	(0.30)	(0.18)	(0.19)
Days of All Prescription Drugs	1.09	8.30	-13.61	6.11
	(5.94)	(7.36)	(4.89)	(4.90)
Observations (Patient-Years)	4,284,908	4,245,896	4,273,675	4,257,129

Notes: Each cell reports a point estimate and standard error for the coefficient on normed fragmentation from a separate regression given by Equation 2. These regressions use the main analysis sample. The columns vary in which movers are included. Columns 1 and 3 include movers whose move destination had higher provider and organizational fragmentation than their origin, respectively. Columns 2 and 4 include movers with destinations with lower fragmentation. All columns include all non-movers. Robust standard errors clustered at the patient level in parentheses.

Appendix Table A4 - Results for Opioid Naïve and Non-Naïve Movers

Sample:	(1) Opioid Naïve Movers	(2) Opioid Naïve Movers	(3) Opioid Non-Naïve Movers	(4) Opioid Non-Naïve Movers
Measure of Fragmentation:	Provider	Organizational	Provider	Organizational
A. Individually-Experienced	0.64	0.85	0.54	0.97
Fragmentation (Normalized)	(0.02)	(0.02)	(0.03)	(0.02)
B. Spending, Price-Adjusted	577.12	360.56	838.47	486.39
	(61.58)	(46.88)	(124.28)	(97.50)
C. Measures of Dangerous Opioid Overlap				
Days Overlap with Muscle Relaxants	0.08	0.07	-0.22	-0.10
	(0.06)	(0.04)	(0.23)	(0.17)
Days Overlap with Antipsychotics	-0.02	0.00	-0.29	0.00
	(0.06)	(0.05)	(0.22)	(0.16)
Days Overlap with Sleep Aids	0.02	-0.02	0.28	-0.11
	(0.05)	(0.04)	(0.25)	(0.19)
Days Overlap with Other Opioids	0.06	-0.03	-0.01	-0.10
	(0.07)	(0.04)	(0.29)	(0.21)
1[Any Overlap Above]	-0.0021	-0.0010	-0.0041	-0.0015
	(0.0011)	(0.0009)	(0.0031)	(0.0024)
D. Measures of Dangerous Opioid Receipt				
1[Long Duration] (>210 Days)	-0.0001	-0.0011	0.0013	-0.0011
	(0.0007)	(0.0005)	(0.0024)	(0.0019)
Days with High Dose (>90 MME)	0.42	0.16	0.28	0.37
	(0.20)	(0.12)	(0.37)	(0.30)
1[Long Duration or High Dose]	0.0000	-0.0008	0.0015	-0.0025
	(0.0009)	(0.0007)	(0.0028)	(0.0022)
E. Measures of Prescribing Intensity				
Days of Opioids	-0.12	-0.36	-0.67	-0.71
	(0.28)	(0.20)	(0.88)	(0.68)
MME of Opioids	18.09	0.43	41.15	41.30
	(13.17)	(8.20)	(57.23)	(36.96)
1[Any Opioid]	-0.0031	-0.0006	-0.0086	-0.0031
	(0.0018)	(0.0014)	(0.0031)	(0.0025)
Days of Muscle Relaxant	0.04	0.17	-0.11	-0.12
	(0.12)	(0.09)	(0.38)	(0.27)
Days of Antipsychotics	-0.09	-0.46	-1.11	0.06
	(0.33)	(0.26)	(0.57)	(0.41)
Days of Sleep Aids	-0.19	0.26	0.24	0.52
	(0.20)	(0.16)	(0.50)	(0.38)
Fills of All Prescription Drugs	-0.85	-0.38	-0.81	-0.71
	(0.13)	(0.10)	(0.25)	(0.19)
Days of All Prescription Drugs	0.87	-0.82	9.62	-4.49
	(3.56)	(2.75)	(6.07)	(4.91)
N Observations	2,577,076	2,577,076	2,577,076	2,577,076

Notes: This table presents results for opioid naïve and non-naïve movers, defined as those who did not receive opioids in the year before their move (naïve) or did receive opioids in the year before their move (non-naïve). All non-movers are included. Columns 1 and 2 analyze the sample of opioid naïve movers while columns 3 and 4 analyze the sample of opioid non-naïve movers. All columns use the fragmentation measures of the main analyses, which were calculated from the full sample. See text for more details. Robust standard errors clustered at the patient level in parentheses.

Appendix Table A5 – Multivariate Estimates of Effect of Area Fragmentation Using Movers Identification Strategy

Measure of Fragmentation:	(1) Provider	(2) Organizational
A. Individually-Experienced Fragmentation		
Provider (Normalized)	0.64	-0.07
	(0.02)	(0.01)
Organizational (Normalized)	-0.27	1.09
	(0.02)	(0.02)
B. Spending	537.06	234.80
	(61.14)	(46.82)
C. Measures of Dangerous Opioid Overlap		
Days Overlap with Muscle Relaxants	-0.03	0.03
	(0.08)	(0.06)
Days Overlap with Antipsychotics	-0.11	0.03
	(0.08)	(0.06)
Days Overlap with Sleep Aids	0.13	-0.08
	(0.09)	(0.07)
Days Overlap with Other Opioids	0.08	-0.08
	(0.11)	(0.08)
1[Any Overlap Above]	-0.0027	-0.0001
	(0.0013)	(0.0010)
D. Measures of Dangerous Opioid Receipt		
1[Long Duration] (>210 Days)	0.0011	-0.0015
	(0.0009)	(0.0007)
Days with High Dose (>90 MME)	0.23	0.22
	(0.26)	(0.21)
1[Long Duration or High Dose]	0.0011	-0.0015
	(0.0011)	(0.0009)
E. Measures of Prescribing Intensity		
Days of Opioids	-0.07	-0.43
	(0.36)	(0.27)
MME of Opioids	21.33	6.83
	(20.76)	(12.97)
1[Any Opioid]	-0.0056	0.0013
	(0.0018)	(0.0014)
Days of Muscle Relaxant	-0.06	0.11
	(0.15)	(0.11)
Days of Antipsychotics	-0.28	-0.22
	(0.31)	(0.24)
Days of Sleep Aids	-0.28	0.44
	(0.22)	(0.17)
Fills of All Prescription Drugs	-0.71	-0.26
	(0.13)	(0.10)
Days of All Prescription Drugs	5.31	-3.61
	(3.35)	(2.62)

Notes: Each row reports a separate regression based on a modified version of Equation 2 that includes provider and organizational fragmentation in the same regression. Rows give two point estimates and standard errors for the coefficient on normed provider fragmentation (column 1) and normed organizational fragmentation (column 2). These regressions use the main analysis sample. *N*=4,459,556 patient-years in each regression. Robust standard errors clustered at the patient level in parentheses.

Appendix Table A6 – Robustness of Mover Results to Residualized Fragmentation Measures

Calculation of Fragmentation:	(1) Original	(2) Original	(3) Residualized	(4) Residualized
Measure of Fragmentation:	Provider	Organizational	Provider	Organizational
A. Individually-Experienced Fragmentation (Normalized)	0.61	0.89	0.63	0.90
	(0.02)	(0.01)	(0.02)	(0.01)
B. Spending, Price-Adjusted	653.15	400.68	727.80	445.06
	(56.96)	(43.70)	(57.75)	(44.45)
C. Measures of Dangerous Opioid Overlap				
Days Overlap with Muscle Relaxants	-0.01	0.03	-0.01	0.02
	(0.08)	(0.06)	(0.08)	(0.06)
Days Overlap with Antipsychotics	-0.10	0.00	-0.11	0.00
	(0.08)	(0.06)	(0.08)	(0.06)
Days Overlap with Sleep Aids	0.09	-0.04	0.10	-0.03
	(0.08)	(0.06)	(0.08)	(0.06)
Days Overlap with Other Opioids	0.04	-0.05	0.06	-0.05
	(0.10)	(0.07)	(0.10)	(0.07)
1[Any Overlap Above]	-0.0028	-0.0009	-0.0029	-0.0009
	(0.0012)	(0.0009)	(0.0013)	(0.0010)
D. Measures of Dangerous Opioid Receipt				
1[Long Duration] (>210 Days)	0.0004	-0.0012	0.0006	-0.0011
	(0.0009)	(0.0007)	(0.0009)	(0.0007)
Days with High Dose (>90 MME)	0.34	0.29	0.31	0.27
	(0.24)	(0.19)	(0.25)	(0.19)
1[Long Duration or High Dose]	0.0004	-0.0012	0.0004	-0.0012
	(0.0010)	(0.0008)	(0.0011)	(0.0008)
E. Measures of Prescribing Intensity				
Days of Opioids	-0.28	-0.45	-0.19	-0.42
	(0.33)	(0.24)	(0.34)	(0.25)
MME of Opioids	24.70	13.41	25.13	11.38
	(19.34)	(12.16)	(20.30)	(12.47)
1[Any Opioid]	-0.0050	-0.0004	-0.0051	-0.0005
	(0.0017)	(0.0013)	(0.0017)	(0.0013)
Days of Muscle Relaxant	-0.01	0.09	-0.06	0.08
	(0.14)	(0.10)	(0.15)	(0.10)
Days of Antipsychotics	-0.39	-0.31	-0.34	-0.26
	(0.29)	(0.22)	(0.29)	(0.22)
Days of Sleep Aids	-0.07	0.35	-0.06	0.37
	(0.20)	(0.16)	(0.21)	(0.16)
Fills of All Prescription Drugs	-0.84	-0.48	-0.71	-0.39
	(0.12)	(0.09)	(0.12)	(0.09)
Days of All Prescription Drugs	3.53	-1.97	6.58	-0.32
	(3.09)	(2.42)	(3.16)	(2.46)

Notes: This table presents the robustness of our findings to residualized measures of provider and organizational fragmentation. Columns 1 and 2 repeat results from the original fragmentation measures in Table 2. Columns 3 and 4 use residualized fragmentation measures. The residualized measures are calculated by regressing individually-experienced fragmentation on area fixed effects, age fixed effects, sex (female/not female) and race (white/not white) and extracting the area fixed effects. See text for more details. *N*=4,459,556 patient-years in each regression. Robust standard errors clustered at the patient level in parentheses.

Appendix Table A7 – Miscellaneous Robustness of Mover Results

Robustness Specification:	(1) Baseline (Provider Fragmentation)	(2) Share in Health Systems	(3) Baseline + State-Year FE	(4) Col 3 + Never Lived in State with Must-Access PDMP
A. Individually-Experienced Fragmentation (Normalized)	0.61	N/A	0.61	0.62
	(0.02)		(0.02)	(0.02)
B. Spending	653.15	66.69	515.69	530.98
	(56.96)	(46.80)	(64.09)	(72.34)
C. Measures of Dangerous Opioid Overlap				
Days Overlap with Muscle Relaxants	-0.01	-0.07	-0.05	-0.01
	(0.08)	(0.06)	(0.09)	(0.10)
Days Overlap with Antipsychotics	-0.10	-0.13	-0.11	-0.07
	(0.08)	(0.06)	(0.09)	(0.10)
Days Overlap with Sleep Aids	0.09	0.01	0.09	0.10
	(0.08)	(0.07)	(0.09)	(0.10)
Days Overlap with Other Opioids	0.04	0.11	0.05	0.08
	(0.10)	(0.08)	(0.11)	(0.12)
1[Any Overlap Above]	-0.0028	-0.0002	-0.0027	-0.0034
	(0.0012)	(0.0010)	(0.0014)	(0.0015)
D. Measures of Dangerous Opioid Receipt				
1[Long Duration] (>210 Days)	0.0004	0.0001	0.0005	0.0005
	(0.0009)	(0.0007)	(0.0010)	(0.0011)
Days with High Dose (>90 MME)	0.34	-0.06	0.26	0.40
	(0.24)	(0.19)	(0.27)	(0.31)
1[Long Duration or High Dose]	0.0004	0.0010	0.0009	0.0009
	(0.0010)	(0.0008)	(0.0011)	(0.0013)
E. Measures of Prescribing Intensity				
Days of Opioids	-0.28	0.07	-0.32	-0.20
	(0.33)	(0.26)	(0.36)	(0.41)
MME of Opioids	24.70	1.88	33.95	50.05
	(19.34)	(15.72)	(21.53)	(25.01)
1[Any Opioid]	-0.0050	-0.0013	-0.0038	-0.0049
	(0.0017)	(0.0013)	(0.0018)	(0.0021)
Days of Muscle Relaxant	-0.01	-0.18	-0.10	-0.11
	(0.14)	(0.11)	(0.16)	(0.18)
Days of Antipsychotics	-0.39	0.25	-0.38	-0.31
	(0.29)	(0.23)	(0.33)	(0.37)
Days of Sleep Aids	-0.07	0.06	-0.16	-0.26
	(0.20)	(0.17)	(0.22)	(0.26)
Fills of All Prescription Drugs	-0.84	0.11	-0.61	-0.50
	(0.12)	(0.10)	(0.14)	(0.15)
Days of All Prescription Drugs	3.53	8.71	4.57	5.81
	(3.09)	(2.49)	(3.44)	(3.87)

Notes: Each cell reports a point estimate and standard error for the coefficient on normed fragmentation from a separate regression given by equation 2. Main analysis sample, *N*=4,459,556 patient-years in each regression. Robust standard errors clustered at the patient level in parentheses. Column 1 reproduces Table 2, column 1. Column 2 uses an alternative fragmentation measure, the share of providers in an area that are in a health system (we did not calculate individually-experienced share of providers in a health system, so pass-through to this measure of fragmentation is not available in this specification). Column 3 uses provider fragmentation, but now adds state-year fixed effects to the regression. Column 4 runs the same regression as Column 3, limiting the sample to individuals who never lived in a state with an active must-access PDMP as coded in the RAND OPTIC dataset (https://www.rand.org/pubs/external_publications/EP68218.html).

Appendix Table A8 – Cross-Sectional Regressions Relating Area Fragmentation to Spending and Prescribing, Using Individuals Who Moved Only

	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Fragmentation	Provider			Organizational		
A. Spending, Price-Adjusted	778.73	683.24	541.70	547.61	395.35	113.71
	(45.03)	(37.99)	(46.70)	(43.09)	(34.84)	(49.21)
B. Measures of Dangerous Opioid Overlap						
Days Overlap with Muscle Relaxants	-0.42	-0.47	-0.26	-0.05	-0.09	-0.16
	(0.07)	(0.07)	(0.10)	(0.05)	(0.06)	(0.09)
Days Overlap with Antipsychotics	-0.32	-0.32	-0.35	-0.14	-0.14	-0.16
	(0.06)	(0.06)	(0.09)	(0.05)	(0.05)	(0.08)
Days Overlap with Sleep Aids	-0.14	-0.18	-0.08	0.04	0.00	-0.04
	(0.06)	(0.07)	(0.10)	(0.05)	(0.05)	(0.09)
Days Overlap with Other Opioids	-0.66	-0.73	-0.50	-0.29	-0.38	-0.21
	(0.09)	(0.10)	(0.14)	(0.07)	(0.08)	(0.13)
1[Any Overlap Above]	-0.0150	-0.0184	-0.0113	-0.0052	-0.0079	-0.0053
	(0.0013)	(0.0013)	(0.0015)	(0.0012)	(0.0012)	(0.0015)
C. Measures of Dangerous Opioid Receipt						
1[Long Duration] (>210 Days)	-0.0107	-0.0121	-0.0081	-0.0049	-0.0063	-0.0047
	(0.0009)	(0.0009)	(0.0012)	(0.0008)	(0.0009)	(0.0011)
Days with High Dose (>90 MME)	-0.54	-0.42	-0.33	-0.07	-0.05	-0.23
	(0.17)	(0.17)	(0.22)	(0.14)	(0.14)	(0.22)
1[Long Duration or High Dose]	-0.0120	-0.0144	-0.0085	-0.0044	-0.0064	-0.0037
	(0.0010)	(0.0011)	(0.0012)	(0.0010)	(0.0010)	(0.0012)
D. Measures of Prescribing Intensity						
Days of Opioids	-5.26	-6.09	-4.21	-2.23	-2.99	-2.12
	(0.42)	(0.41)	(0.51)	(0.40)	(0.42)	(0.52)
MME of Opioids	-167.84	-189.40	-128.55	-39.18	-58.87	-84.31
	(21.87)	(23.13)	(33.53)	(18.60)	(19.74)	(32.50)
1[Any Opioid]	-0.0178	-0.0259	-0.0112	-0.0057	-0.0111	-0.0058
	(0.0020)	(0.0019)	(0.0018)	(0.0019)	(0.0020)	(0.0019)
Days of Muscle Relaxant	-0.78	-0.94	-0.45	-0.11	-0.23	-0.11
	(0.12)	(0.13)	(0.19)	(0.11)	(0.11)	(0.17)
Days of Antipsychotics	-0.44	-0.27	-1.14	-0.47	-0.38	-1.14
	(0.28)	(0.26)	(0.35)	(0.23)	(0.22)	(0.35)
Days of Sleep Aids	1.24	1.02	0.86	1.22	1.11	0.60
	(0.22)	(0.24)	(0.27)	(0.17)	(0.18)	(0.28)
Fills of All Prescription Drugs	-2.04	-2.81	-2.10	-1.13	-1.82	-1.33
	(0.22)	(0.19)	(0.18)	(0.20)	(0.19)	(0.19)
Days of All Prescription Drugs	5.05	-28.69	-6.29	-1.57	-31.27	-12.53
	(5.26)	(4.04)	(4.73)	(4.28)	(3.45)	(4.64)
Controls						
Age, Race, Sex, Year	Y	Y	Y	Y	Y	Y
Prior Chronic Conditions	N	Y	Y	N	Y	Y
Hospital Referral Region FE	N	N	Y	N	N	Y

Notes: This table repeats the analyses reported in Table 1 but uses patients who moved regions. Each cell reports a point estimate and standard error for normed fragmentation from a separate regression given by equation 1. The number of patient-year observations is 619,025 in Columns 1 and 4. In the other columns there are 566,074 observations (the number is smaller due to missing chronic conditions data). Robust standard errors clustered at the HSA level in parentheses.

Appendix Table A9 - Results for Disabled Beneficiaries

	(1)	(2)	(3)	(4)
Sample:	Original (Old Age Beneficiaries)		Disabled Beneficiaries	
Measure of Fragmentation:	Provider	Organizational	Provider	Organizational
A. Individually-Experienced	0.61	0.89	0.61	0.68
Fragmentation (Normalized)	(0.02)	(0.01)	(0.03)	(0.02)
B. Spending, Price-Adjusted	653.15	400.68	473.11	214.45
	(56.96)	(43.70)	(102.81)	(95.81)
C. Measures of Dangerous Opioid Overlap				
Days Overlap with Muscle Relaxants	-0.01	0.03	0.05	0.04
	(0.08)	(0.06)	(0.32)	(0.26)
Days Overlap with Antipsychotics	-0.10	0.00	-0.47	-0.05
	(0.08)	(0.06)	(0.23)	(0.20)
Days Overlap with Sleep Aids	0.09	-0.04	-0.02	0.30
	(0.08)	(0.06)	(0.24)	(0.19)
Days Overlap with Other Opioids	0.04	-0.05	0.05	0.30
	(0.10)	(0.07)	(0.33)	(0.26)
1[Any Overlap Above]	-0.0028	-0.0009	-0.0039	0.0019
	(0.0012)	(0.0009)	(0.0022)	(0.0018)
D. Measures of Dangerous Opioid Receipt				
1[Long Duration] (>210 Days)	0.0004	-0.0012	-0.0026	0.0010
	(0.0009)	(0.0007)	(0.0019)	(0.0015)
Days with High Dose (>90 MME)	0.34	0.29	1.08	0.87
	(0.24)	(0.19)	(0.54)	(0.43)
1[Long Duration or High Dose]	0.0004	-0.0012	-0.0022	0.0007
	(0.0010)	(0.0008)	(0.0020)	(0.0016)
E. Measures of Prescribing Intensity				
Days of Opioids	-0.28	-0.45	-1.49	0.60
	(0.33)	(0.24)	(0.83)	(0.69)
MME of Opioids	24.70	13.41	107.97	123.06
	(19.34)	(12.16)	(82.93)	(67.74)
1[Any Opioid]	-0.0050	-0.0004	-0.0021	-0.0001
	(0.0017)	(0.0013)	(0.0023)	(0.0019)
Days of Muscle Relaxant	-0.01	0.09	0.22	-0.26
	(0.14)	(0.10)	(0.47)	(0.37)
Days of Antipsychotics	-0.39	-0.31	0.16	-0.51
	(0.29)	(0.22)	(0.76)	(0.66)
Days of Sleep Aids	-0.07	0.35	-0.38	0.23
	(0.20)	(0.16)	(0.40)	(0.33)
Fills of All Prescription Drugs	-0.84	-0.48	-0.97	-0.60
	(0.12)	(0.09)	(0.20)	(0.17)
Days of All Prescription Drugs	3.53	-1.97	-2.86	-9.99
	(3.09)	(2.42)	(5.52)	(4.61)
N Observations	4,459,556	4,459,556	1,669,765	1,669,765

Notes: This table presents results for disabled beneficiaries, defined as individuals who originally joined Medicare via SSDI. Columns 1 and 2 repeat results from the original sample of old-age beneficiaries in Table 2. Columns 3 and 4 analyze the sample of disabled beneficiaries. All columns use the fragmentation measures of the main analyses, which were calculated from the old-age sample. See text for more details. Robust standard errors clustered at the patient level in parentheses.

Appendix Table A10 – Summary Statistics for Movers and Non-Movers

	Movers (By Direction)		Non-Movers
	Higher	Lower	
A. Indices of Fragmentation			
Provider Fragmentation	0.65	0.65	0.63
Organizational Fragmentation	0.25	0.25	0.24
Share of Providers in Health Systems	0.43	0.43	0.43
B. Spending	8,663	8,664	8,493
C. Measures of Dangerous Opioid Overlap			
Days Overlap with Muscle Relaxants	2.15	2.31	1.96
Days Overlap with Antipsychotics	1.31	1.54	1.23
Days Overlap with Sleep Aids	2.26	2.41	2.11
Days Overlap with Other Opioids	3.85	3.93	3.50
Share with Any Overlap Above	0.13	0.14	0.12
D. Measures of Dangerous Opioid Receipt			
Share Long Duration (>210 Days)	0.06	0.06	0.06
Days with High Dose (>90 MME)	5.44	5.52	5.48
Share with Long Duration or High Dose	0.08	0.09	0.08
E. Measures of Prescribing Intensity			
Days of Opioids	31.3	32.3	30.6
MME of Opioids	1,039	1,075	1,016
Share Any Opioid	0.32	0.32	0.31
Days of Muscle Relaxants	5.63	6.02	5.21
Days of Antipsychotics	11.9	13.2	10.5
Days of Sleep Aids	12.0	12.9	10.6
Fills of All Prescription Drugs	34.4	34.7	34.8
Days of All Prescription Drugs	1,402	1,409	1,379
F. Patient Characteristics			
Age	76.4	76.5	75.7
Asthma	0.04	0.05	0.04
Depression	0.14	0.15	0.11
Alzheimers or Dementia	0.11	0.11	0.09
Diabetes	0.25	0.26	0.27
Heart Condition	0.34	0.34	0.32
Any Cancer	0.07	0.08	0.07
Stroke or Hypertension	0.56	0.57	0.54
Patients	53,163	44,058	916,642
Observations (Patient-Years)	341,207	278,013	4,071,248

Notes: This table uses the analysis sample, with each column representing a subset of it. Number of observations for chronic conditions in Panel F (Asthma – Stroke or Hypertension) slightly smaller due to requirement to have these indicators from data in previous year.