Partial Outsourcing of Public Programs: Evidence on Determinants of Choice in Medicare.*

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Abstract

Many public programs let individuals choose between publicly provided benefits and a subsidized private alternative. We investigate the determinants of health insurance choice in Medicare—a setting with vast geographic variation in the share of individuals selecting the public option versus private alternative. We analyze insurance decisions among individuals who move to quantify the relative importance of individual-specific factors (such as preferences or income) and place-specific factors (such as local health insurance options) on insurance decisions. We find roughly 40% of the geographic variation in the share selecting private coverage is due to place-based factors, while the remainder is explained by individuals. Our findings highlight the importance of individual factors in these decisions and may inform discussions about the use of policy to address geographic disparities.

Keywords: Public provision of health insurance, geographic variation, Medicare, health insurance

JEL Codes: H51 (Government Expenditures and Health), I11 (Analysis of Health Care Markets), I13 (Health Insurance, Public and Private)

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A perpetual policy debate is whether the government should directly provide public benefits or outsource provision. With this debate in the background, many government programs have turned to partial outsourcing, giving individuals choice between direct government provision or a subsidized private alternative. Allowing choice between public and private provision has the potential to harness the benefits of competition, while accommodating variation in beneficiary preferences for the form of benefits. A leading example is the case of government provision of health insurance for the elderly and disabled through the federal Medicare program—where beneficiaries are given the choice between government-provided public Traditional Medicare (TM) coverage and government-subsidized private Medicare Advantage (MA) coverage. These two health insurance options are horizontally differentiated. Relative to TM, private MA coverage typically provides more generous financial protection, in exchange for greater utilization management and a more restrictive network of providers.

While nearly half of Medicare beneficiaries currently choose this private option (KFF, 2022), there has always been wide geographic variation in MA enrollment. The share of Medicare beneficiaries choosing MA exceeds 67% in Minnesota but is less than 10% in Alaska or Wyoming. Disparities in coverage are large even within states, with the share selecting MA varying from 5.8% to 67.4% across Texas counties and 5.1% to 73.1% across California counties. Concerns over these geographic disparities were raised at Congressional hearings prior to the last major reform to MA (Committee on Energy and Commerce, 2001; Committee on Ways and Means, 2001) and are reflected in the numerous adjustments to MA subsidies designed to raise payments in areas with low enrollment (DeParle, 2002). However, it is unclear whether low MA take-up in some areas is explained by supply-side factors or whether individuals in these areas simply have weaker preferences for private coverage. Understanding the extent to which supply-side versus demand-side factors explain geographic variation in private insurance enrollment in Medicare is critical for informing both the objectives of policymakers and the impacts of policies aimed at achieving these objectives.

In this paper, we investigate the determinants of the choice of public versus private health

insurance in the context of Medicare. Using a "movers" research design (Finkelstein, Gentzkow and Williams, 2016), we compare health insurance decisions before and after a move among individuals who move between areas with differing MA popularity. Individual insurance decisions may be influenced by place-based factors, such as competition among private insurers or local provider networks, or individual factors such as preferences, income, and health. The intuition behind the movers research design is simple: an individual who moves carries with them their tastes and attributes——both observed and unobserved—but is faced with new place-based factors after the move. Thus, we can analyze changes in individual decisions upon moving to distinguish the relative importance of place- and individual-based factors on these insurance decisions.

Our event study analysis correlates MA enrollment trends among movers in the years surrounding a move with their destination-origin difference in the share enrolled in MA. This analysis reveals no correlation in movers' insurance choices prior to the move. Upon moving, there is a sharp increase in MA enrollment among individuals moving to areas with greater MA prevalence, with estimates indicating a 4 percentage point (p.p.) increase in the likelihood of selecting MA after moving to an area with 10 p.p. higher MA enrollment. Additionally, the observed change in movers' propensity to select MA appears linear in the destination-origin difference in MA enrollment. Our estimates indicate that 43% of the difference in MA enrollment across areas in the top- and bottom-quartile of MA prevalence is due to place-based factors, with the remaining 57% due to individual factors. Further, our estimates suggest that 41% of the observed cross-sectional variance in MA enrollment would persist if all place-based factors were counterfactually made uniform across places.

We then present supplemental evidence related to possible mechanisms behind our findings. First, we examine correlates of the estimated place effects and average individual effects. Findings from this correlational analysis are broadly consistent with intuition and institutional features. For instance, place effects are positively correlated with county-level MA per-capita subsidies and negatively correlated with MA insurer concentration. Second, we provide addi-

tional evidence on the potential determinants of place effects by examining how prescription drug utilization patterns (and inferred health care delivery patterns) change when moving to areas with differing MA prevalence among movers who are consistently enrolled in either TM or MA throughout. We find that moving to a region where MA is more prevalent results in a greater share of prescriptions from primary care physicians and mid-level providers (as opposed to specialists), regardless of whether an individual is consistently in TM or MA. We also find moving to an area with higher MA enrollment is associated with increases in prescription drug utilization among individuals who are always in MA. While only suggestive, these findings highlight potential features of local health care markets—and local MA plans—that could allow MA to achieve large market shares.

This paper contributes to a broader literature investigating public programs with parallel public and private provision. Prior work has explored the consequences of public versus private provision on outcomes in settings such as housing assistance programs (e.g., Katz, Kling and Liebman (2001), Chetty, Hendren and Katz (2016)), education (e.g., Abdulkadiroğlu et al. (2011), Dobbie and Fryer (2011)), and health care (e.g., Chan, Card and Taylor (2022), Knutsson and Tyrefors (2022)). Our work complements this literature by investigating the determinants of choice between public and private options and by providing evidence on these determinants in one of the largest social insurance programs in the U.S.

Our work is also related to a literature on the Medicare program which has explored the impact of the design of federal subsidies for private MA coverage—focusing on specific policies targeting place (e.g., Cabral, Geruso and Mahoney (2018), Curto et al. (2021), Miller et al. (2019)), risk (e.g, Brown et al. (2014)), and quality (e.g., Vatter (2022), Layton and Ryan (2015)). This paper contributes to this literature by taking a step back to ask: How much of the large geographic variation in MA enrollment can be explained by all place-based factors collectively? The answer to this question has important implications for policy. Policymakers have often interpreted the large observed geographic variation in MA enrollment as *prima facie* evidence of disparities in access to high-quality MA plans. In contrast to this

interpretation, our findings suggest that more than half of the geographic variation in MA enrollment is due to variation in individual factors. An important implication of these findings is that geographic variation in MA enrollment alone may not provide a rationale for policy intervention. Moreover, our analysis indicates that even if adjustments in MA policy could fully offset differences in place-based factors across areas, more than 40% of the existing variation in MA enrollment would remain. Thus, our findings suggest that substantial variation in MA enrollment would persist regardless of policy efforts to equalize access and that this variation is not an appropriate metric for measuring the success of such policies.

More broadly, our findings suggest individual factors—such as preferences and health—play an important role in explaining insurance decisions in Medicare. Given the characteristics that differentiate the public and private options in Medicare, our results suggest there may be substantial variation in individual preferences for insurance providers, networks, and out-of-pocket costs and point to the potential value of offering choice along these dimensions. By highlighting possible benefits of offering choice between public and private options, our work complements a literature exploring policy challenges that arise with partial outsourcing in Medicare and other public programs.[1]

Finally, our work contributes to a growing literature investigating geographic variation in health care settings, which has primarily focused on health (e.g., Finkelstein, Gentzkow and Williams (2021)) and health care production (e.g., quantity (e.g., Finkelstein, Gentzkow and Williams (2016)), price (e.g., Cooper et al. (2018)), and practice styles (e.g., Cutler et al. (2019), Molitor (2018))). Our work extends this literature by documenting geographic variation in health insurance choices and exploring determinants of this variation.

[1]For example, prior work has explored market power and selection in Medicare (e.g., Brown et al. (2014), Duggan, Starc and Vabson (2016), Cabral, Geruso and Mahoney (2018), Geruso and Layton (2020)) and other public programs with partial outsourcing (e.g., Figlio and Stone (2001), Altonji, Huang and Taber (2015), Bergman and McFarlin (2018), Bauhoff (2012), Polyakova (2016), Nuscheler and Knaus (2005)).

1 Background & Data

1.1 Background

Elderly and disabled individuals in the U.S. are eligible for health insurance through Medicare and can select either public TM or private MA coverage. MA coverage typically requires less patient cost-sharing but often offers a more restricted network of providers. MA plans may also offer supplemental benefits not offered by TM such as vision, dental, or hearing services. Each MA plan specifies a set of counties—a service area—in which to market the plan; in these counties, they must accept all beneficiaries who apply. For each enrollee, the plan collects a premium and a federal subsidy. The subsidies are tied to TM costs in the enrollee's county and are risk adjusted based on the enrollee's documented medical conditions.

Any Medicare beneficiary can switch between TM and MA or among MA plans each fall, and TM represents the default for MA enrollees in cases of disenrollment due to missed premiums, plan exit, or a beneficiary's move to an excluded region. After a move, many beneficiaries may be able to continue their previous coverage[2]; a TM enrollee can always remain in TM, and many MA enrollees can remain in the same MA plan. However, even among movers with the option to remain in the same MA plan, many may want to select among the locally offered MA plans in the destination, which often include more nearby providers in their network. Movers who would like to change between TM and MA or among MA plans can usually do so right away (a "Special Enrollment Period") or during the fall open enrollment period (CMS, 2006).

1.2 Data and Measurement

This paper leverages administrative data on enrollment, coverage, and demographics for the universe of Medicare beneficiaries from the Medicare Beneficiary Summary File and administrative prescription drug claims from the Prescription Drug Event (PDE) file covering a

[2]Many MA plans have a broad or nationwide service area. In addition, many MA plans opt to retain individuals who move out of the plan's service area.

random 20% subsample of Medicare beneficiaries with Part D prescription drug coverage. These datasets span 2007 to 2017. Appendix Section A provides more details on additional data sources and sample restrictions.

Throughout the analysis, we focus on Medicare beneficiaries who are at least 65 years of age—thereby excluding non-elderly beneficiaries with disabilities or end-stage renal disease. We use "county" as our key geographic unit of analysis because MA service areas are specified as sets of counties. The data reflect beneficiary county of residence on file with the Social Security Administration (SSA) as of March 31^{st} of each calendar year. To align with this timing, we define "year" t throughout as a twelve-month interval that begins on April 1^{st}. We define an individual as "moving" in year t if their county of residence at the beginning of year t differs from their county of residence at the beginning of year $t+1$. We limit our attention to Part D enrollees, and further restrict our sample of movers to those whose claims appear in the PDE data.[3] We define event time as years since individual i's move, denoted $r(i,t)$, where $r(i,t) = 0$ represents the year of the move. We exclude individuals who move in 2007 (who are only observed after moving) or who move more than once over the analysis period.

We restrict attention to movers who appear to have shifted their prescription drug consumption from the origin to the destination coincident with the move. This restriction excludes individuals who update their residence on file with SSA without altering their behavior (e.g., those who change their address to that of an adult child or secondary residence). Specifically, we restrict our attention to movers who increase the share of prescription drug fills at destination pharmacies (among fills at either the origin or destination) by at least 75 p.p.[4] Among all movers in the PDE data, approximately 57% or 348,199 movers change their prescription filling behavior consistent with an actual move. Appendix Figure A1 demonstrates that, after this restriction, our "first stage" change in prescription filling behavior is essentially one—with movers filling nearly no prescriptions in the destination before the move and nearly all pre-

[3]Roughly 65% of Medicare beneficiaries have Part D, with a random 20% of these individuals represented in the PDE data. While we make these sample restrictions to examine how consumption patterns change with recorded residence, we obtain very similar findings when dropping these restrictions (Appendix Figure A2).

[4]This sample restriction parallels an analogous restriction on medical claims used in Finkelstein, Gentzkow and Williams (2016).

scriptions in the destination after the move. Appendix Figure A2 shows that our main findings are very similar if we drop this restriction and scale the resulting event study estimates by the smaller "first stage" for this broader group of movers.

Our key dependent variable, MA_{it} is set to 1 whenever individual i has any months of MA enrollment in year t. Let $\overline{MA}_j = \frac{1}{T}\sum_t \left\{ \mid \mathcal{C}_{jt} \mid^{-1} \left(\sum_{i \in \mathcal{C}_{jt}} MA_{it} \right) \right\}$ represent the average MA enrollment in county j over the sample period, where $\mathcal{C}_{jt}$ represents the universe of Medicare beneficiaries living in county j in year t. The difference between MA enrollment ($\overline{MA}_j$) in individual i's destination and origin is captured in the variable $\widehat{\delta}_i$, and serves as a continuous measure of the "treatment" to which a mover is exposed upon moving.

Appendix Table A1 reports summary statistics on our sample. Movers are slightly more likely to be female, white, and older than nonmovers, and are observed for more years. Throughout we include individual fixed effects to account for any time-invariant differences between movers and nonmovers. In some supplemental analyses, we use a sample of "matched nonmovers" consisting of a randomly selected nonmover for each mover who is matched at the individual level on origin county, gender, race, five-year age bin, and enrollment in Medicare during the relevant years. Since our counterfactual analysis assumes that the behavior of movers is informative for nonmovers, it is reassuring that movers, nonmovers, and matched nonmovers all enroll in MA at similar rates, even net of county fixed effects.

Appendix Table A1 panel (b) summarizes transition patterns between TM and MA in the years surrounding a move (for movers and matched nonmovers) or other three-year intervals (for the broader nonmover sample). A large majority—85%—of movers maintain their pre-move choice of either TM or MA. However, movers are about twice as likely as matched nonmovers to either join or leave MA in the three-year interval surrounding their move.

2 Empirical Strategy

2.1 Econometric Specification

Our movers research design follows methods developed in Finkelstein, Gentzkow and Williams (2016) and subsequent related work.[5] We use two specifications to analyze MA enrollment decisions. First, we estimate an event study specification that investigates how movers' MA choices reflect differences in MA prevalence in their destination relative to origin. Specifically, we estimate the following equation:

$$MA_{it} = \sum_{r \neq -1} \theta_r I[r(i,t) = r]\widehat{\delta}_i + \tau_t + \alpha_i + x_{it}\beta + \varepsilon_{it}, \tag{1}$$

where the key coefficients are θ_r which are event-time-specific coefficients on $\widehat{\delta}_i$—the difference in MA enrollment between individual i's destination and origin. This specification also includes year fixed effects, τ_t, to flexibly account for national trends in MA enrollment. We also include individual fixed effects, α_i, to account for the possibility that movers differ from nonmovers in their MA enrollment behavior or that individuals with high MA demand choose to move to destinations with high MA enrollment. Additionally, we include other controls (x_{it}) for age (in five-year bins) and for event time. Both movers and nonmovers are included in the estimation, where event time is set to zero for nonmovers. Standard errors are clustered at the individual level.[6] Beyond estimating the event-time-specific θ_r coefficients, we also summarize these coefficients via a linear combination of the post-period coefficients weighted by the number of movers contributing to each coefficient.

The identification assumption is that MA enrollment would have evolved similarly for movers exposed to different changes in MA prevalence upon moving. While this is fundamen-

[5]For example, see other research on the determinants of health care that exploits moves among individuals (Agha, Frandsen and Rebitzer, 2019; Godøy and Huitfeldt, 2020; Finkelstein et al., 2022; Ding, 2022; Zeltzer et al., 2021) and physicians (Molitor, 2018; Beheshti and Neller, 2021; Doyle and Staiger, 2021; Badinski et al., 2023).

[6]The confidence intervals are virtually unchanged when using two-way clustering on origin and destination county.

tally untestable, we find the identification assumption plausible given that individuals likely choose to move to particular destinations based on a number of factors (e.g., family, housing costs) and consideration of MA enrollment options may be second order. Further, our event study estimates provide support for the plausibility of the identification assumption by illustrating that pre-move MA enrollment evolved similarly for movers differentially exposed to changes in MA prevalence upon moving.

Second, we estimate a fixed-effects specification with data from both movers and nonmovers using the following equation:

$$MA_{it} = \alpha_i + \gamma_{j(i,t)} + \tau_t + x_{it}\beta + \varepsilon_{it}. \tag{2}$$

This specification includes a full set of individual (α_i), place (county) (γ_j), and time (τ_t) fixed effects. This specification also includes additional controls (x_{it}) for five-year age bins and event time (all set to zero for nonmovers). For movers, we exclude the year of the move and the year following it because our event study estimates suggest these are periods of adjustment.

Using estimates from this specification, we calculate each county's "place effect" (the estimated fixed effects, γ_j) and "average individual effect" ($\overline{y}_j \equiv \overline{MA}_j - \gamma_j$). We use these county-level place and individual effects to measure the relative contribution of features of a place and its residents in determining MA enrollment. First, we can compare groups of counties to decompose how much of the overall difference in MA enrollment is attributable to differences in their place effects versus differences in the mean individual effects. The share attributable to individual factors can be interpreted as the share of the difference in MA enrollment we would expect to remain if place effects were counterfactually made equal across these groups of places.

As a natural extension, we can predict the reduction in the cross-sectional variance in MA enrollment that would result from equalizing place effects across *all* counties. Mathematically, this is given by $1 - \text{var}(\overline{y}_j)/\text{var}(\overline{MA}_j)$ (where "var" is the variance over counties, weighted by the number of Medicare beneficiaries in the county over the analysis period). Alternatively,

suppose Medicare beneficiaries were randomly reallocated such that individuals are (on average) uniform across counties and hence mean individual effects would be equalized across areas; this would reduce the cross-sectional variance by $1 - \text{var}(\gamma_j)/\text{var}(\overline{MA}_j)$.

2.2 Descriptive Evidence and Identifying Variation

First, we describe geographic variation in MA enrollment. Figure 1 displays county-level MA enrollment, representing each quintile of the MA enrollment distribution in a different shade. The fraction of beneficiaries enrolled in MA varies widely nationally, with an interquartile range spanning 14.7% to 37.8%. There is also substantial variation in MA enrollment within states, with 24 states containing counties from both the top and bottom quintile. While MA tends to be more popular in urban areas, high MA enrollment is observed in many rural areas, such as the upper Midwest and Appalachia.

Appendix Figure A3 plots a histogram of the destination-origin difference in average MA enrollment ($\widehat{\delta}_i$) among movers. The distribution is centered on zero, indicating that movers are just as likely to move to regions with lower or higher MA enrollment compared to their origin. Further, the figure illustrates that movers are commonly subject to very different MA environments in their destination relative to their origin, with the interquartile range of this destination-origin difference spanning -0.114 to 0.126, i.e. 11.4 p.p. lower or 12.6 p.p. higher MA enrollment relative to their origin.

3 Results

3.1 Event Study Results

We begin by showing non-parametric evidence on the relationship between the destination-origin difference in MA enrollment and changes in an individual's own MA enrollment upon moving. Figure 2 plots this relationship, where the horizontal axis measures the destination-origin difference in MA enrollment ($\widehat{\delta}_i$) binned into ventiles, and the vertical axis measures the

average change in MA enrollment between two to five years before and after the move. The figure illustrates that individuals moving to areas with higher (lower) MA coverage have an increased (decreased) likelihood of selecting MA coverage after the move. The magnitude of this relationship is notable: a 10 p.p. increase in the destination-origin difference is associated with a 3.9 p.p. increase in probability that the mover selects MA coverage after the move. Further, this figure suggests this relationship is roughly linear, providing support for δ_i entering linearly in the event study specification.

Next, we consider whether individuals who move to areas with higher MA enrollment differ systematically in their taste for MA, as captured by their pre-move MA enrollment behavior. Appendix Figure A4 plots the relationship between destination-origin MA enrollment differences and pre-move MA enrollment differences comparing movers to matched nonmovers. This figure depicts a small positive slope (0.07) illustrating that movers who will move to higher MA enrollment regions have slightly higher pre-move MA enrollment propensities than their nonmover counterparts; however, this relationship is much weaker than that depicted in Figure 2. Importantly, any time-invariant differences between movers and nonmovers in their MA enrollment are accounted for by including individual fixed effects in the analysis throughout.

Figure 3 reports the main event study estimates. There is no correlation between pre-move MA enrollment and the destination-origin MA enrollment difference associated with their future moves. However, we see a sharp increase in MA enrollment upon moving among movers exposed to higher MA enrollment in their destination relative to their origin. The move year and the following year are a period of adjustment, which is expected since individuals may move in any month within the move year and often adjust MA enrollment during the following annual open enrollment period. By two years after the move, MA enrollment starts to stabilize and fully levels off by the end of our analysis period, suggesting that any potential short-run enrollment frictions or learning in this setting play a limited role in the medium-run. Excluding the adjustment period, the event study coefficients average to 0.414 in years two and beyond, indicating the likelihood of MA enrollment increases by roughly 4 p.p. when

moving to a county with 10 p.p. higher MA enrollment. The effects are precisely estimated with a 95% confidence interval spanning 0.405 to 0.422.

Our findings are very similar when we use alternative strategies that address potential issues related to heterogeneity in treatment effects by treatment timing (see de Chaisemartin and D'Haultfœuille (2022) for a discussion). See Appendix Figure A5 for estimates from the event study specification by year of move and Appendix Figure A6 for estimates from an imputation-based estimation strategy.

3.2 Decomposition of Variation in MA Enrollment

Using variation from movers, we estimate equation (2) to assess how much of the observed MA enrollment differentials are attributable to features of places versus individuals living in these places. In Appendix Table A2, we use our estimates to compare counties in the top quartile of the MA enrollment distribution (average MA share 57%) to those in the bottom quartile (average MA share 10%). The average difference in place factors between these sets of counties is 20 p.p., or 43% of the overall difference in MA enrollment. Implicitly, the remaining 57% of the difference in MA enrollment is attributable to individuals. We find a similar portion of the difference in MA enrollment is attributable to place when considering other characterizations of the top and bottom of the MA enrollment distribution. The last column splits counties into urban and rural. MA enrollment averages 49% in urban counties, while just 29% in rural counties. We again find that just over half of this difference is attributable to differences in individuals residing in urban and rural counties.

The fact that both place and individual effects contribute to MA enrollment suggests that variation in MA enrollment would persist even if either effect were made uniform nationwide. For example, we can use our estimates to consider the effect of hypothetically equalizing place-based factors—the features of the local MA plans, health care system, or place more broadly that lead to different levels of MA enrollment—across all counties. Even if place-based factors were equalized, Appendix Table A3 illustrates that 41% of the observed variance in

MA enrollment would remain.

Two caveats apply when interpreting this analysis. First, this analysis holds fixed individual factors. The fact that our event study coefficients level off by the end of our analysis period is consistent with persistent individual factors. While this suggests our estimates may be appropriate for evaluating short- to medium-term counterfactuals, more caution is warranted in predicting impacts in the long run when changes to individual health or preferences (e.g., habit formation) may be more of a concern. Second, this analysis applies coefficients identified by movers to all beneficiaries. While movers and nonmovers are similar in terms of (premove) MA enrollment levels and trends, other factors may differ across movers and other beneficiaries that limit the broader applicability of our estimates. For instance, the extent to which beneficiaries make active decisions—and hence their sensitivity to place-based factors—may differ among movers and others, though the direction of any potential difference is unclear. Movers may make more active decisions than continuing Medicare beneficiaries who do not move—as movers are prompted to re-evaluate many health care and insurance decisions after a move. At the same time, our movers research design excludes newly-eligible beneficiaries, and it is not clear how movers compare to newly-eligible Medicare beneficiaries in terms of making active decisions.[7] If movers engage in more active decision-making than Medicare beneficiaries overall, our counterfactual analysis understates the share of the MA enrollment variation that would remain in the short-run if place-based factors were hypothetically equalized. Our results are less informative about the long-run implications of equalizing place effects, as predicting long-run impacts would rely on extrapolating further from our estimates based on movers to decisions of newly-eligible beneficiaries.

In light of these caveats, we view our estimates as most useful for evaluating the short- to medium-run responses in these counterfactuals. Nevertheless, this analysis suggests that variation in the composition of individuals across areas plays a central role in explaining the cross-sectional variance of MA enrollment, and policy aiming to equalize place-based factors

[7]Both newly-eligible beneficiaries and movers are prompted to carefully evaluate enrollment options and are subject to defaults if they do not make an active decision.

would leave substantial geographic variation in MA enrollment in the short- to medium-run.

3.3 Supplemental Evidence

The place and individual components of MA enrollment decisions could reflect a range of underlying factors. We consider potential mechanisms through two sets of supplemental analyses. First, we examine correlates of the estimated place and average individual effects. Second, we examine health care utilization changes among movers moving to places with differential MA prevalence. Appendix Section A describes data and measures used in these analyses.

Correlates of Place and Average Individual Effects We consider place characteristics such as features of the health care market—provider availability (primary care physicians or specialists per capita), hospital market concentration (hospital network HHI), and urbanization—as well as features of the MA insurance market—MA market concentration (MA insurer HHI), MA insurer advertising spending, and MA subsidy generosity (MA benchmarks). We also consider individual characteristics, such as demographic characteristics (age, sex, race) and economic characteristics (disability, dual eligibility, Medicare enrollment, household income, poverty rate, fraction completed high school) of the entire Medicare or elderly population that resides within the place. Additionally, as proxies for overall health risk and costs in a county, we use mean risk adjustment scores and mean risk-adjusted costs per capita among TM beneficiaries. We restrict attention to counties for which all measures are available; these 1,839 counties represent 85% of Medicare beneficiaries. Appendix Figure A7 illustrates the results are similar when dropping this restriction.

Figure 4 displays coefficients from separate bivariate OLS regressions on the indicated characteristic on the left and coefficients from a multivariate OLS regression on all characteristics on the right. The reported coefficients reflect the estimated effect (in standard deviation units) of a one standard deviation increase in the characteristic. The discussion below focuses on the associations that appear in both the bivariate and multivariate regressions.

Figure 4 panel (a) displays the correlations for the estimated place effects. These estimates

indicate that place effects are higher in counties that have less concentrated MA markets, have higher MA subsidies (benchmarks), and are more urbanized. Further, place effects are higher in areas where on average individuals are younger and in worse health (have higher risk-adjustment scores), and where (risk-adjusted) costs per capita are lower. This evidence broadly aligns with intuition and evidence from the prior literature, suggesting that—all else equal—higher MA subsidies and more MA insurer competition are associated with higher quality MA plans and higher MA enrollment (Cabral, Geruso and Mahoney, 2018).

Figure 4 panel (b) presents the analogous results associating average individual effects with place and individual characteristics. The estimates indicate that average individual effects are higher in areas where individuals on average are younger, are in worse health, and have lower (risk-adjusted) costs per capita. Average individual effects are also higher in counties that are more urban.[8] This evidence suggests age and health are key correlates of demand for MA, adding to a literature that has identified age and health as key predictors of health care consumption in other settings (Finkelstein, Gentzkow and Williams, 2016; Brot-Goldberg et al., 2017; Marone and Sabety, 2022).

Health Care Utilization and MA Prevalence To complement the correlates analysis above, we examine how aspects of health care delivery are related to MA prevalence. This analysis provides suggestive evidence on features of a local health care market (or local MA options) that differ across places with higher or lower MA penetration. In this way, this analysis points to potential factors that could contribute to the estimated place effects. To do this, we focus on individuals who consistently elected the same type of coverage—either TM or MA—before and after moving, and investigate how their health care utilization changes after moving to areas with higher or lower MA penetration.[9] Specifically, we reestimate our event study specification replacing the dependent variable with measures of health care utilization inferred

[8]Because place and average individual effects are positively correlated, it is not surprising that these qualitative patterns roughly follow the correlations in panel (a).

[9]We exclude movers who ever switch between TM and MA because their outcomes change both as a result of the move as well as any causal effects of the change in insurance enrollment.

from Medicare Part D prescription drug claims—data which are available for both TM and MA enrollees. We estimate this specification separately for those consistently enrolled in TM and those consistently enrolled in MA over the sample period. This analysis considers measures of prescription drug utilization, as well as broader measures of health care delivery patterns as inferred from prescription drug claims. These measures are summarized in Appendix Table A1 panel (c).

Figure 5 reports event studies for these outcomes. Panels (a) through (c) examine prescription drug utilization. Among MA beneficiaries, moving to an area where MA is more prevalent increases the likelihood of having any prescription drugs (by 0.3 p.p. for a 10 p.p. increase in the share MA) and the total days supplied (by 2% for a 10 p.p. increase in the share MA). MA beneficiaries who move to a region with higher MA prevalence also increase their adherence to their medication. In contrast, we find little evidence of changes in prescription drug utilization for TM beneficiaries. These results indicate that areas where MA is more prevalent have higher prescription drug utilization among MA beneficiaries but not TM beneficiaries. These patterns suggest potential ways in which MA plans may differ in areas where MA is more popular. For example, areas with higher MA prevalence may have higher quality MA plans with more generous prescription drug coverage.

Panels (d) through (f) examine additional aspects of health care utilization through the lens of the prescription drug claims data. Among both those with TM or MA, the share of prescription drugs prescribed by primary care physicians or mid-level providers (e.g., nurse practitioners) increases after moving to an area where MA is more prevalent, with analogous declines in the share prescribed by specialists. The estimates indicate the share prescribed by primary care physicians or mid-level providers increases by 0.8 p.p. among MA beneficiaries and 0.5 p.p. among TM beneficiaries when moving to an area with 10 p.p. higher MA penetration. For both TM and MA beneficiaries, the estimates also suggest a decline in the likelihood of obtaining a prescription through the emergency department (ED) after moving to an area where MA is more prevalent, though these patterns are less precise. Collectively, the estimates

in panels (d) through (f) point to features of the health care delivery system—as experienced by all Medicare beneficiaries, regardless of TM or MA enrollment—that are associated with greater MA prevalence. In particular, the results suggest that MA is more prevalent in areas where a larger share of care is managed by primary care or mid-level providers (as opposed to specialists) and where individuals are less likely to seek care through the ED.

It is important to exercise caution when interpreting these results, as these patterns could be driven by a number of factors. For example, patterns common to TM and MA beneficiaries could reflect place-based factors that influence MA insurer entry decisions or that influence consumer decisions to enroll in MA (e.g., being on MA may be more attractive in areas where care is more often managed by primary care providers). The patterns could also reflect the causal effect of increased MA penetration or competition on the broader health care market.

4 Conclusion

This paper explains the determinants of the vast geographic variation in the use of private health insurance in Medicare. Leveraging variation among movers, we find roughly 40% of the variation in MA enrollment is due to place-based factors, while the remainder is explained by the composition of individuals across places.

Enrollment in private MA coverage varies widely, and some areas have very low enrollment—20% of counties have less than 13% enrolled in MA. Policymakers have often interpreted low enrollment as a problem of unequal access to be solved via supply-side policies, such as increased subsidies to private MA plans. In contrast to this interpretation, our results indicate that variation in individual factors (e.g., preferences, health) also plays a large role in driving the observed geographic variation in MA take-up. In this way, our findings inform the interpretation of the geographic variation in MA enrollment and the rationale for (and potentially the targeting of) supply-side policy interventions. Moreover, our findings suggest interventions aimed at equalizing supply-side factors are unlikely to eliminate geographic disparities in coverage.

More broadly, geographic disparities may arise in any program that offers choice between public and private provision; for example, there are large geographic disparities in charter school enrollment (Epple, Romano and Zimmer, 2016). Our findings highlight the importance of determining the role of place and individual factors in interpreting geographic disparities and in considering policies that affect them.

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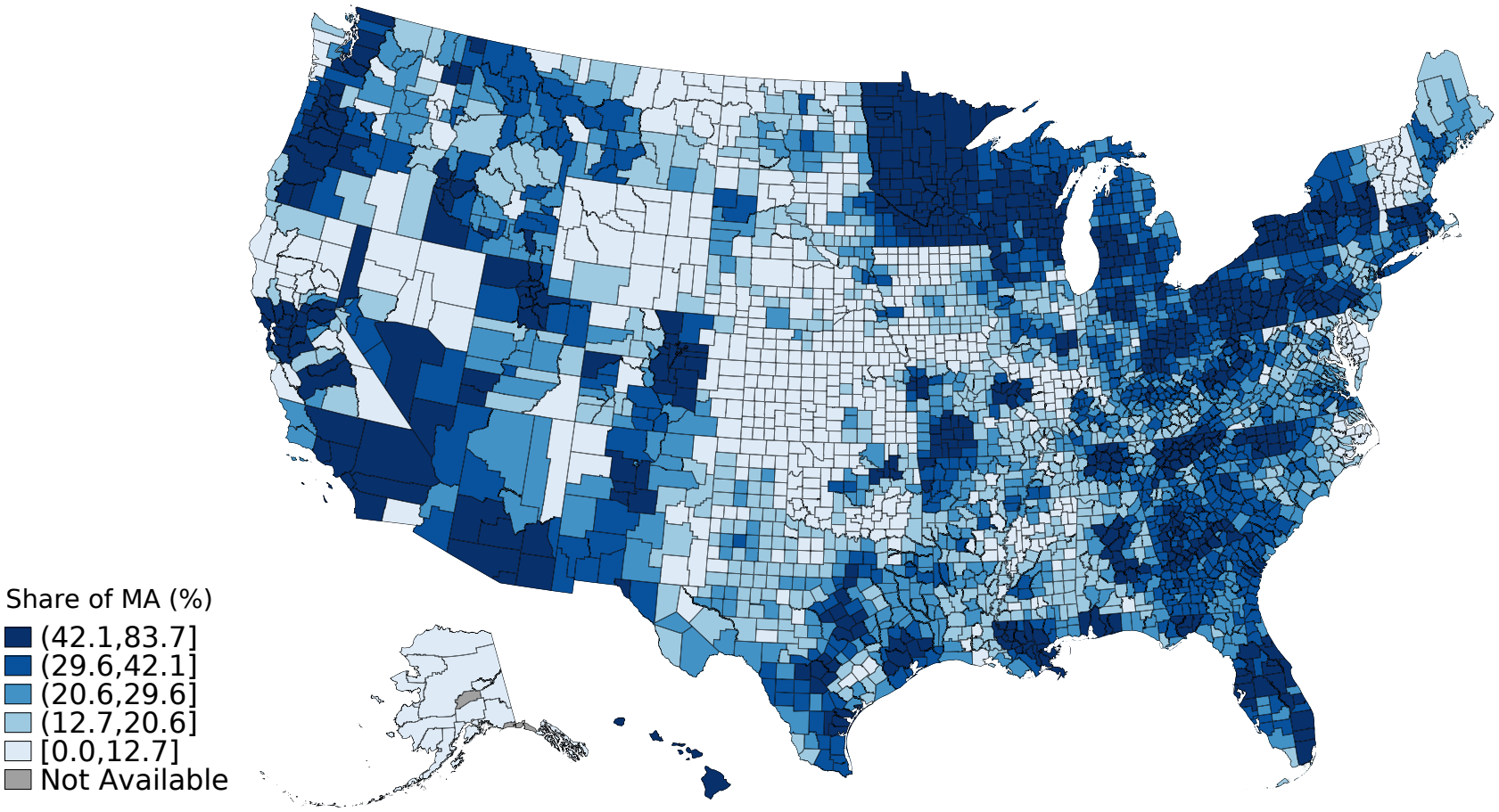
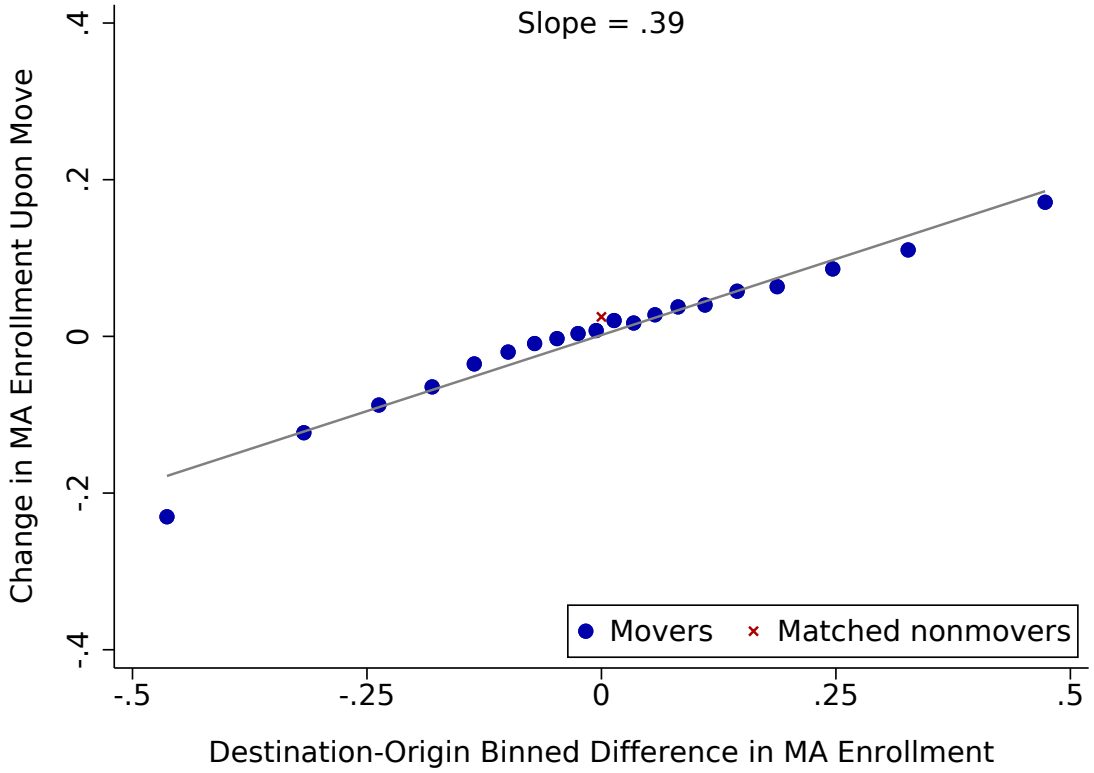
Figure 1: Medicare Advantage Enrollment Share By County



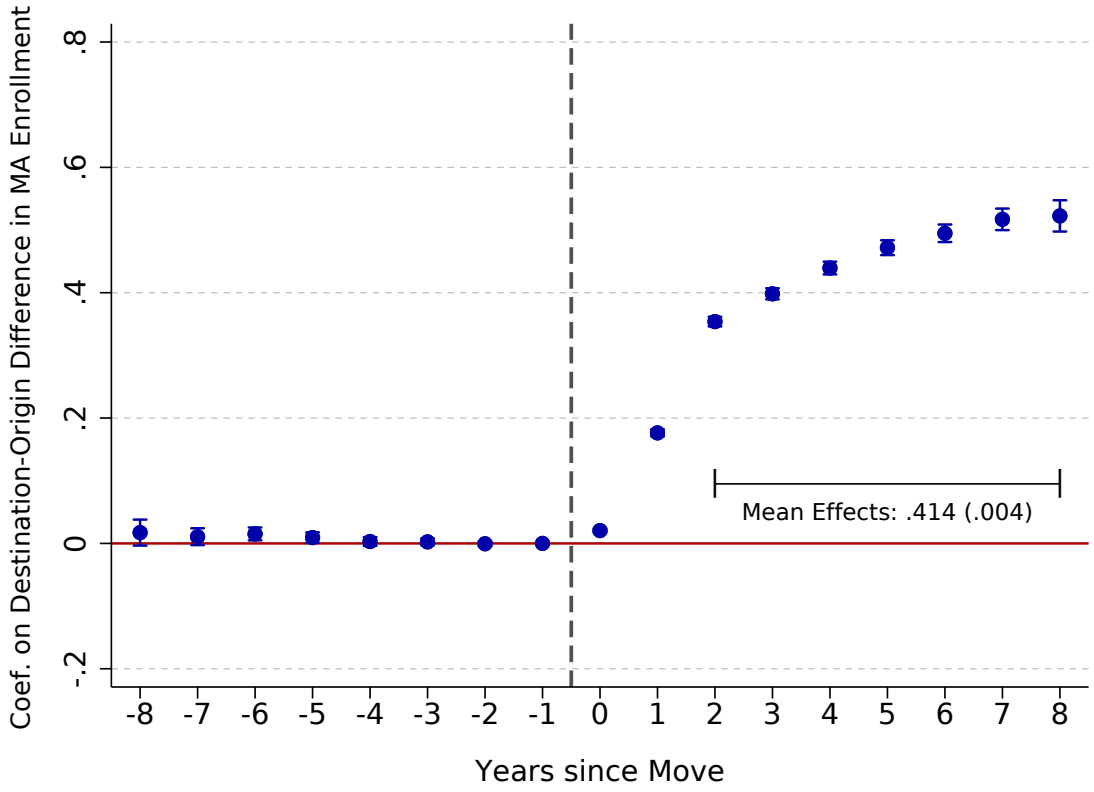
Notes: The map above displays the geographic (or county-level) distribution of Medicare Advantage (MA) enrollment rates in quintiles over the years 2007–2016. The MA enrollment rates are obtained by first calculating the MA enrollment share in the county in each year and then taking a simple average across years. A beneficiary with any months of MA enrollment in a given year is identified as an MA enrollee. The range of each quintile is displayed in the legend. The sample is *all* movers and nonmovers ($N = 236,810,684$ beneficiary-years).

Figure 2: Change in MA Enrollment Probability by Destination-Origin Difference



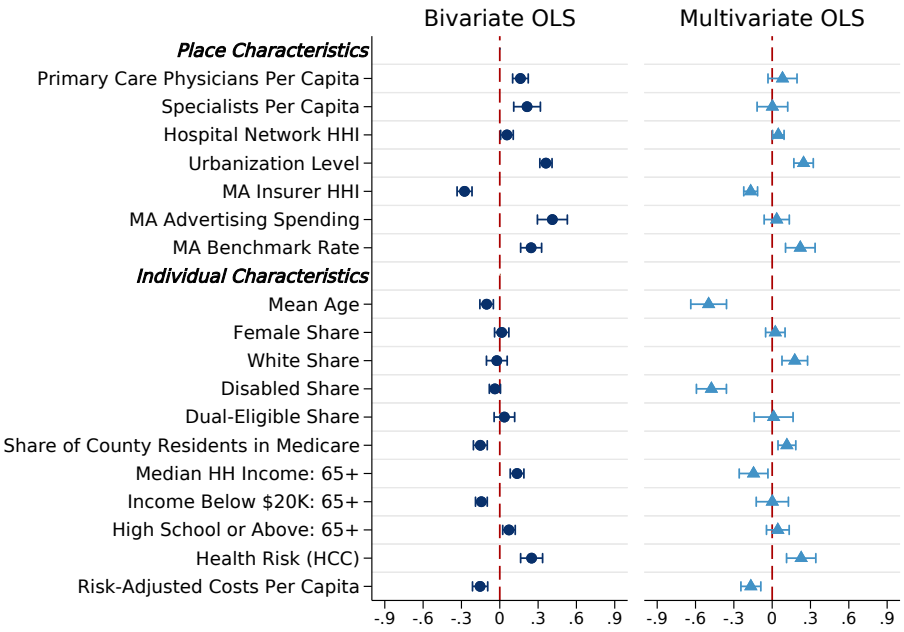
Notes: The figure above displays the change in MA enrollment probability before and after move by the size of movers' treatment intensity, $\widehat{\delta}_i$ (i.e., the destination-origin difference in the MA enrollment rates). Movers are grouped into ventiles by $\widehat{\delta}_i$. For each ventile, the x-axis displays the mean of $\widehat{\delta}_i$, and the y-axis displays the mean MA enrollment probability two to five years after move minus the mean MA enrollment probability two to five years before move. The line of best fit and its slope are obtained from a simple OLS regression using the 20 plotted points. For reference, we also display the analogous change among matched nonmovers, as indicated by x (in red). The sample is *baseline* movers and matched nonmovers observed between two to five years before and after move ($N = 933,354$ beneficiary-years).

Figure 3: Baseline Event Study

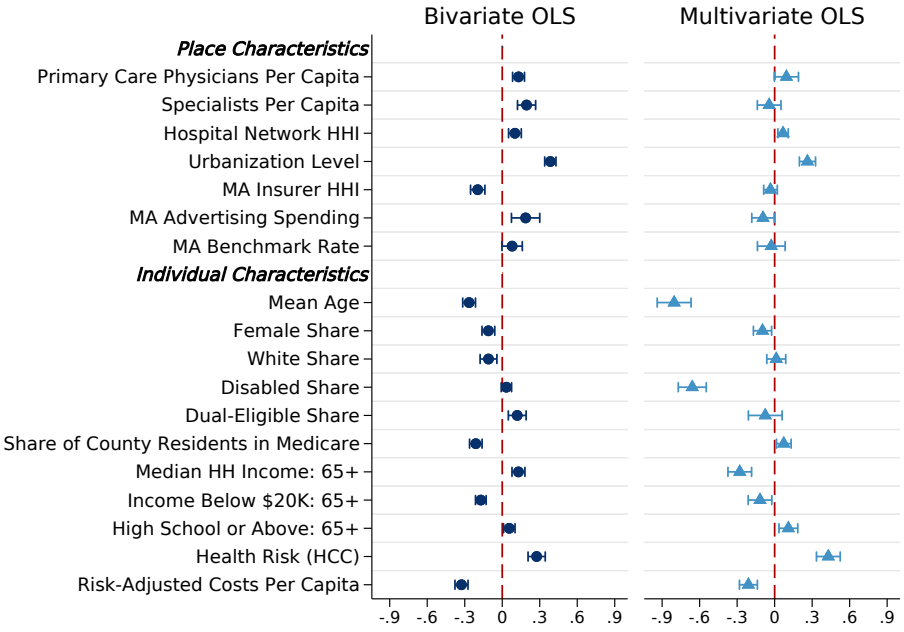


Notes: The figure above displays estimates, θ_r (i.e., the coefficients on relative years since move interacted with the treatment intensity $\widehat{\delta}_i$), from the event study estimation described in equation (1). The dependent variable is an indicator for any MA months. The regression includes place (or county) fixed effects, individual fixed effects, time (or year) fixed effects, indicators for relative years since move, and five-year age bins. Capped vertical bars indicate 95% confidence intervals, and robust standard errors are clustered at the beneficiary level. The reported mean effects are obtained by a linear combination of coefficient estimates in post-periods 2 to 8, weighted by the number of movers contributing to each period. The sample is *baseline* movers and all nonmovers ($N = 211,196,256$ beneficiary-years).

Figure 4: Correlates Analysis



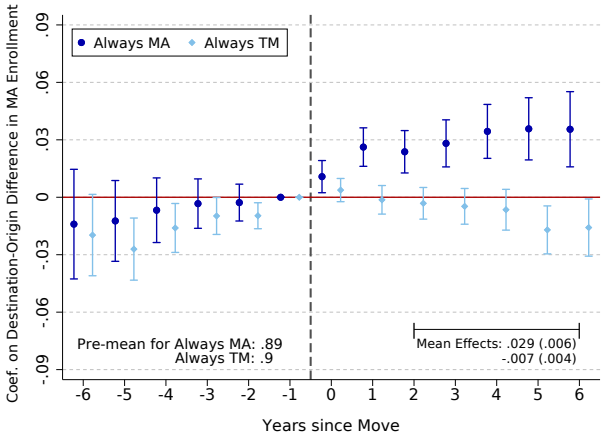
(a) Place Effects



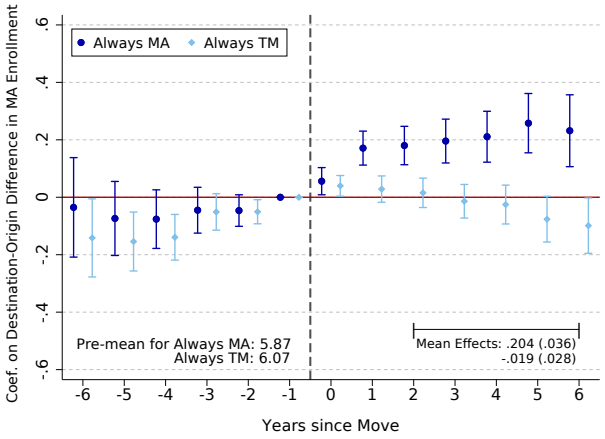
(b) Individual Effects

Notes: The figure above displays bivariate (left panel) and multivariate (right panel) OLS results of place effects (panel (a)) and individual effects (panel (b)) on various county-level characteristics. All measures and dependent variables are standardized to mean zero and variance one. Among individual characteristics, measures for income and education (i.e., Median HH income, income below $20K, high school or above) are estimated among those who are 65 or above, while all the other measures are estimated among Medicare beneficiaries. The sample is 1,839 counties (representing 85% of beneficiary-years) for which all 18 measures are available. See Appendix Section A.3 for more detail on the measures used for this analysis.

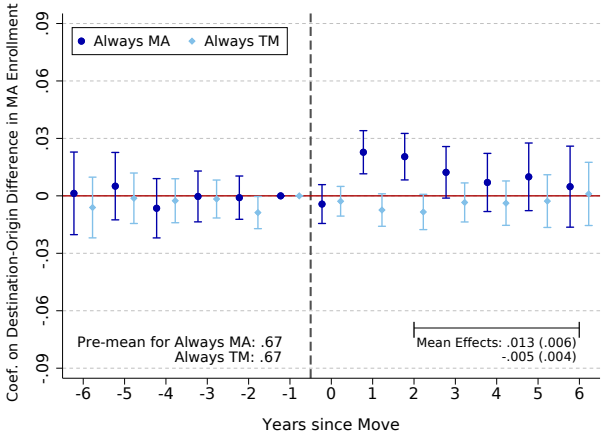
Figure 5: Effect on Prescription Drug Use and Care Delivery Patterns



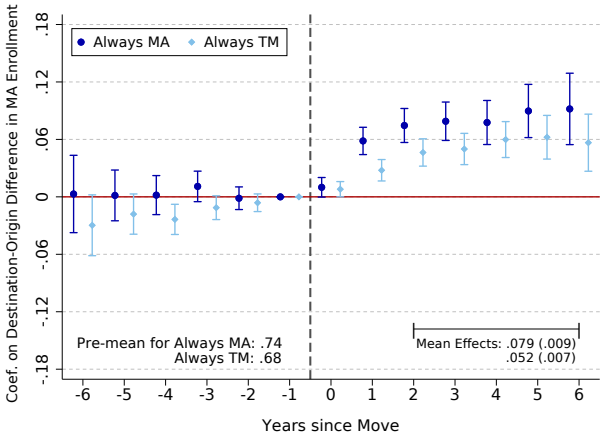
(a) 1(Any Script)



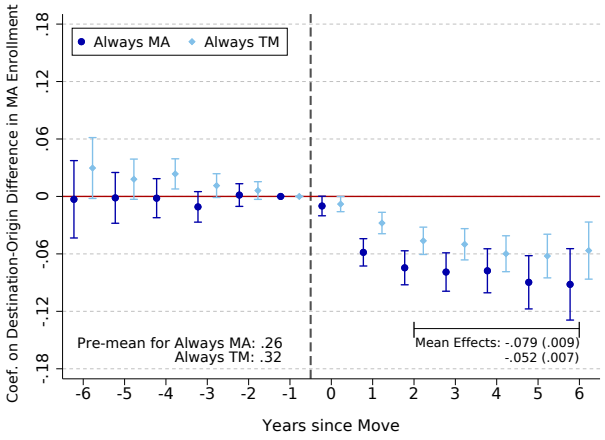
(b) Log(1+Days Supplied)



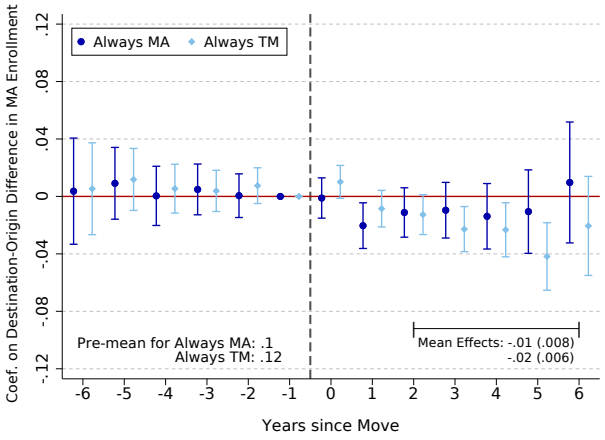
(c) Adherence



(d) Share by PCPs and Mid-levels



(e) Share by Specialists



(f) 1(Any Script by ED Doctor)

Notes: The figure above displays estimates, θ_r, from separate regressions of equation (1) by the type of consistent coverage. The dependent variables are as indicated in each panel. The reported mean effects are obtained by a linear combination of coefficient estimates in post-periods 2 to 6, weighted by the number of movers contributing to each period. The sample includes *baseline* movers and all nonmovers observed in the PDE datasets and who consistently elect either MA (Always MA) or TM (Always TM). See Appendix Section A.4 for more detail on the measures used for this analysis.

APPENDIX

A Sample and Variable Construction with Data Sources

This section provides details on the construction of the baseline sample and key variables used in this paper, along with the underlying data sources.

A.1 Baseline Sample

Primary Data Sources The primary data used to construct the baseline sample come from the Centers for Medicare and Medicaid Services (CMS) and cover 2007 through 2017. The Master Beneficiary Summary File (MBSF) contains data on the universe of Medicare enrollees and includes information on Medicare Advantage (MA) enrollment, Medicare Part D (prescription drug) enrollment, and demographics (e.g., age, sex, race, and location of residence). To investigate the location of prescription drug consumption among movers, we combine the MBSF with the Prescription Drug Event (PDE) data containing all prescription drug claims for a 20 percent random sample among Medicare enrollees obtaining prescription drug benefits from Medicare Part D. Finally, we obtain provider specialty information from Medicare Part B Carrier Line datasets.

Definition of Year t The MBSF includes the enrollee's residence location information as of March 31 of each year, based on the mailing address obtained from the Social Security Administration (SSA). To be consistent with the timing with which we observe the enrollee's residence, we define year t as the 12 months from April 1 of year t to March 31 of year $t+1$. We reorganize the MBSF datasets across years so that our analytical data representing year t include only appropriate monthly variables. Specifically, we merge the MBSF datasets for calendar years t and $t+1$ and then drop monthly variables outside of our notion of year t (i.e., January–February of calendar year t and April–December of calendar $t+1$). We also recode the enrollee's age as of the end of our definition year t. This reconstruction leads to the exclusion of enrollees in our dataset for year t if they do not appear for both calendar years t and $t+1$ and reduces our sample period by one year to 2007–2016.

Sample Restriction We apply the following four sample restrictions: (i) restrict individuals to those from the 50 states and District of Columbia, (ii) drop non-elderly individuals,[1] (iii) retain individuals who are *continuously* enrolled in Medicare Part D within a year, and (iv) exclude individuals without valid Federal Information Processing Series (FIPS) county codes (as seen in Section A.2 below).

Movers and Nonmovers We define individuals as *nonmovers* if their county of residence remains the same throughout our sample period.[2] We define individuals as *movers* with moving

[1] We include individuals aged 65 to 99 years old.

[2] The number of all nonmovers is 40,294,278.

year t, if their county of residence in year t differs from year t+1.[3] We need to observe an individual at least for two years to classify them as a mover, whereas if an individual is observed only once during our sample period, they are mechanically classified as a nonmover. We exclude individuals who moved in 2007 (the first year of our sample period) because some of our analysis (e.g., change in MA enrollment probability upon move) requires pre-move periods. However, those who moved in 2007 are only observable for post-move periods. To be consistent across the analysis in terms of included movers, we drop 2007 movers throughout our analysis. We also drop movers who moved more than once during our sample period.

We further restrict our attention to movers who appear to have shifted their health care consumption from the origin to the destination coincident with their move. This sample restriction intends to exclude individuals who change their official residence without altering their behavior. For example, an individual could begin sending mail to an adult child. Specifically, we limit our movers to those who increase the share of prescription drug fills at destination pharmacies (among fills at either the origin or the destination) by at least 75 percentage points.[4] Among movers net of previous exclusions (excluding 2007 movers and multiple-move movers; $N = 2,952,623$) Part D claims data are available for about 21 percent of movers ($N = 615,894$) due to the 20 percent random sampling of the PDE data. Out of these movers, approximately 57 percent of movers ($N = 348,199$) change their prescription filling behavior consistent with an actual move. Panels (a) and (b) in Appendix Figure A2 show that our results are robust to the inclusion of all movers with Part D claims data. The key estimate from the event study specification is 0.361 when including the broader set of these movers, which is equivalent to 0.490 after scaling by the corresponding first-stage estimate in this broader sample (0.736). This scaled estimate is very similar to the analogous estimate when using the baseline sample of movers.

Panel (c) in Appendix Figure A2 replicates the event study analysis using all movers ($N = 2,952,623$) regardless of their appearance in the PDE data. In panel (d) in Appendix Figure A2, we further drop one of our sample restrictions, which is continuous Medicare Part D coverage for a given year (i.e., the restriction (iii) in the paragraph of Sample Restriction). We find that our event study estimates in both cases are almost identical to those in panel (b) in Appendix Figure A2.

Matched Nonmover Some of our analysis relies on comparing movers to a matched sample of nonmovers. We match each mover in the data to a similar nonmover on the basis of origin county, gender, race, five-year age bin, and years of enrollment in Medicare. Specifically, for each mover, we randomly draw a matched nonmover who shares the same characteristics above and follow this matched nonmover over the sample periods. This individual level matching (as opposed to individual-year level matching) allows us to track time-invariant-matched nonmovers' MA choice for every period for which their counterpart mover is observed.

[3]Given that our rearranged MBSF reflects an individual's residence at the beginning of each period, the change in the county of residence between year t and $t+1$ implies that the move must have occurred at some point during year t.

[4]A small number of movers have prescription drug fills only in pre- or post-move periods. For these individuals, we include them if they fill less than 5 percent of prescriptions at destination pharmacies before their move (among those who have only pre-move claims) or more than 95 percent of prescriptions at destination pharmacies after their move (among those who have only post-move claims).

A.2 Geographic Boundary of County

We use *county* as our geographic unit of analysis because MA service areas are specified as sets of counties. Specifically, our county boundaries are defined as of 2017 when there were 3,142 counties in the U.S. Given some changes to counties and county-equivalent entities during our sample period,[5] we reassign (FIPS) county information to some individuals so that we can maintain our county boundary definition consistent across years. For instance, Bedford City (FIPS code, 51515) in Virginia was added to Bedford County (FIPS code, 51019) in 2013, in which case we change the county code for individuals in Bedford City (51515) to the code for Bedford County (51019) for the years before 2013.

The MBSF also includes information on SSA county codes instead of FIPS county codes. As one actual county (or FIPS county) could have multiple distinct SSA county codes,[6] we first use the CMS's SSA to FIPS state and county crosswalk (NBER, 2017*a*) to obtain FIPS county codes for each individual. For some individuals with either too old or invalid SSA county codes which are not included in the crosswalk, we additionally use their five-digit zip codes to obtain their FIPS county, relying on the USPS zip-county code crosswalk (HUD PD&R, 2017). These adjustments ensure we define those who experienced county code changes as nonmovers.

A.3 Measures for County Characteristics

We construct 18 measures of county-level characteristics (7 place-related and 11 individual-related) using various sources of restricted and/or publicly available datasets. We create a measure for a single year and then take a simple average across years whenever the underlying data are available for multiple years. The Intercensal Population estimates from the U.S. Census (Census, 2021*a*; Census, 2021*b*) are used when we construct per capita measures. Below, we describe the construction of each measure along with the underlying data sources in more detail.

Physicians Per Capita We construct two measures of health professional resources: per capita primary care physicians (PCPs) and specialists, using the Area Health Resources File (AHRF) over 2010–2016 (HRSA, 2021). The data include information on counts of doctors with Doctor of Medicine (M.D.) or Doctor of Osteopathic (D.O.) Medicine credentials for each county. Following the AHRF's definition, we define PCPs as doctors with specialties in general family medicine, general practice, general internal medicine, and general pediatrics. Specialist counts are derived by subtracting counts of PCPs from the total number of doctors with M.D. or D.O. credentials.

Hospital Network HHI We measure concentration using the Herfindahl–Hirschman Index (HHI) calculated for hospital networks (as opposed to individual hospitals). We obtain admissions, hospital network, and location from the American Hospital Association Survey (AHA, 2016) for almost all hospitals in the U.S. and cover 2012–2015. To account for the

[5]Detailed information on substantial changes to counties and county-equivalent entities since 1970 can be found here: `https://www.census.gov/programs-surveys/geography/technical-documentation/county-changes.html`.

[6]We find 6,841 distinct SSA county codes in our MBSF datasets, which is more than double the actual number of counties.

fact that some counties do not have any hospitals, we first construct Hospital Referral Region (HRR) level HHIs by aggregating the total admissions across networks within an HRR. We then combine the MBSF with the zip-HRR crosswalk (DAP, 2016) to construct the variable representing the fraction of Medicare beneficiaries served by each HRR within a county. Using this variable as weight, we finally calculate county-level HHIs as the weighted average of HRR-level HHIs.

Urbanization Level We use the NCHS Urban-Rural Classification Scheme for Counties (NCHS, 2014) for a measure of urbanization level. The data categorize all the U.S. counties and county-equivalent entities into six discrete urbanization levels, with the value of one being the most urbanized areas (large central metro) and the value of six being the most rural areas (non-core). We reverse-code these values so that higher values represent more urbanized counties: in our analysis, the value of six represents the most urbanized regions. When defining "urban" in Appendix Tables A1 and A2, we use counties classified as large central metro, large fringe metro, or medium metro, and define "rural" as counties classified as small metro, micropolitan, or non-core.

MA Contract-Level (or Insurer) HHI We calculate the MA HHIs with MA contracts as the firm definition using the MBSF for 2007–2017. We first restrict individuals to those who hold MA Part D contracts for which their contract IDs start with the letters H or R (as opposed to standalone prescription drug plans starting with S). Next, we calculate monthly HHIs for a given county and then take a simple average across 12 months for that year to obtain annual HHIs. The Part D contract IDs are encrypted to comply with the CMS privacy rules for some (calendar) years, making creating one-step annual HHIs given our notion of year t (i.e., April–March year) infeasible.

Advertisement Spending on MA We construct a measure for advertisement spending on MA using the AdSpender data.[7] The data contain information on the amount in dollars spent for advertisement for health insurance products along with product and brand descriptions at the designated market area (DMA) level for 2014–2017. Based on product names, we first identify advertisement spending on Medicare by retaining products containing the word *Medicare* in their product descriptions. We further exclude products related to either Medigap or standalone prescription drug plans. We then sum up advertisement spending across the remaining products for each DMA and year. Finally, we create a county-level measure by assigning the same amount of advertisement spending for all counties within each DMA.

MA Benchmark We use the Medicare Advantage rate book (CMS, 2016*a*) provided by the CMS to obtain MA benchmark rates over 2007–2016. Specifically, we use rates for risk parts A&B (2007–2011), risk parts A&B with a star rating of 2.5 (2012–2014), and risk parts A&B with a zero percent bonus rate (2015–2016).

[7]We accessed the AdSpender database through the subscribed service from the Johnson Graduate School of Management at Cornell University.

Individual Characteristics We construct most of our measures for individual characteristics among Medicare beneficiaries over 2007–2016 by using reported statistics in the Medicare Geographic Variation Public Use files (CMS, 2022): mean age, female share, dual eligible share, Medicare beneficiary share (out of county population), mean Hierarchical Condition Category (HCC) score, and risk-adjusted per capita costs.

We also use the MBSF to construct two additional demographic measures: white share and disabled share. While creating these two measures, we do not use our baseline sample because our baseline sample excludes non-elderly individuals as well as those who are not in Medicare Part D, so it may not represent the whole Medicare market with respect to these two measures. Instead, we construct these two measures using the entire enrollees as long as they have valid FIPS county information.

Finally, we turn to the American Community Surveys (ACS) to create income and educational attainment measures among the elderly (age 65 or above). Specifically, we use the five-year ACS estimates representing 2011–2015 (Census, 2016), which report educational attainment and income by age group at the county level. We use reported statistics in the data for a measure of median household income among householders aged 65 or over. We measure the share of the population aged 65 or older who holds a high school degree or above. As a proxy for poverty measure, we also compute the fraction of households with income below $20,000 with householders aged 65 or older analogously, using the numbers of all households (denominator) and those with incomes below $20,000 (numerator) out of households with elderly householders.

A.4 Measures for Prescription Drug Use and Care Delivery Patterns

We construct six measures of prescription drug use and care delivery patterns. All the measures are created using the Prescription Drug Event (PDE) datasets at the beneficiary-year level. Since the level of observation in the PDE data is prescription fill (or event), we aggregate prescriptions at the beneficiary-year level over characteristics of interest (e.g., days supplied, drug code, and provider specialty) and then use them to create the associated variables.

We note that we drop the first two years of the data for the analysis of care delivery patterns because provider specialty information is not available for these two years.[8] The analysis that utilizes measures of prescription drug use does not suffer from this issue. For this reason, we use the full sample years in this analysis. However, panels (a) through (c) (for prescription drug use) in Figure 5 display coefficient estimates for only relative years -6 to 6 (not -8 to 8) to be more consistent with and comparable to panels (d) through (f) (for care delivery patterns). We also note that the regression for each outcome includes beneficiary-year-level observations for which that outcome is definable and thus measurable. For instance, the regression using adherence as a dependent variable excludes individuals with either zero prescriptions or no "full-year drugs" (as defined below).

[8]The PDE datasets use other types of provider identifiers (e.g., Drug Enforcement Administration identification number) instead of National Provider Identifier (NPI) for these two years, which prevents us from merging these datasets with NPI-based provider specialty information.

Prescription Drug Use Our primary measures of prescription drug use are an indicator for any prescription and a $\text{Log}(1+x)$ transformation of the *annual* days of supply across *all* drugs. Given the definitions, both measures can be constructed in a straightforward manner. We further define and use a proxy measure of medication "adherence." To group National Drug Codes (NDCs) for the same ingredient (or ingredients) in the same strength and dosage form, we first convert NDCs to RxCUIs (RxNorm Concept Unique Identifiers) using the RxNorm Medical thesaurus created by the National Libraries of Medicine (NNLM, 2014). Then, for each RxCUI, we sum up the days of supply at the beneficiary-year level and repeat this process for each (calendar) year. Next, we find the mode of days supplied for each RxCUI across all beneficiaries and years and define the subset of drugs with modal days equal to or greater than 270 days as "full-year drugs." For individuals with prescriptions for a full-year drug (or RxCUI), adherence is computed by dividing the number of days that the individual is supplied that RxCUI by the modal days of the same RxCUI. If an individual takes multiple full-year drugs, the adherence measure is simply the mean across all full-year drugs they take.

Care Delivery Pattern Care delivery pattern measures are based on the prescriber's specialty. The PDE datasets include the prescriber's identifier (i.e., National Provider Identifier) without their specialty information. So, we supplement the PDE with Medicare Part B Carrier Line datasets, which allow us to link NPIs to Health Care Financing Administration (HCFA) specialty codes. Using the HCFA codes, we first identify primary care physicians (PCPs) and mid-level providers as those with certain specialty codes,[9] and then the remaining NPIs are assumed to be specialists. A few providers could start out as PCPs (e.g., internal medicine residents) and later become specialists (e.g., oncologists after a fellowship). In such cases, we treat these physicians as specialists. We define the prescription share of either PCPs (and mid-level providers) or specialists as the number of prescriptions given by each group over the total number of prescriptions from both groups. Given this definition, the shares of prescriptions from both groups sum to 1 by construction. An indicator of any prescription from an emergency department (ED) doctor is constructed by confirming whether an enrollee has any prescription with the prescriber's HCFA code of "93" (emergency medicine) in a given year.

B Robustness to an Alternative Estimator (Imputation Method)

In this section, we demonstrate that our baseline event study results are robust to an alternative estimation strategy that allows for treatment effect heterogeneity by move timing. The setup of this alternative specification closely follows that used in Finkelstein et al. (2022), which builds on the imputation strategy developed by Borusyak, Jaravel and Spiess (2021). Below, we describe each step of the alternative method in more detail.

- **Step 1**: As suggested by Borusyak, Jaravel and Spiess (2021), we first regress MA_{it} on county-year (γ_{jt}) and five-year age bin ($agebin_g$) fixed effects, using the sample of all

[9]Specifically, the HCFA codes for primary care physicians include 01, 03, 06, 08, 10, 11, 29, 37, 38, 39, 44, 46, 66, 81, 82, 83, and 90, and those for mid-level providers include 42, 43, 50, 89, and 97. For a full list of the HCFA codes, see here: `https://resdac.org/cms-data/variables/line-cms-provider-specialty-code`.

nonmovers to generate (coefficient) estimates that are uncontaminated by the behavior of movers:

$$MA_{it} = \gamma_{j(i,o)t} + agebin_{g(i,t)} + u_{it}, \tag{1}$$

where $j(i,o)$ is an individual i's origin county, and $g(i,t)$ is an individual i's five-year age bin in year t.

- **Step 2**: Next, we construct a counterfactual outcome for each mover, using estimates of $\widehat{\gamma}_{jt}$ and $\widehat{agebin}_g$ obtained in Step 1. Specifically, we sum the appropriate five-year age bin fixed effects and county-year fixed effects associated with the *origin* county (*even after move*). Then, we difference this counterfactual outcome from the true value of MA_{it} to form a residualized outcome, $\widetilde{MA}_{it}$:

$$\underbrace{\widetilde{MA}_{it}}_{\text{residual}} = MA_{it} - \underbrace{\left(\widehat{\gamma}_{j(i,o)t} + \widehat{agebin}_{g(i,t)}\right)}_{\text{counterfactual}}. \tag{2}$$

- **Step 3**: We separately estimate the following specification by year of move (m) using only movers:

$$\widetilde{MA}_{it} = \alpha_i + \beta\widetilde{\delta}_{it} + \sum_{r\neq -1} \theta_r^m I_r \widetilde{\delta}_{it} + \epsilon_{it}, \tag{3}$$

where

$$\widetilde{\delta}_{it} \equiv \overline{MA}_{j(i,d)t} - \overline{MA}_{j(i,o)t}.$$

Note that $\widetilde{\delta}_{it}$ is the difference in average MA enrollment among all *nonmovers* between the mover i's destination ($\overline{MA}_{j(i,d)t}$) and origin ($\overline{MA}_{j(i,o)t}$) in year t.[10]

- **Step 4**: To obtain an aggregated event study coefficient ($\widehat{\theta}_r$) for an event time r, we aggregate the event study coefficients $\widehat{\theta}_r^m$ across move years by weighting the number of movers associated with the estimates of $\widehat{\theta}_r^m$. The standard errors of the weighted average coefficients are calculated analogously with an additional assumption that θ_r^m are independent across move years. These aggregations can be written as:

$$\widehat{\theta}_r = \sum_{m=2008}^{2015} \left(\frac{N_r^m}{N_r}\right) \widehat{\theta}_r^m \quad \text{and} \quad \widehat{SE}(\theta_r) = \sqrt{\sum_{m=2008}^{2015} \left(\frac{N_r^m}{N_r}\right)^2 \widehat{VAR}\left(\theta_r^m\right)}, \tag{4}$$

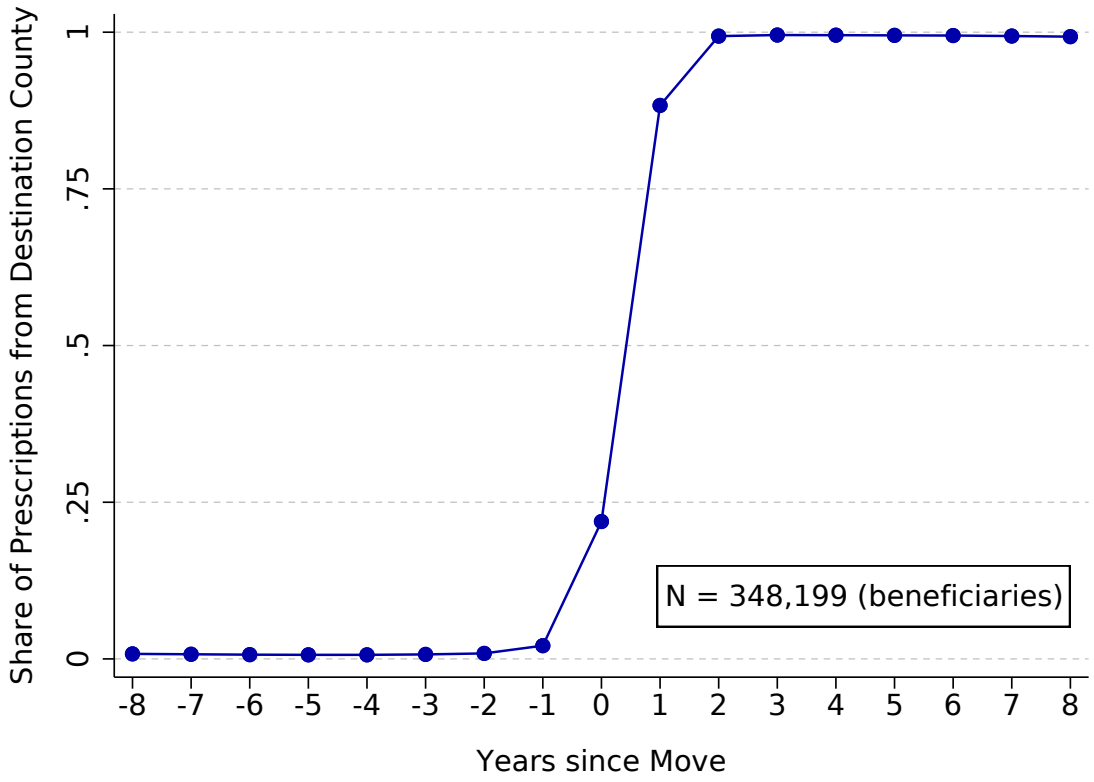
where N_r^m is the number of movers observed for an event time r among those who moved in year m, and N_r is the total number of movers observed for an event time r across all move years (i.e., $N_r \equiv \sum_{m=2008}^{2015} N_r^m$).

Appendix Figure A6 displays our baseline event study coefficients (equation (1) in the text) as well as the (aggregated) event study coefficients ($\widehat{\theta}_r$) that result from the alternative

[10] Note that $\widetilde{\delta}_{it}$ differs from $\widehat{\delta}_i$ (used in the baseline event study) in that (i) we use only nonmovers to estimate $\widetilde{\delta}_{it}$, and (ii) $\widetilde{\delta}_{it}$ is time-varying as we separately construct $\widetilde{\delta}_{it}$ for each year t. We use different notations ($\widetilde{\delta}$ and $\widehat{\delta}$) to distinguish one from the other.

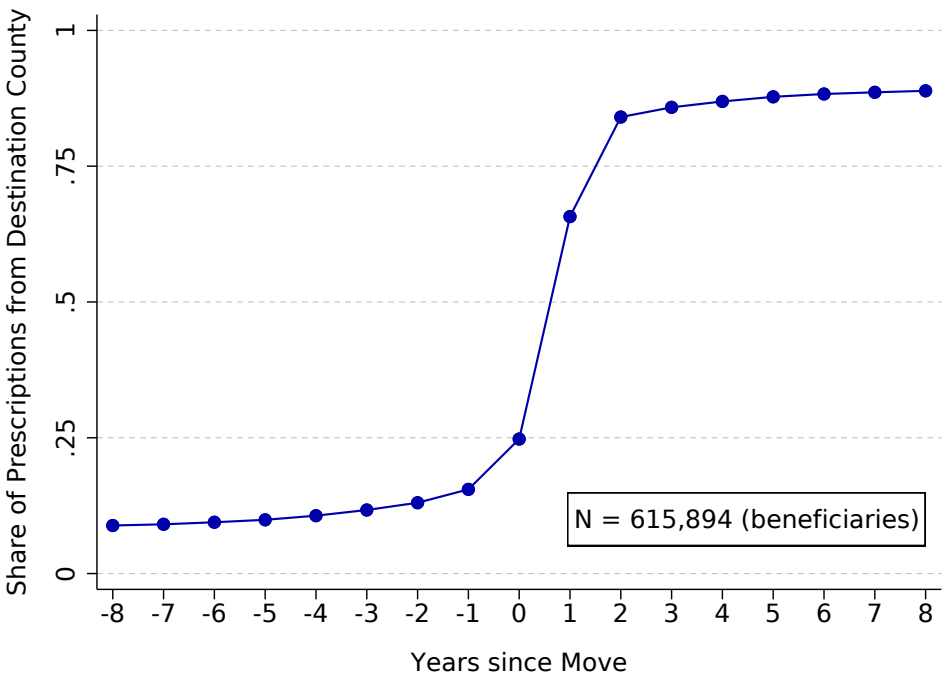
method. We find essentially no difference in our estimates when employing this alternative imputation method.

Figure A1: First Stage: Share of Prescription Drug Claims in Destination County by Relative Year to Move

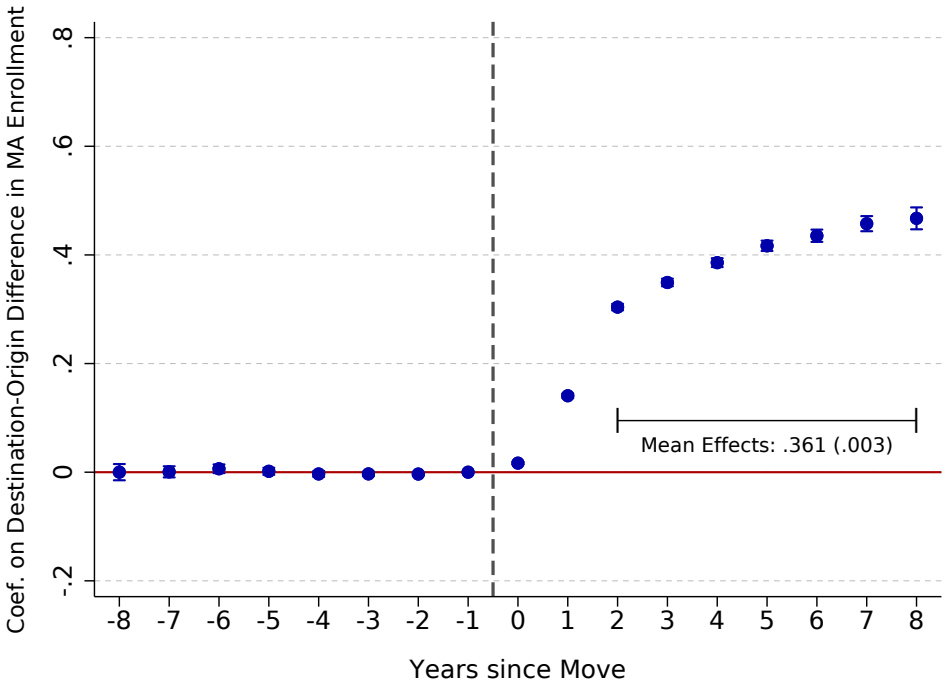


Notes: The figure above displays the share of prescription drug claims from movers' destination counties among those from either their origin or destination counties by relative year since move. The sample is *baseline* movers ($N = 2,040,217$ beneficiary-years). See Appendix Section A.1 for more detail on our baseline mover definition.

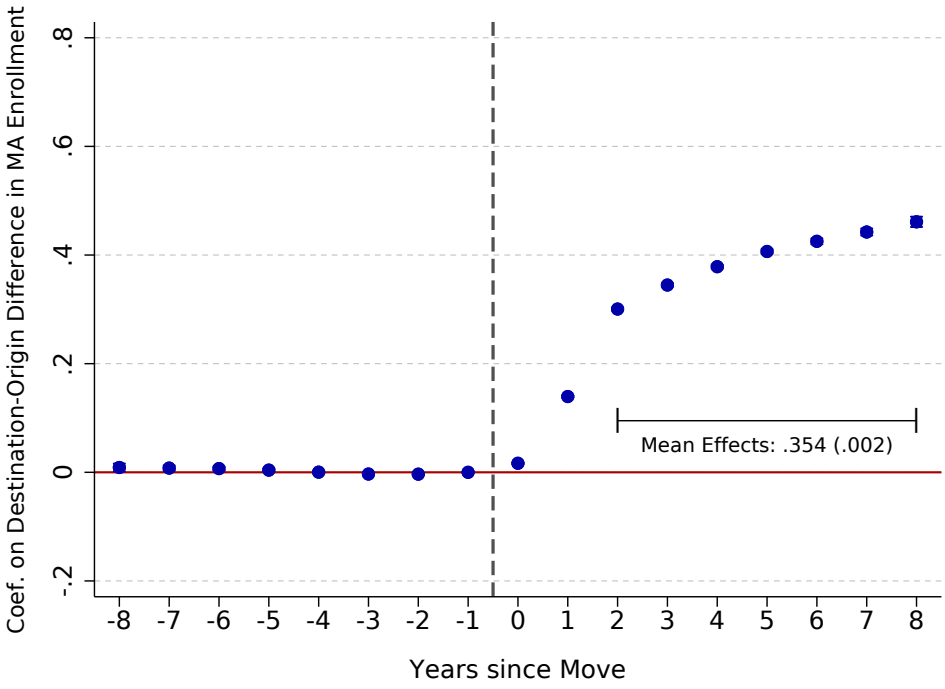
Figure A2: Robustness: Relaxing Sample Restrictions for Movers



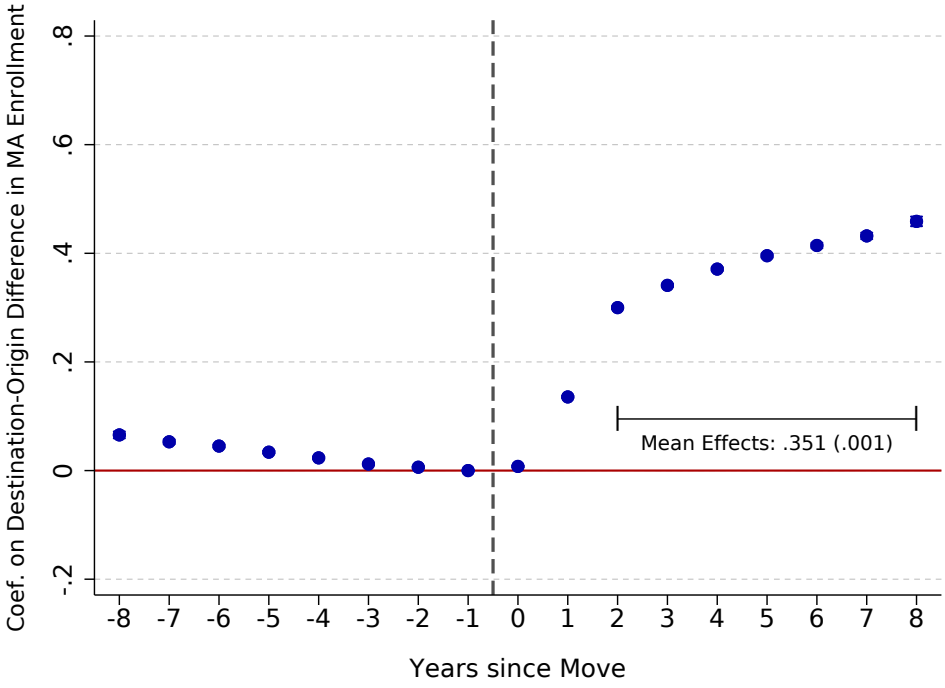
(a) First Stage: All Movers with Part D Coverage and 20% PDE Subsample



(b) Event Study: All Movers with Part D Coverage and 20% PDE Subsample



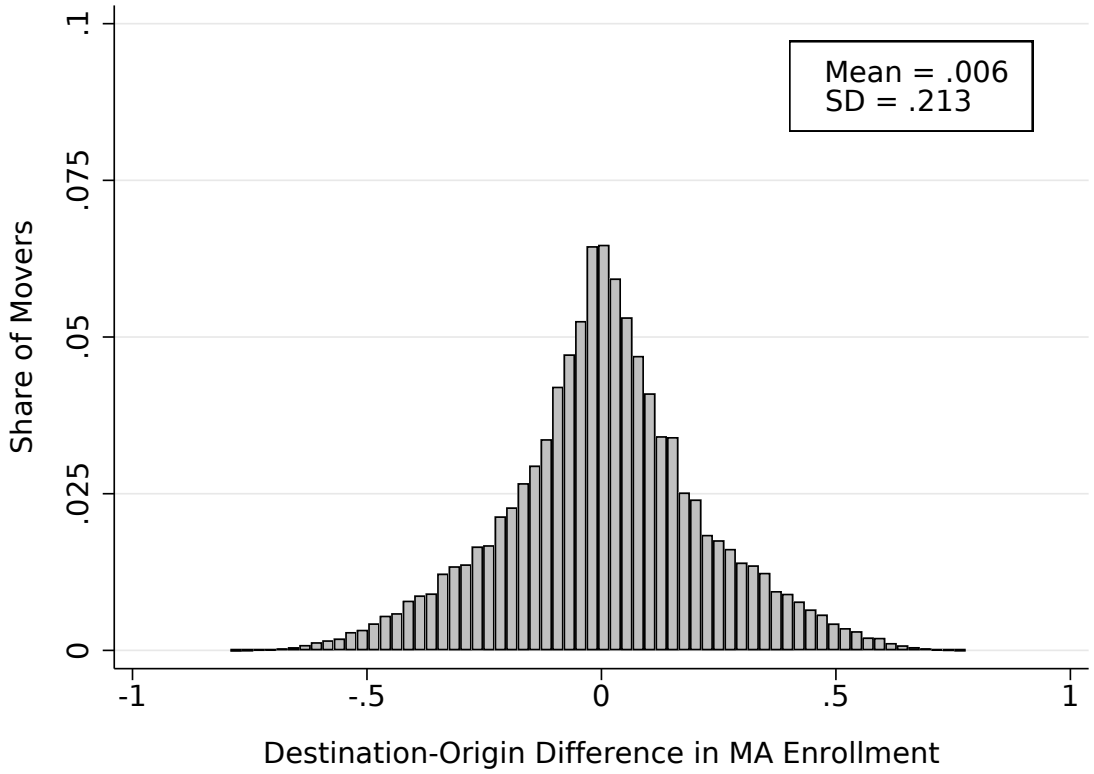
(c) Event Study: All Movers with Part D Coverage



(d) Event Study: All Movers

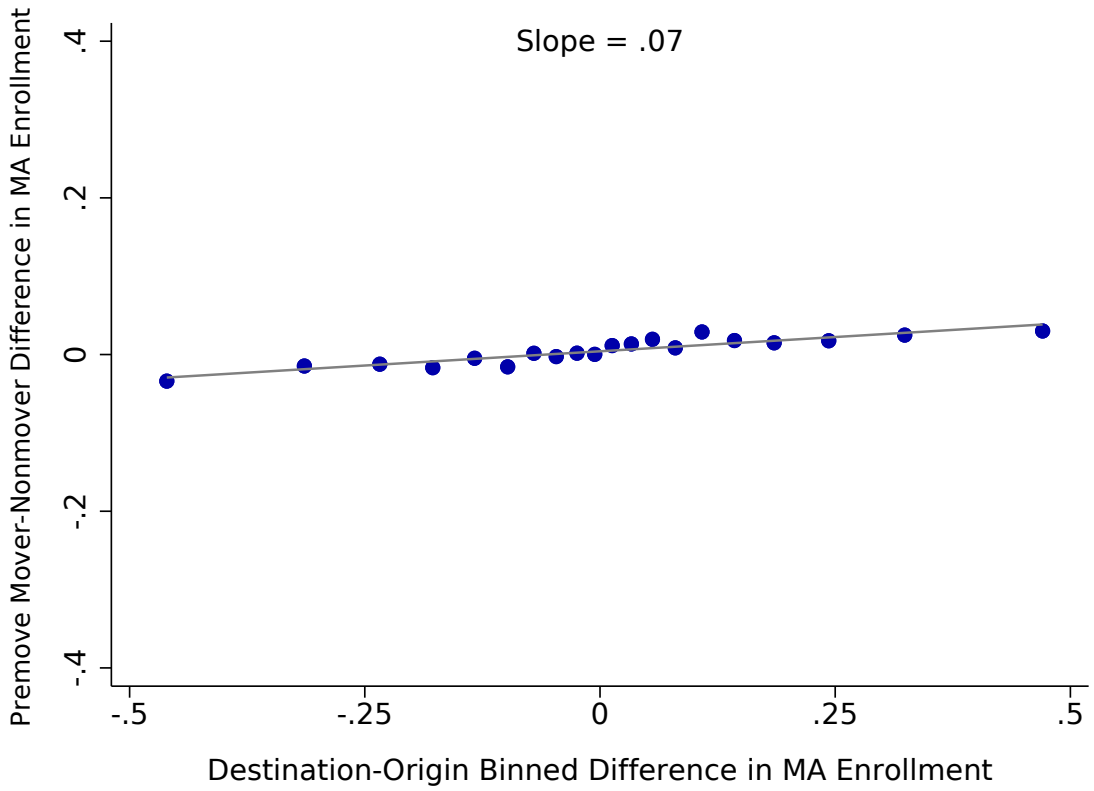
Notes: The panels in this figure successively relax sample restrictions. Panel (a) repeats the first-stage analysis (analogous to Appendix Figure A1) and panel (b) repeats the event study analysis (analogous to Figure 3) using all movers observed in Prescription Drug Event (PDE) datasets (N movers $= 615,894$), regardless of the change in their prescription fills. Panel (c) replicates the event study analysis using all movers in Part D, even if not in the 20% subsample represented in the PDE dataset (N movers $= 2,952,623$). Panels (a)–(c) also include nonmovers with Part D coverage. In panel (d), we further remove the sample restriction of Part D coverage for both movers and nonmovers (N movers $= 4,999,801$).

Figure A3: Distribution of Destination-Origin Differences in MA Enrollment Rates



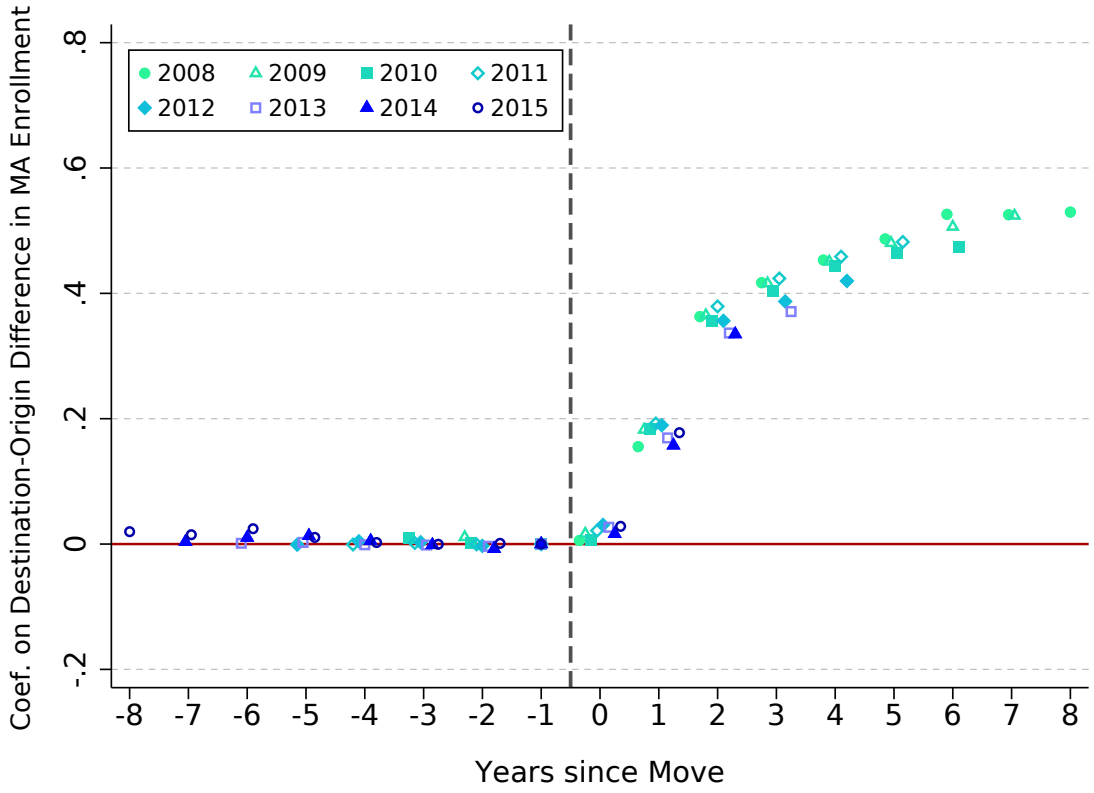
Notes: The figure above displays the distribution of $\widehat{\delta}_i$ (i.e., the destination-origin difference in the MA enrollment rates) among movers. The sample is *baseline* movers ($N = 2,545,438$ beneficiary-years).

Figure A4: Movers-Nonmovers Pre-Move Difference in MA Enrollment Probability by Destination-Origin Difference



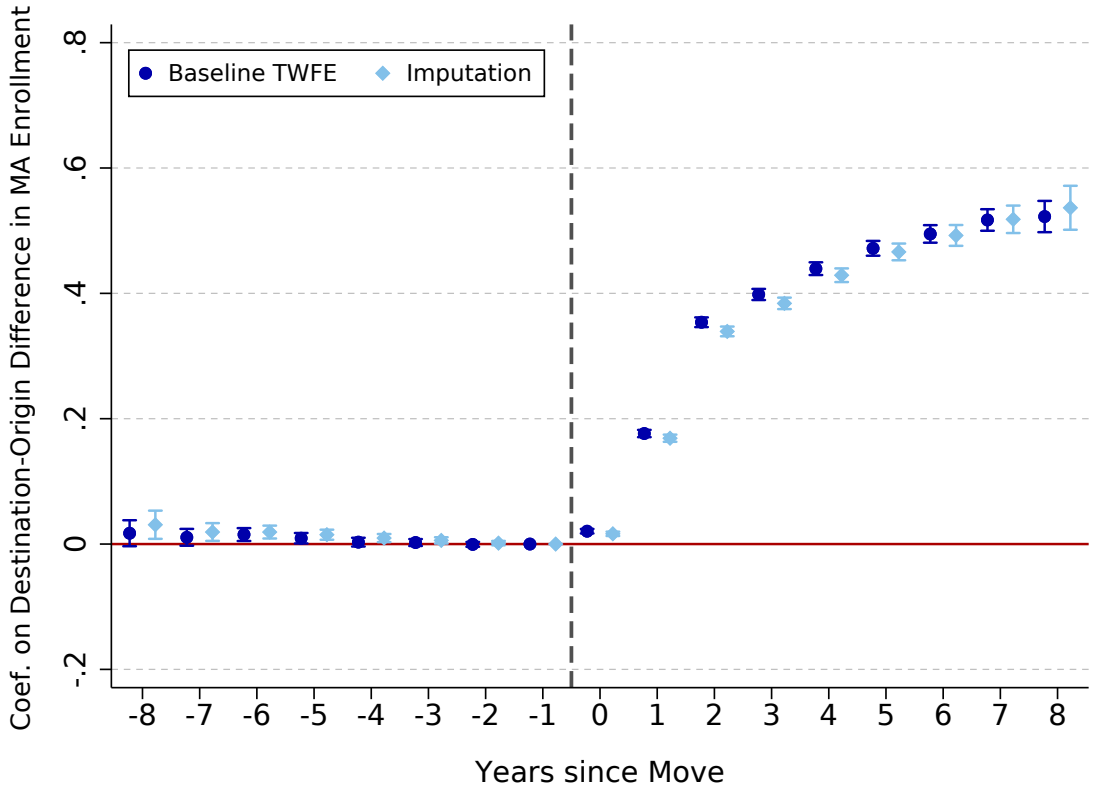
Notes: The figure above displays the difference in MA enrollment probability between movers relative to matched nonmovers by the size of movers' treatment intensity, $\widehat{\delta}_i$. Movers are grouped into ventiles by $\widehat{\delta}_i$. For each ventile, the x-axis displays the mean of $\widehat{\delta}_i$, and the y-axis displays the mean difference in MA enrollment probability two to five years before move. The line of best fit and its slope are obtained from a simple OLS regression using the 20 plotted points. The sample is *baseline* movers and matched nonmovers observed two to five years before move ($N = 658,163$ beneficiary-years).

Figure A5: Robustness: A Separate Event Study Estimation by Year of Move



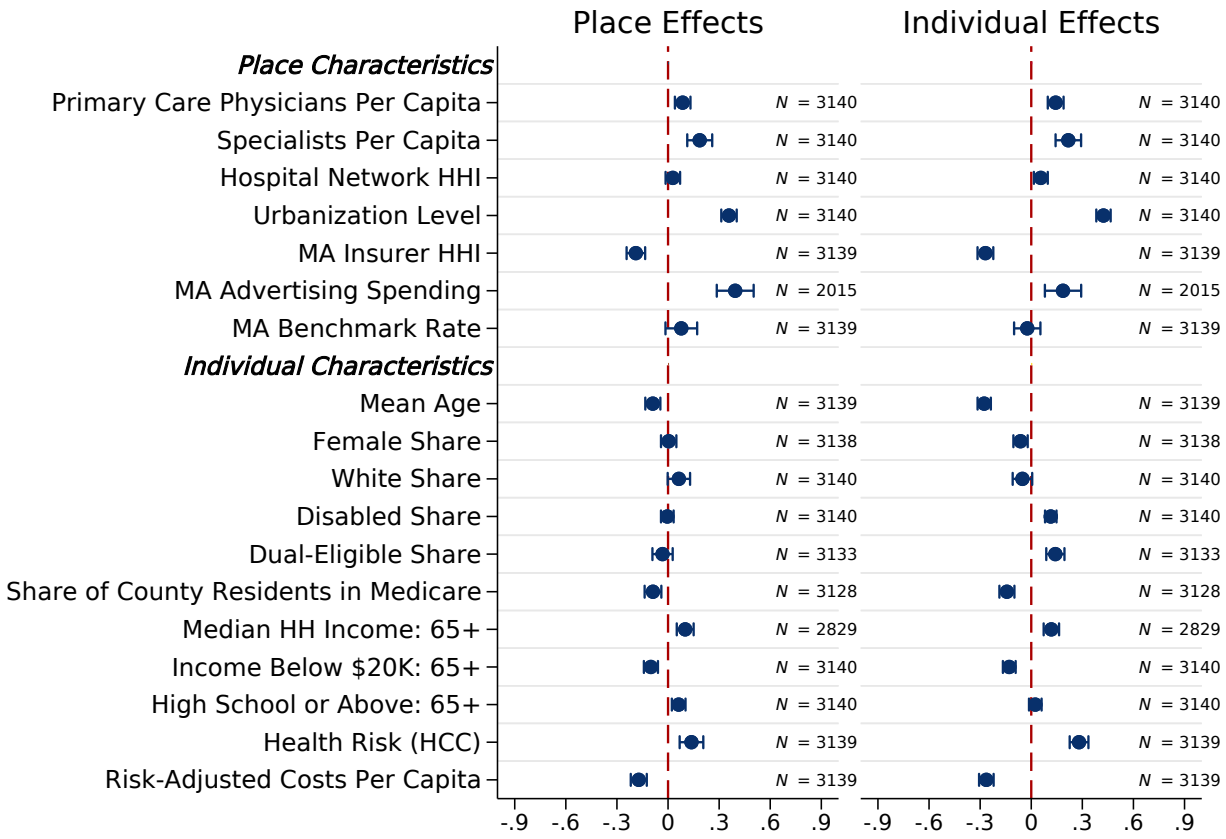
Notes: The figure above displays estimates, θ_r (i.e., the coefficients on relative years since move interacted with the treatment intensity $\widehat{\delta}_i$), from separate regressions of equation (1) by year of move. The dependent variable is an indicator for any MA months. All regressions include place (or county) fixed effects, individual fixed effects, time (or year) fixed effects, indicators for relative years since move, and five-year age bins. To improve visualization, 95% confidence intervals (with robust standard errors clustered at the beneficiary level ranging from 0.004 to 0.018 across all estimates) are not displayed.

Figure A6: Robustness: Comparison of Baseline Event Study and Imputation-Based Approach



Notes: The figure above compares baseline estimates from the standard two-way fixed effects (TWFE) event study estimation (in dark blue) described in equation (1) and those from the imputation-based approach (in light blue) described in Appendix Section B.

Figure A7: Correlates Analysis: All Counties



Notes: The figure above displays bivariate OLS results of place effects (left panel) and individual effects (right panel) on various county-level characteristics (analogous to left panels in Figure 4). All measures and dependent variables are standardized to mean zero and variance one. The sample includes all counties for which each measure is available, as indicated in the right corner of each panel. See Appendix Section A.3 for more detail on the measures used for this analysis.

Table A1: Summary Statistics

	Nonmover (1)	Mover (2)	Matched Nonmover (3)
Panel (a): Demographics			
Female	0.58	0.66	0.66
White	0.82	0.87	0.87
Age First Observed			
65–74	0.68	0.62	0.62
75–84	0.23	0.28	0.28
≥ 85	0.09	0.10	0.09
Years Observed	5.31	7.31	7.47
MA Enrollment			
Any Month	0.44	0.43	0.43
Any Month, Net of County FEs	0.44	0.43	0.44
Share of Twelve Months	0.42	0.40	0.41
Dual-Eligible	0.21	0.21	0.19
Residence First Observed			
Northeast	0.20	0.18	0.18
South	0.36	0.38	0.37
Midwest	0.23	0.21	0.20
West	0.22	0.24	0.24
Urban Counties First Observed	0.72	0.71	0.72
N of Beneficiary	40,294,278	348,199	346,067
N of Beneficiary-year	213,873,570	2,545,438	2,532,505
Panel (b): Transition Pattern			
TM to TM	0.51	0.50	0.54
TM to MA	0.05	0.07	0.04
MA to TM	0.03	0.08	0.03
MA to MA	0.41	0.34	0.39
Panel (c): Prescription Drug Use and Care Delivery Pattern			
1(Any Script)	0.91	0.89	0.90
Log(1 + Days Supplied)	6.29	6.08	6.16
Adherence	0.69	0.68	0.70
Share of Scripts by PCPs (and Midlevel)	0.72	0.72	0.72
Share of Scripts by Specialist	0.28	0.28	0.28
1(Any Script from ED Doctor)	0.12	0.13	0.12

Notes: The table above reports the mean (or share) of the given characteristics for each group: *all* nonmovers, *baseline* movers, and matched nonmovers. The means displayed in panel (a) are calculated at the beneficiary level except for MA enrollment and dual-eligible, which are calculated at the beneficiary-year level. "Urban" counties are defined as the NCHS urban-rural classification levels: large central metro, large fringe metro, or medium metro. In panel (b), transition patterns are determined based on MA enrollment status one year before move (i.e., $r = -1$) and two years after move (i.e., $r = 2$) for movers and matched nonmovers. Unlike movers and matched nonmovers, relative years to move (i.e., $r = -1$ and 2) are not defined for nonmovers, and thus transition patterns are repeatedly examined in other three-year intervals: if a nonmover is observed in 2010–2014, we check the nonmover's MA enrollment status in 2010 and 2013 and in 2011 and 2014. The means displayed in panel (c) are calculated at the beneficiary-year level among those observed in Prescription Drug Event (PDE) datasets.

Table A2: Decomposing Sources of Variation Across Groups of Counties

	Above/ Below Median (1)	Top/ Bottom 25% (2)	Top/ Bottom 10% (3)	Top/ Bottom 5% (4)	Urban vs. Rural (5)
Difference in Average MA Enrollment					
Overall (A)	0.333	0.466	0.590	0.665	0.193
Due to Place (B)	0.137	0.202	0.262	0.281	0.091
Due to Individual (C)	0.196	0.264	0.329	0.385	0.102
Share of Difference Due to					
Place (B/A)	41.17%	43.37%	44.34%	42.19%	46.96%
Individual (C/A)	58.83%	56.63%	55.66%	57.81%	53.04%

Notes: The table above reports additive decomposition results, which are based on estimation of equation (2). Each column indicates a set of included counties based on their MA enrollment rates, $\overline{MA}_j$, except for column (5) for which we define "Urban" using the NCHS urban-rural classification levels large central metro, large fringe metro, or medium metro. The first three rows report the difference in $\overline{MA}_j$, $\widehat{\gamma}_j$, and $\overline{y}_j$ between the two sets of counties as indicated in each column. The last two rows report the share of the difference in average MA enrollment rates between the two sets of counties, which is attributable to place of individual effects. The differences in the first three rows are weighted by the average number of Medicare beneficiaries in each county during our sample period. The sample is *baseline* movers and all nonmovers, excluding the year of the move and the year following for movers ($N = 210,509,518$ beneficiary-years).

Table A3: Decomposing the Variance in MA Enrollment: Role of Place and Individual Factors

	(1)
Cross-County Variance of Average	
MA Enrollment (A)	0.0361
Place Effect Estimates (B)	0.0084
Individual Effect Estimates (C)	0.0149
Correlation of Place and Individual Effect Estimates	0.5736
Share of Variance of MA Enrollment Would Be Reduced If	
Place Effect Estimates Were Made Equal $(1 - \frac{C}{A})$	58.73%
Individual Effect Estimates Were Made Equal $(1 - \frac{B}{A})$	76.78%

Notes: The table above reports variance decomposition results, which are based on estimation of equation (2). The first three rows report the variance of $\overline{MA}_j$, the variance of $\widehat{\gamma}_j$, and the variance of $\overline{y}_j$, respectively. The fourth row reports the correlation between $\widehat{\gamma}_j$ and $\overline{y}_j$. The last two rows report the share of variance in cross-county MA enrollment rates that would be eliminated if place (or individual) effects were equalized across counties. The variances and correlation coefficient are weighted by the average number of Medicare beneficiaries in each county during our sample period. The sample is *baseline* movers and all nonmovers, excluding the year of the move and the year following for movers ($N = 210,509,518$ beneficiary-years).