Does an increase in Medicare Advantage (MA) Penetration Lead to Hospital Closures?*

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Medicare Advantage (MA) enrollment has increased tremendously over the last two decades. In this paper, I examine how this increased MA penetration at the county-level affects the likelihood of a county losing all its hospital establishments. I leverage variation in MA penetration within the county across the years during the sample period by combining multiple microdata at the county-level. The estimates show that an increase in MA penetration increases the likelihood that the county loses all its hospital establishments. I establish the robustness of this conclusion through multiple empirical checks, including allowing for staggered increases in MA penetration across the counties and the dynamic heterogeneous impact of increased MA penetration on the loss of all the hospital establishments in the county.

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1 Introduction

In 2024, approximately 45% of eligible Medicare beneficiaries are enrolled in Medicare Advantage (MA) plans, starting from about 15% in 2008. This massive increase in MA enrollment has the potential to alter the healthcare landscape, especially in areas where the population share of Medicare-eligible residents is relatively larger. Recent anecdotal evidence suggests that MA plans reimburse the hospitals less than traditional Medicare for the services to the MA enrollees (Zionts, 2025). Along with lower reimbursement levels, hospitals complain that MA plans delay payments and are resistant to authorizing patient care, jeopardizing both the patient's health and the hospital's finances.

MA plans through contracting with local providers can improve their financial conditions by steering their enrollees towards the in-network providers. Existing work also provides evidence, albeit associational, that the growth of MA plans in rural areas is associated with increased financial stability for hospitals and a reduced risk of closure (Henke, Fingar, Liang and Jiang, 2023). Despite the apparent growth of MA across the years, there is a dearth of causal evidence on how it affects the availability of hospital establishments. In this work, I aim to fill this gap. Specifically, I uncover the causal effect of increased MA penetration at the county-level on the availability of hospital establishments in the county.

To examine the causal impact of an increase in MA penetration on local hospital availability, I combine multiple microdata at the county-level. I use County Business Patterns (CBP) establishment-level data to construct the measures of hospital availability for each county in the analytical sample (U.S. Census Bureau, 2023). CBP provides a six-digit North American Industry Classification System (NAICS) code that allows me to construct measures of hospital availability at the county-level. Due to severe financial penalties in case of misreporting of the industry of the establishment on the Internal Revenue Service (IRS) tax filings, CBP accurately captures the hospital availability in the county. To construct a county-level MA penetration measure, I use data from the Centers for Medicare & Medicaid Services's Medicare Advantage/Part D Contract and Enrollment Data series.

The main empirical specification includes fixed-effects for counties and calendar years. Therefore, the impact of MA penetration on hospital availability in the county is estimated by leveraging within county changes in MA penetration across the years in the analytical sample. For the estimates from this specification to be interpreted causally, I need to establish that counties with low penetration of MA are a good counterfactual for counties with relatively higher levels of MA penetration. To this end, I report event-study estimates using estimators that allow for staggered treatment adoption and dynamic heterogeneous impacts of MA penetration on hospital availability in the county (de Chaisemartin and D'Haultfœuille, 2024). The event-study estimates clearly show that the counties with lower MA penetration levels are trending similarly in the periods before the county with relatively higher levels of MA penetration breaches multiple MA penetration thresholds.

The estimates show that for each percentage point increase in MA penetration, the likelihood of the county losing all hospital establishments increases by 0.097 percentage point. Relative to the sample mean, this marginal increase in no hospital establishment in the county is a large increase of 4% and is highly statistically significant. The estimates do not suggest any effect on the count of hospital establishments due to an increase in MA penetration in the county. I also establish that the main estimates are robust to a host of empirical checks. In particular, I show that the estimates do not change when I alter the analytical sample, empirical specification, or use different MA penetration measures.

To the best of my knowledge, this is the first paper that provides the nationwide causal impact of increased MA penetration on hospital availability at the county-level. The closest to this work is Henke et al. (2023). This work differs from theirs in two crucial ways. First, Henke et al. (2023) does not provide causal estimates of the increase in MA penetration on local hospital availability. Second, their analytical sample is restricted to only 12 states. Furthermore, Henke et al. (2023) find that increased MA penetration in the county is associated with lower risk of hospital closure. This finding is in direct contrast to the negative causal impact of increased MA penetration on the likelihood of a county losing all its hospital establishments.

This work sits within the broader research on the role of increased MA penetration on hospital availability and finances (Baker, Bundorf, Devlin and Kessler, 2016; Cataife and Liu, 2025; Henke et al., 2023; Kim, Reiter, Thompson and Pink, 2025). This work has found mixed evidence on how increased MA penetration affects the financial standing of the hospitals. I add to this existing literature by providing the first causal evidence on the impact of increased MA penetration on the likelihood of a county losing all its hospital establishments.

The rest of the paper proceeds as follows. Section 2 provides detailed background on MA. Section 3 provides details on the data, while Section 4 presents empirical specifications to uncover the causal effect of increased MA penetration on the likelihood of a county losing all its hospital establishments. Results are reported in Section 5 and Section 6 concludes.

2 Background

Medicare Advantage (MA), originally known as Medicare Part C, represents a significant alternative within the broader Medicare program, allowing beneficiaries to opt out of traditional fee-for-service (FFS) Medicare and enroll in private insurance plans.[1] Established in the early 1980s, the program was designed with two primary objectives: to broaden the choices available to Medicare beneficiaries and to achieve cost savings through managed care models (Curto et al., 2021). While MA encompasses plans for individual beneficiaries, it also includes provisions for employers to sponsor plans for their Medicare-eligible employees or retirees.

The foundational structure of Medicare's engagement with private plans began with the Tax Equity and Fiscal Responsibility Act (TEFRA) of 1982. TEFRA legislation authorized Medicare to contract with Health Maintenance Organizations (HMOs) to deliver managed care coverage for Medicare beneficiaries. Under this initial framework, HMOs received a monthly capitation fee directly from the Medicare program for each enrollee, covering the services typically provided under Medicare Parts A and B. To attract beneficiaries, HMOs were also permitted to offer supplementary services not covered by traditional Medicare. From 1985 to 1997, these capitation payments were largely based on actuarial

[1] This section borrows heavily from Baicker, Chernew and Robbins (2013) and Curto, Einav, Levin and Bhattacharya (2021).

estimates of per-person traditional Medicare expenditures within a beneficiary's county of residence, with limited demographic adjustments (Baicker et al., 2013).

A pivotal moment in the program's evolution was the enactment of the Balanced Budget Act (BBA) of 1997. This legislation dramatically expanded the landscape of private Medicare plans by authorizing new types of entities to contract with Medicare. These included Preferred Provider Organizations (PPOs), Provider-Sponsored Organizations (PSOs)—which shared similarities with HMOs—and Private Fee-for-Service (PFFS) plans, designed to mimic indemnity plans. Beyond diversifying plan types, the BBA fundamentally altered the payment methodology. Instead of solely relying on average traditional Medicare costs, plans were compensated based on the maximum of three amounts: a "blended" payment rate (a weighted average of county and national traditional Medicare costs), a statutory "floor amount" (e.g., $367 per month in 1998), and a 2% increase over the previous year's rates. Crucially, the BBA also introduced individual-level adjustments to the county-level base rate, incorporating enrollee health status alongside demographics. This health status risk adjustment was phased in gradually, with 10% of payments from 2000 to 2003 based on an enhanced system accounting for inpatient diagnoses.

The Medicare Modernization and Improvement Act (MMA) of 2003 further refined the payment methodology. Under the MMA, Medicare calculated a benchmark based on the highest of five amounts: an urban or rural floor payment; 100% of county risk-adjusted traditional Medicare costs (calculated using a five-year moving average); an update based on the prior year's national average growth in traditional Medicare costs; a 2% update over the prior year's payment; and a "blend" update (similar to the BBA blend, discontinued after 2004). A significant enhancement in individual risk adjustment was the adoption of the Hierarchical Condition Category (HCC) risk-adjustment model. This more comprehensive system, which factored in information from ambulatory care claims, inpatient admissions, and demographic data, was given 30% weight in 2004 and fully phased in by 2007.

A significant shift occurred in 2006 with the introduction of a competitive bidding process for plan payments, a change that replaced the previously fixed reimbursement rates. Annually, plans began to bid their estimated cost to provide traditional Medicare-covered benefits for an average-risk patient. This bid was then compared to the county's benchmark. If a plan's bid exceeded the benchmark, the difference was collected from enrollees as a premium. Conversely, if the bid was lower than the benchmark, 75% of the difference was returned to enrollees in the form of enhanced benefits, while the remaining 25% was returned to Medicare. These changes, coupled with an increase in maximum capitation rates set by the Centers for Medicare and Medicaid Services (CMS), coincided with a significant expansion in MA plan offerings and enrollment. Interestingly, MA enrollment continued its upward trajectory even after the Affordable Care Act (ACA), signed into law in 2010, gradually reduced payments to MA insurers.

From a Medicare beneficiary's standpoint, enrolling in an MA plan involves a clear set of trade-offs. A key characteristic of MA plans is the typical restriction on access to healthcare providers. Approximately 85% of MA enrollees are in HMO or PPO plans, which operate with limited provider networks and various utilization restrictions. However, this limitation is often balanced by the appeal of additional benefits offered by MA plans. These benefits frequently include more generous cost-sharing or supplemental coverage for services like dental, vision, or prescription drugs, making private plans attractive compared to traditional Medicare, where enrollees can face substantial out-of-pocket costs. While traditional Medicare beneficiaries can mitigate these costs by purchasing supplemental Medigap policies, these policies often entail annual costs of a few thousand dollars. MA plans, in contrast, offer a "one-stop shop" solution, covering these costs and providing a range of additional benefits. These additional benefits must be funded, either through a supplemental premium paid by the enrollee or, more commonly, through a rebate paid by CMS, determined through the competitive bidding process.

Among the various plan types, Private Fee-for-Service (PFFS) plans experienced a unique trajectory. These plans were designed to broadly mimic traditional Medicare in terms of provider access and reimbursement for non-network providers. PFFS plans saw a significant proliferation in the mid-2000s, a period characterized by very favorable benchmark rates. By 2008, they accounted for 23% of all MA enrollees. However, subsequent regulatory changes made PFFS participation more challenging, leading to a sharp decline in their share to 7% by 2011. Consequently, PFFS plans are now a relatively minor component of the Medicare Advantage landscape.

Historically, the Medicare Advantage program has navigated a persistent tension between its twin goals of expanding beneficiary choice and containing costs. Insurers have demonstrated a tendency to participate more actively during periods of higher payments and to selectively offer plans in areas with more favorable payment rates. The challenge of setting appropriate capitation rates has been further complicated by the tendency of plans to enroll relatively healthier beneficiaries. The reforms implemented over the years, including the introduction of risk scoring and competitive bidding, have aimed to address these complexities, contributing to the program's continued growth and evolution.

3 Data

To uncover the causal effect of the increase in Medicare Advantage (MA) penetration on the likelihood of a county losing all hospital establishments, I combine multiple data sources at the county-level. In this section, I describe each data source and provide descriptive statistics for the analytical sample.

3.1 County-level Hospital Establishment Data

I rely on County Business Patterns (CBP) establishment-level data to construct the measures of hospital availability for each county in the analytical sample (U.S. Census Bureau, 2023). These data have been used in the existing literature to study the effect of access to various healthcare services on human capital outcomes (Bradford and Maclean, 2023; Deza, Maclean and Solomon, 2022a; Deza, Lu and Maclean, 2022b). CBP provides annual data on establishments with paid employees for each county in the United States. These data are available at a detailed industry level. Specifically, CBP provides a six-digit North American Industry Classification System (NAICS) code for each establishment. Before 1998, CBP data are available only at the four-digit Standard Industrial Classification (SIC) level. This precludes me from constructing my measure of hospital availability in the county before 1998. I, therefore, restrict the estimation sample to years since 1998. Each establishment has only one NAICS code. CBP provides information for each county on the number of establishments, employment during the week of March 12, first-quarter payroll, and annual payroll. CBP defines an establishment as a “single physical location at which business is conducted or services or industrial operations are performed”.

To construct county-level measures of hospital availability, I use a single three-digit NAICS code, 622. For each county-year pair, I measure hospital availability using the number of establishments in that pair that have the NAICS code 622. NAICS description for this three-digit code is “Hospitals”. I use contemporaneous hospital count measures. My measure of hospital availability does not fully capture all the aspects of access to hospitals. Access to hospitals depends on, among other things, communication skills, patience, and telephone connectivity. Nonetheless, a larger presence of hospitals might be the most important aspect of access to hospitals.

CBP data are obtained from the U.S. Census Bureau. These data are based on the annual tax filing of the establishments with the Internal Revenue Service (IRS). While the quality of data in CBP is high, I note some potential reporting issues that might bias the estimates. I construct the measure of access to ambulance services using the reported three-digit NAICS code by the establishment. If the establishments misreport this code, then the estimates will be biased. Misattributing the existence of such services to their absence and depending on the sign of the omitted variable bias, the effect can either be an underestimate or an overestimate of the true effect.

However, establishments have an incentive to report their principal business code correctly. This is due to the heightened risk of an IRS audit in case a tax return by the establishment turns out to be an “outlier” in its reported principal business code. Further, inaccurate reporting might attract fines and incarceration. Due to these reasons, I am confident that the measures of hospital availability are an accurate reflection of actual access.

The analytical sample uses data from CBP for the years 1999 to 2016. As noted above, the starting year is governed by the absence of three-digit NAICS codes before 1998. Further, since 2017, a cell in CBP is only published if it contains three or more establishments. Since I will designate counties that have at least one hospital establishment but less than three as having lost access to hospitals, I refrain from extending the sample beyond 2016.

3.2 County-level Medicare Advantage (MA) Penetration Data

Data on MA penetration are derived from the Centers for Medicare & Medicaid Services's Medicare Advantage/Part D Contract and Enrollment Data series. These data are available from 2008 onwards for each county and calendar month. MA enrollment counts are suppressed if there are fewer than 10 eligible beneficiaries enrolled. All counties that have all months in a given year with suppressed enrollment information are dropped from the analytical sample. In some instances, I impute the suppressed counts by top-coding the suppressed values with 10. I make explicit whenever these imputed counts are used.

3.3 Other Data

As counties across the USA that experience changes in hospital availability are likely to be different than counties that do not, I use data from various sources to account for potential confounding factors associated with hospital access and MA penetration. I derive information on time-varying county-level covariates from the National Institute for Health Surveillance, Epidemiology and End Results (SEER) Program (Program(2023)Surveillance, Epidemiology, and End Results (SEER) Program, SEER) and from the Regional Economic Information System (REIS) ((2023)Bureau of Economic Analysis (BEA), BEA). From REIS, I obtain personal income for each county in the analytical sample. In particular, I construct measures of per-capita net earnings, per-capita personal current transfer receipts, and employment-population ratio from the REIS data. These measures describe the economic profile of the county along with the welfare receipts. SEER data provides me with information on the total and age category population counts. These measures relate to the demographic profile of the counties that constitute the estimation sample. Additionally, I also use 1993 rural-urban continuum codes obtained from the U.S. Department of Agriculture Economic Research Service. Rural counties are those classified as non-core or micropolitan in the 1993 urban/rural classification.

3.4 Analytical Sample Construction

The main analytical sample consists of counties in the continental United States. Additionally, I drop counties in Virginia, Washington, and the District of Columbia from the analytical sample. This is either due to the unique geographical characteristics of these states or because county borders frequently change in these states (Fischer, Royer and White, 2024). Further, for the main analytical sample, I also drop counties that lose or gain access over the sample period multiple times. In the sample, 121 counties lost access to hospital establishment at some point during the sample period. Of these counties, 57 experienced a loss of hospital establishment without a subsequent operationalization of a new hospital. I also exclude counties that never have access to hospital establishments (521 counties) and those that only gained access to hospitals during the sample period (34 counties), as this paper focuses on reduced access to hospitals. In a robustness check later, I establish the robustness of the main estimates to the inclusion of these counties. The analytical sample consists of 2354 counties with 57 of these counties losing access to ambulance services in some year during our sample period. Figure 1 plots these counties.

I measure access to hospitals both on the extensive and intensive margins. For the extensive margin measure, I designate a county in a given year to have hospitals if it has any hospital establishments in that year. For the intensive margin measure, I count the number of hospital establishments.

3.5 Summary Statistics

Figure 2 presents the temporal variation in the MA penetration rate. In 2025, approximately 45% of eligible beneficiaries are enrolled in MA plans, starting from about 15% in 2008. This massive increase in MA plan enrollment is also reflected in Figure 3, where I report the county-level MA penetration rate in 2008 and 2024. During the overlapping period, estimates in Figure 4 also show that the count of counties with no hospital establishment has steadily increased. As was reported earlier, in the analytical sample, there are 57 counties that lost access to the hospital establishments without a new hospital commencing operations during the sample period. Thus, approximately six counties lost hospital establishments every year, on average.

Table 1 reports means of observable characteristics for the counties that lost hospital establishments during the sample period without a subsequent operationalization of a new hospital. These counties are labeled as "No Hospital Counties" in Table 1. Counties that continue to have at least one hospital establishment are labeled as "Hospital Counties". The estimates in this table show that counties that had hospital closures during the sample period are less populated, losing population, have lower earnings per-capita, receive more transfers per-capita, have a lower employment-to-population ratio, and are likely to be more rural. The empirical strategy used to uncover the causal effect of increased MA penetration on hospital closures, discussed in the next section, addresses how these differences across observable characteristics between the two sets of counties do not weaken the causal interpretation of the estimates.

4 Empirical Strategy

This paper aims to identify the causal effect of the Medicare Advantage (MA) penetration on hospital availability. The main empirical specification is the following.

$$y_{ct} = \alpha_c + \alpha_t + \beta MAPenetration_{ct} + \varepsilon_{ct} \tag{1}$$

In Equation 1, y_{ct} is the outcome for county c in period t. Since the County Business Patterns (CBP) data are available annually, the t corresponds to the year. In Equation 1, I also control for county and year fixed-effects. These are denoted by α_c and α_t, respectively. The county fixed-effects control for all time-invariant characteristics at the county-level, while the year fixed-effects control for all time-specific unobservable characteristics that are common across all the counties in the analytical sample.

By including these fixed-effects, I leverage variation in MA penetration within a county over time to estimate its effect on the availability of hospital establishments in that county. ε_{ct} is the idiosyncratic error terms that I cluster at the county-level to account for correlation across years within a county (Abadie, Athey, Imbens and Wooldridge, 2022; MacKinnon, Ørregaard Nielsen and Webb, 2023).

The parameter of interest in Equation 1 is β. The estimate of β is the marginal effect of a percentage point increase in MA penetration on the outcome of interest. I note that the specification in Equation 1 is akin to a difference-in-differences empirical framework. Consequently, to interpret estimates from this specification causally, I need certain assumptions to be satisfied. First, I need to ensure that the outcomes for the counties with different levels of MA penetration are trending similarly.

To this end, I present event-study estimates in Figure 5. The event-study estimates are from the estimation of a specification similar to Equation 1, where I replace the MA penetration variable with multiple indicators for each period pre- and post-treatment in the analytical sample. The timing of the treatment is defined as the first year in which the county has at least 15% MA penetration. All the estimates are relative to the period immediately preceding the first post-treatment period, which is denoted by zero in both figures. This specification is as follows.

$$y_{ct} = \alpha_c + \alpha_t + \sum_{i=-5, i\neq -1}^{4} \beta_i \left[\mathbb{1}\left\{Treat_c\right\} \times \mathbb{1}\left\{t - TreatYear_c = i\right\}\right] + \delta_{ct} \tag{2}$$

In Equation 2, all the parameters are the same as in Equation 1, except that the MA penetration measure variable is replaced with the interaction of treatment status of the county indicator, $\mathbb{1}\left\{Treat_c\right\}$, and the indicator for the difference between the year t and the treatment year (i.e., the first year the county has at least 15% MA peentration) for the county, $TreatYear_c$, to be from -5 to 4. In Equation 2, I denote this interaction as $\left[\mathbb{1}\left\{Treat_c\right\} \times \mathbb{1}\left\{t - TreatYear_c = i\right\}\right]$.

In Equation 2, $\beta_i, \forall i \in \{-5, .., 4\}, i \neq -1$ is relative to β_{-1} which is the marginal effect of MA penetration being at least 15% on outcome variable in the year immediately preceding the first year of treatment, $i = 0$. The outcomes for the treatment and control counties are trending similarly in the pre-treatment period if $\beta_i = 0, \forall i \in \{-5, .., -1\}$ in Equation 2.

Note that the specification in Equation 2 is a two-way-fixed-effects (TWFE) specification. Recent literature has highlighted that in the presence of staggered treatment adoption along with dynamic and heterogeneous treatment effects, TWFE estimates are biased (de Chaisemartin and D'Haultfœuille, 2022; Roth, Sant'Anna, Bilinski and Poe, 2023). This bias arises due to "forbidden" comparisons where an earlier treated unit serves as a counterfactual unit for a later treated unit. As counties breach 15% MA penetration in different years during the sample period, the specification in Equation 2 is potentially subject to this bias.

In Figure 5 we present estimates from the estimator proposed in de Chaisemartin and D'Haultfœuille (2024). This estimator removes contamination arising due to "forbidden" comparisons. We observe that the likelihood of the county having no hospital establishment is trending similarly in the control and treatment group before the county has at least 15% MA penetration. I note that the p-value of the joint test for all pre-treatment parameters to be zero is 0.934. Thus, I do not reject the null hypothesis that the likelihood of no hospital establishment in the county is trending similarly in treatment and control counties in the pre-treatment period. Estimates in Figure 5 also show that there is no anticipation of not having any hospital establishment in the counties that ever have at least 15% MA penetration during the sample period. In Figure 6, I use an alternate MA penetration threshold to document dynamics very similar to those observed in Figure 5. Therefore, the conclusion of increased MA penetration increasing the likelihood of a county losing all the hospital establishments is not an artifact of the MA penetration threshold I chose in Figure 5.

To the best of my knowledge, there is no other program that was rolled out during the sample period that specifically targeted counties with at least 15% MA penetration. The empirical design secures contamination from the effects of policies that are likely to affect treatment and control counties similarly.

5 Results

In this section, I present results. I report estimates from the specification in Equation 1. Through multiple empirical checks, I establish the robustness of our main results.

5.1 Main Results

I begin by examining the likelihood of the county not having any hospital establishment as the Medicare Advantage (MA) penetration increases. Table 2 reports point estimates from the specification in Equation 1. For each percentage point increase in MA penetration, the likelihood of the county losing all hospital establishments increases by 0.097 percentage point. Recall that from Table 1, approximately 2% of the counties have no hospital during the pre-treatment period. Thus, the estimates in column (1) of Table 2 show that each percentage point increase in MA penetration increased the likelihood of a county not having any hospital establishment by 4%. The increase in the likelihood of no hospital establishment with increased MA penetration is also highly statistically significant at conventional levels of statistical significance.

Figure 5 reports event-study estimates from the specification in Equation 2. I cannot reject the null hypothesis that all of the pre-treatment parameter estimates are zero. p-value from a Wald test of the null hypothesis that all pre-treatment estimates are zero is 0.934. The likelihood of no hospital establishment in the county increases from the second post-treatment period, and this increase persists for the rest of the post-treatment period, albeit with some loss of statistical precision in the last post-treatment period.

Column (2) of Table 2 reports the estimates from the specification in Equation 1 with the count of hospital establishments as the outcome variable. Increased MA penetration in the county does not affect the count of hospital establishments in the county. The count data nature of the outcome variable in column (2) of Table 2 may not be well suited for ordinary least squares estimation. Thus, I also report average marginal effects from the Poisson pseudo-maximum likelihood estimation. These estimates are reported in column (2) of Table 3 and continue to be statistically insignificant.

In the following subsection, I present various empirical checks to establish the robustness of the conclusions in this subsection. I establish that the main findings are unaltered when I change the estimating specification, modify the analytical sample, or use an alternate MA penetration measure.

5.2 Robustness Checks

I next turn to establish the robustness of the estimates presented in Table 2. I conduct a series of robustness checks in Table 4.

The first column of Table 4 replicates column (1) of Table 2. In column (2), I replace year fixed-effects in the specification in Equation 1 with urban group-by-year fixed-effects. Rural-urban classification for the counties is derived from the 2013 National Center for Health Statistics (NCHS) Urban-Rural Classification Scheme for Counties data. Recall from the estimates in Table 1 that the counties that lose all the hospital establishments sometime during the sample period are more likely to be rural. Including urban group-by-year fixed-effects allows for secular shocks to differ across counties with different extents of urbanization. Reassuringly, the point estimates in column (2) of Table 4 are extremely close to the estimates in the first column.

In column (3) of Table 4, I also include all the counties that never had access to a hospital establishment or only gained at least one hospital establishment during the sample period in the analytical sample. Expansion of the set of control counties by inclusion of these counties is not consequential for the conclusions drawn in Section 5.1.

The final column of Table 4 allows for the increased MA penetration to affect the availability of hospital establishment in the county with a delay. In column (4) of Table 4, I use the lead of the MA penetration measure instead of the contemporaneous MA penetration measure. Allowing for an increase in MA penetration to affect the hospital establishment availability in the county with a delay of one year does not meaningfully change the point estimates reported in the first column.

In Figure 7, I drop one of the 57 counties that are part of the analytical sample and lost access to all the hospital establishments one by one. The estimates reported in this figure help assuage concern that one county is exerting an outsized influence on the estimate reported in the first column of Table 2.

Overall results in this subsection show that increased MA penetration in the county leads to an increased likelihood of the county losing all its hospital establishments. This conclusion is robust to multiple sensitivity checks related to empirical specification, analytical sample, and treatment variable definitions.

6 Discussion and Conclusion

In this paper, I study the impact of increased Medicare Advantage (MA) penetration on the hospital availability at the county-level. I leverage variation in MA penetration within a county over the sample period. I find that an increase in MA penetration increases the likelihood of a county losing all its hospital establishments, an effect that is significant statistically and economically. I show the robustness of this conclusion through multiple empirical checks.

This work has important implications for policymakers. MA enrollees being denied care is a phenomenon that is rampant across vast swathes of the country. In addition to lower reimbursement, delayed payments to the providers by the MA plans jeopardize not only patient health but also the financial standing of the healthcare providers. I show that the economic troubles of the hospitals eventually manifest themselves in the county losing all its hospital establishments. By reforming the reimbursement rate schedules of the MA insurance plans, along with providing incentives for timely payments by the MA plans to the health providers, policymakers can prevent the county from losing all its hospital establishments.

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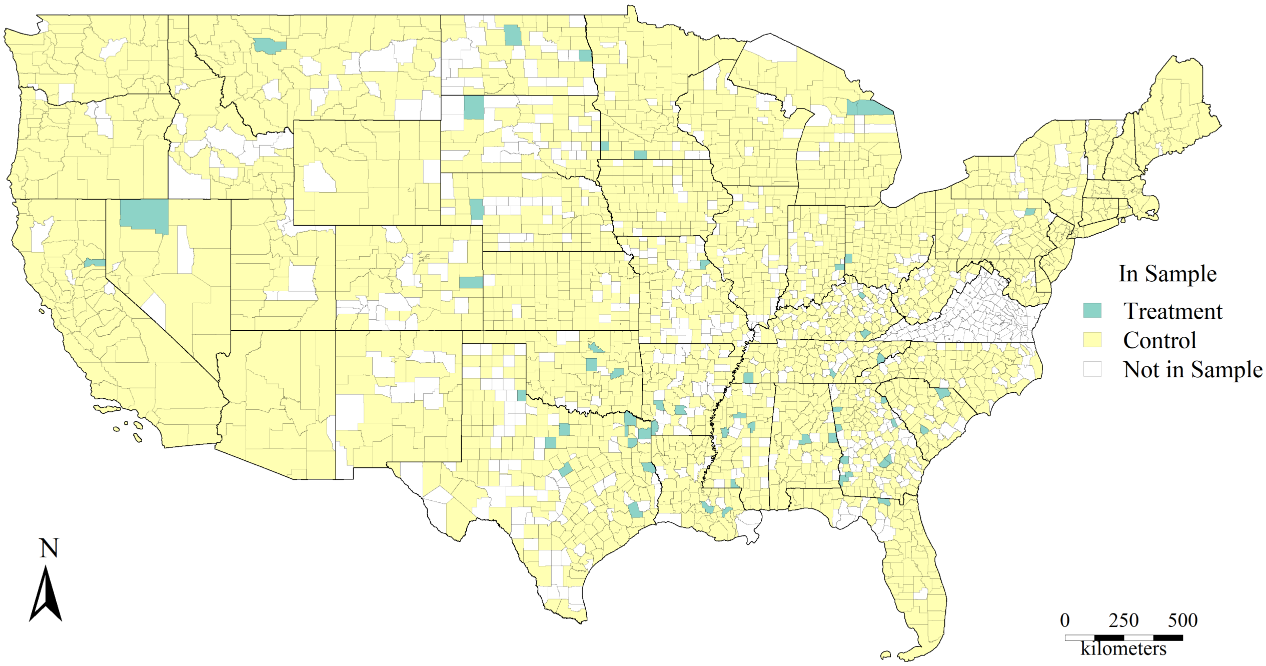
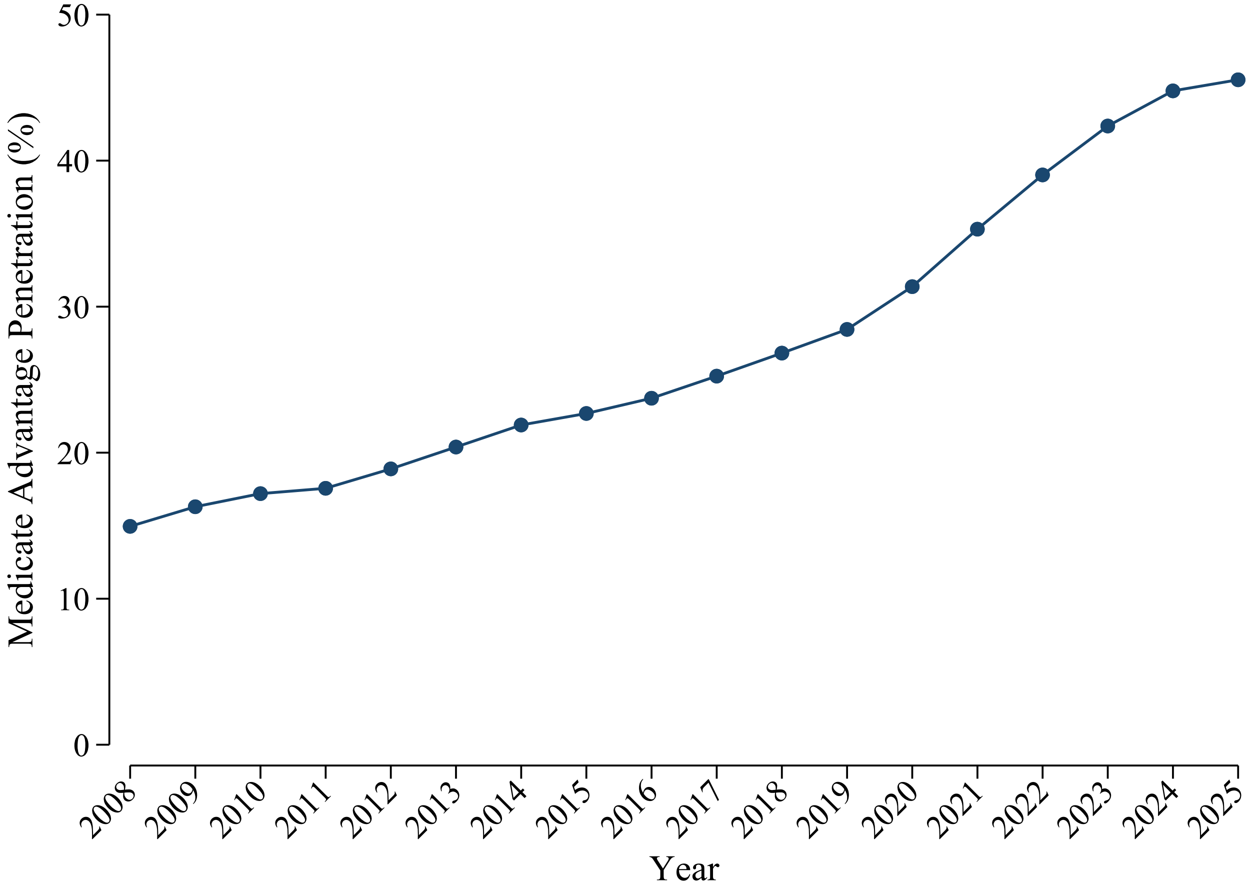
Figure 1: Spatial Distribution of Treatment-Control Counties



Note: Refer to Section 3.4 for more details.

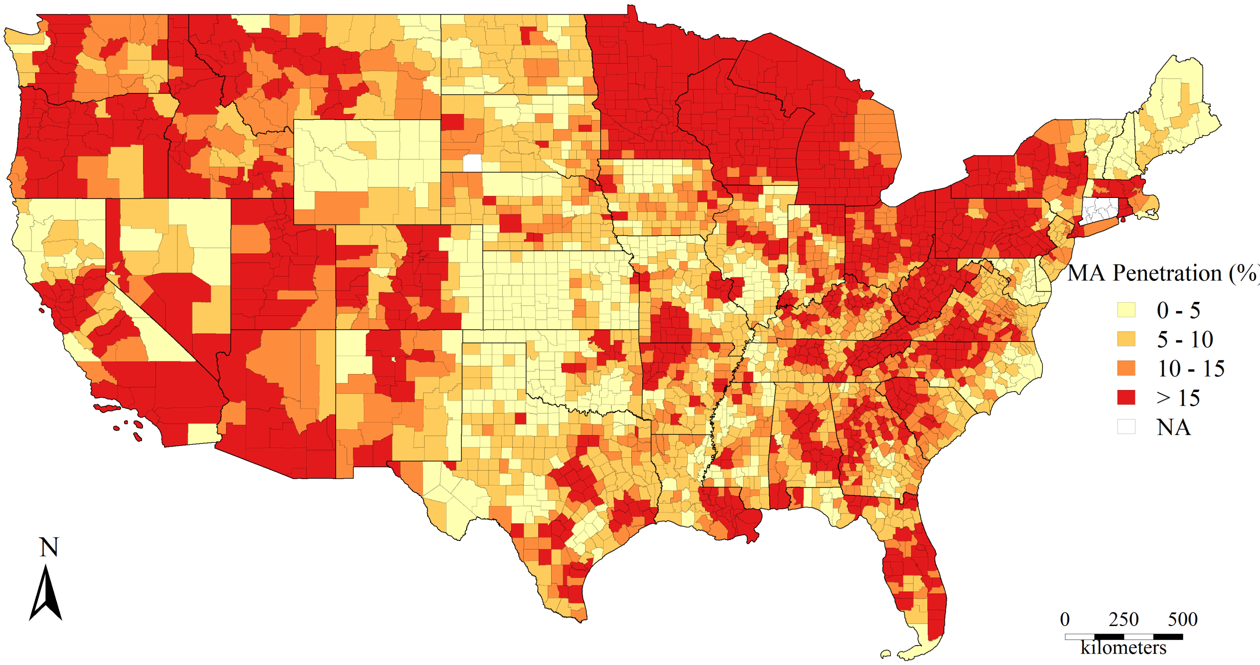
Figure 2: Temporal Variation in Medicare Advantage (MA) Penetration



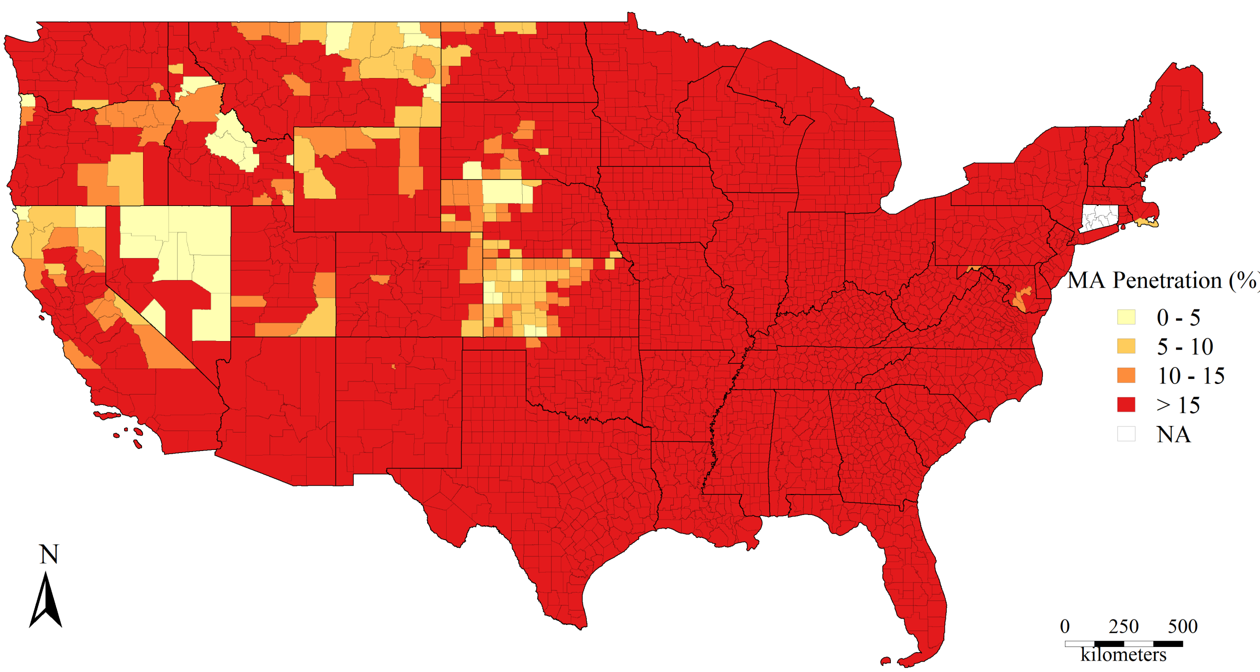
Note: Data on MA penetration are derived from the Centers for Medicare & Medicaid Services's Medicare Advantage/Part D Contract and Enrollment Data series. MA enrollment counts are suppressed if there are fewer than 10 eligible beneficiaries enrolled. For such counts, I top code the missing data with 10. Month-year counts are averaged across the year.

Figure 3: Spatial Distribution of Medicare Advantage (MA) Penetration 2008 and 2024

(a) MA Penetration 2008

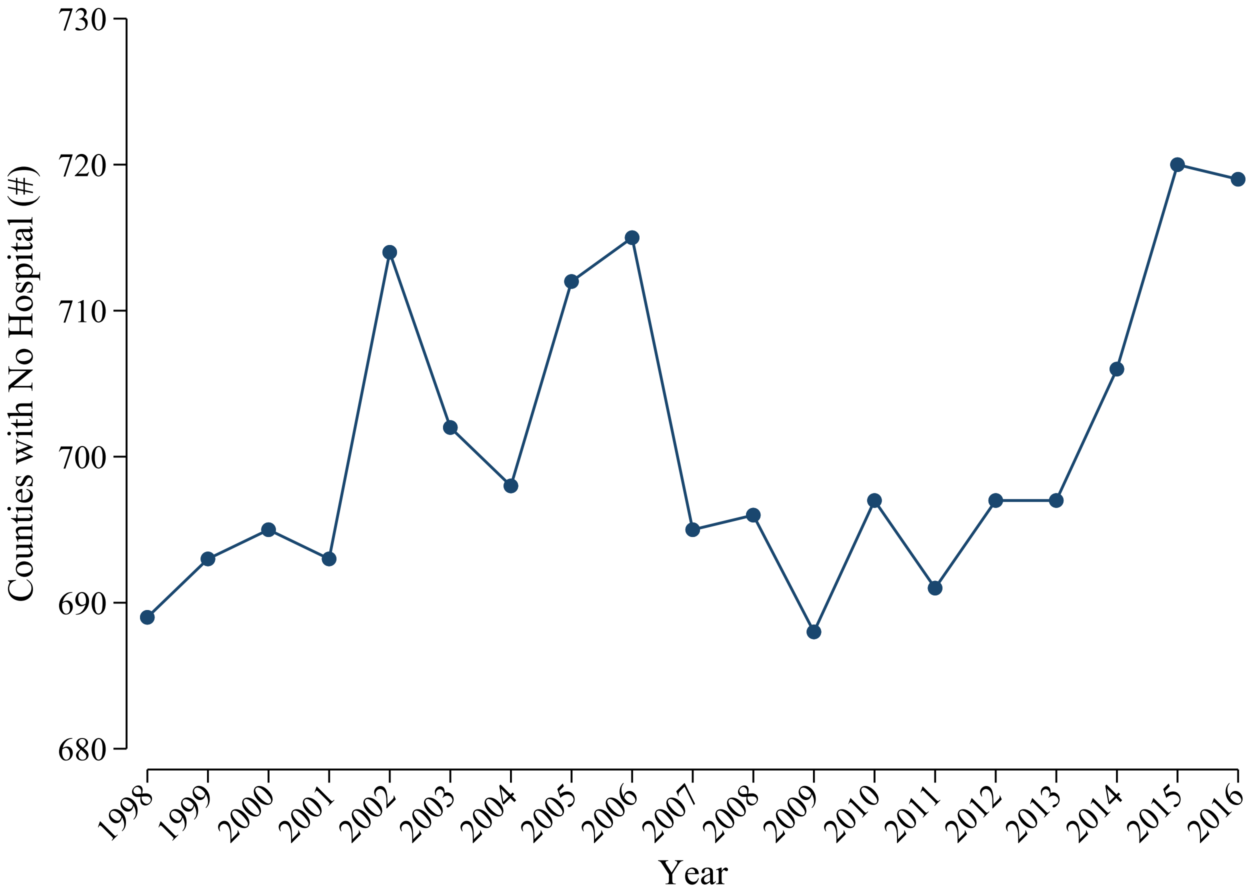


(b) MA Penetration 2024



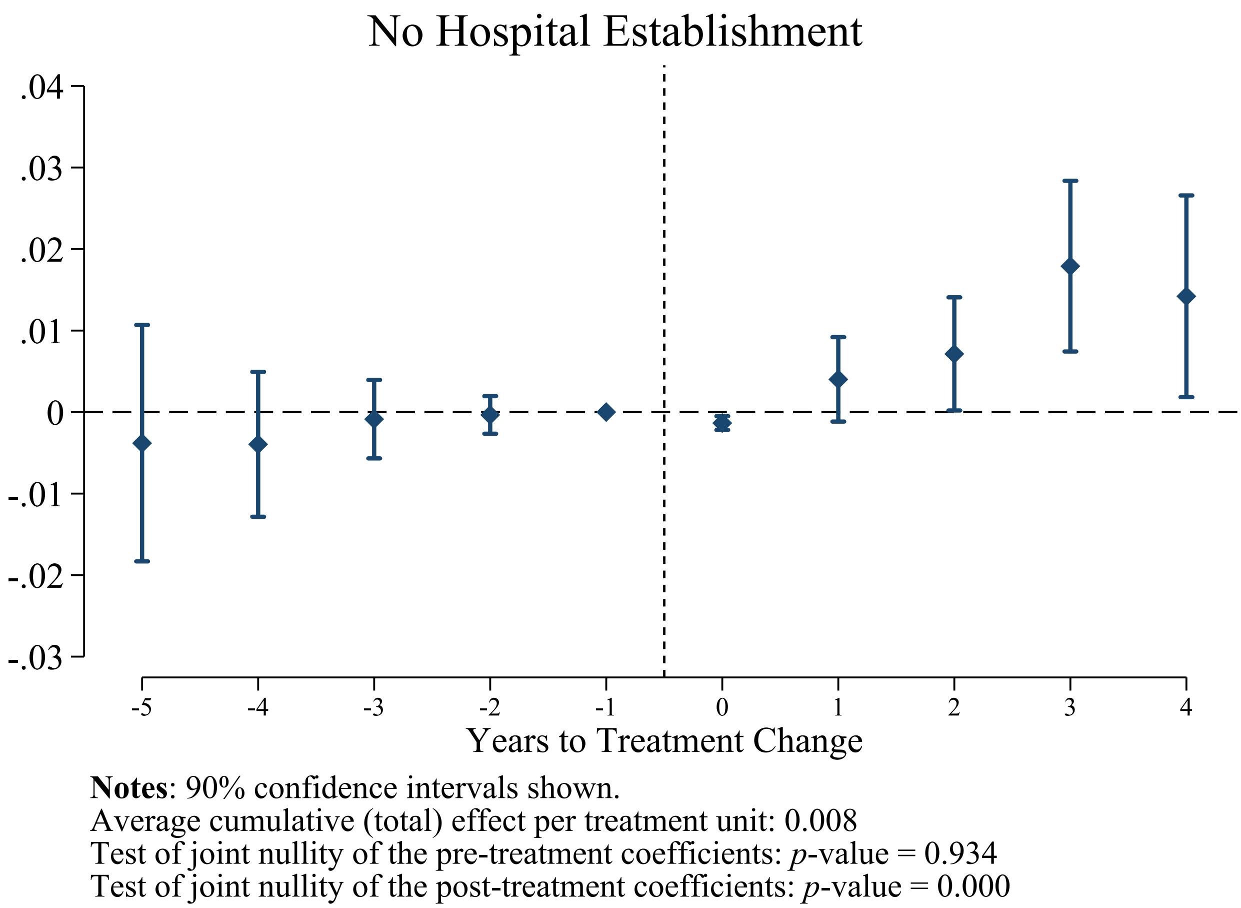
Note: Data on MA penetration are derived from the Centers for Medicare & Medicaid Services's Medicare Advantage/Part D Contract and Enrollment Data series. MA enrollment counts are suppressed if there are fewer than 10 eligible beneficiaries enrolled. For such counts, I top code the missing data with 10. Month-year counts are averaged across the year.

Figure 4: Temporal Variation in Count of Counties with No Hospital Establishment



Note: Data on hospital establishments are derived from the County Business Patterns (CBP). In these data, hospital establishments correspond to the North American Industry Classification System (NAICS) code "622".

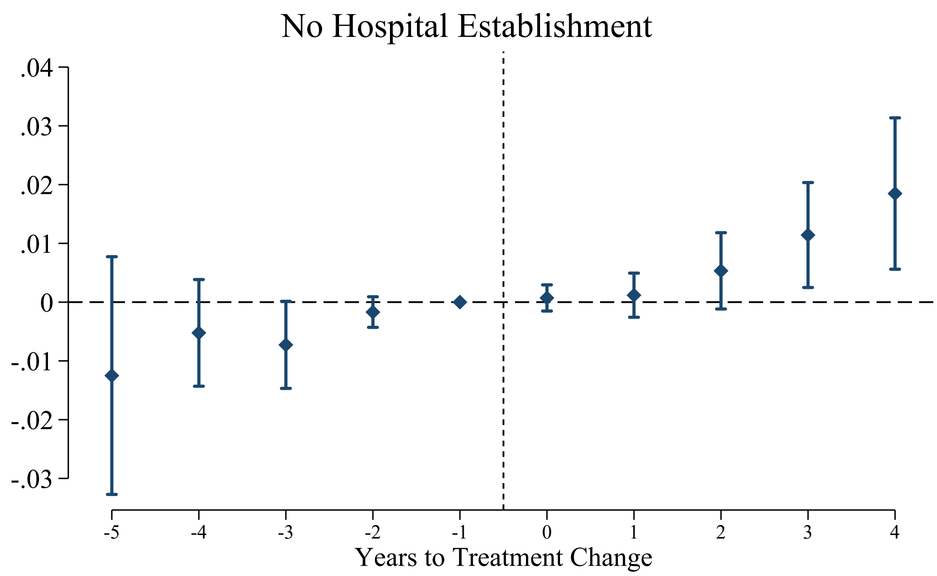
Figure 5: Event-study Estimates for No Hospital Establishment in the County



Note: Estimates from the specification in Equation 2 are reported. Refer to Section 4 for more details. Standard errors are clustered at the county-level.

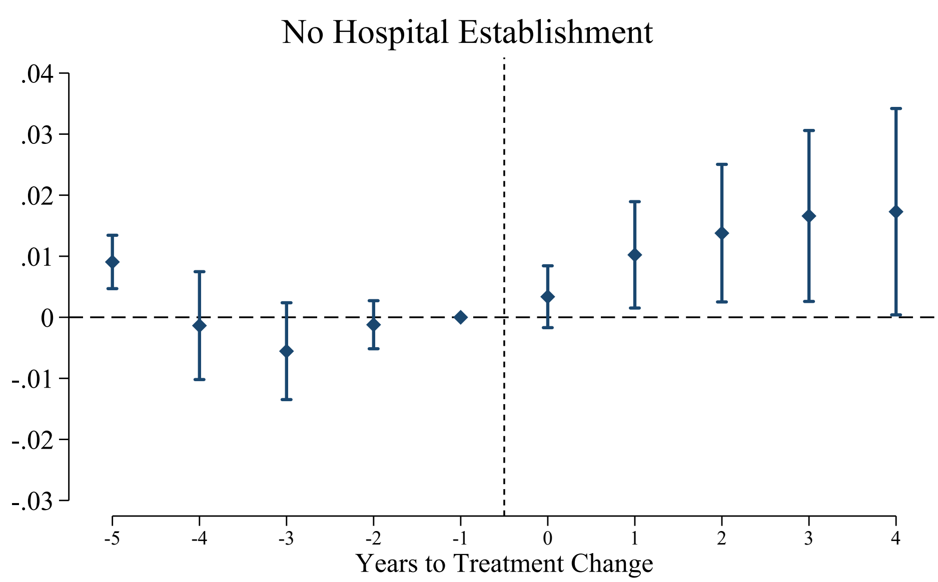
Figure 6: Event-study Estimates for No Hospital Establishment in the County: Alternate Medicare Advantage (MA) Penetration Threshold

(a) At least 10% MA Penetration



Notes: 90% confidence intervals shown.
Average cumulative (total) effect per treatment unit: 0.007
Test of joint nullity of the pre-treatment coefficients: p-value = 0.434
Test of joint nullity of the post-treatment coefficients: p-value = 0.207

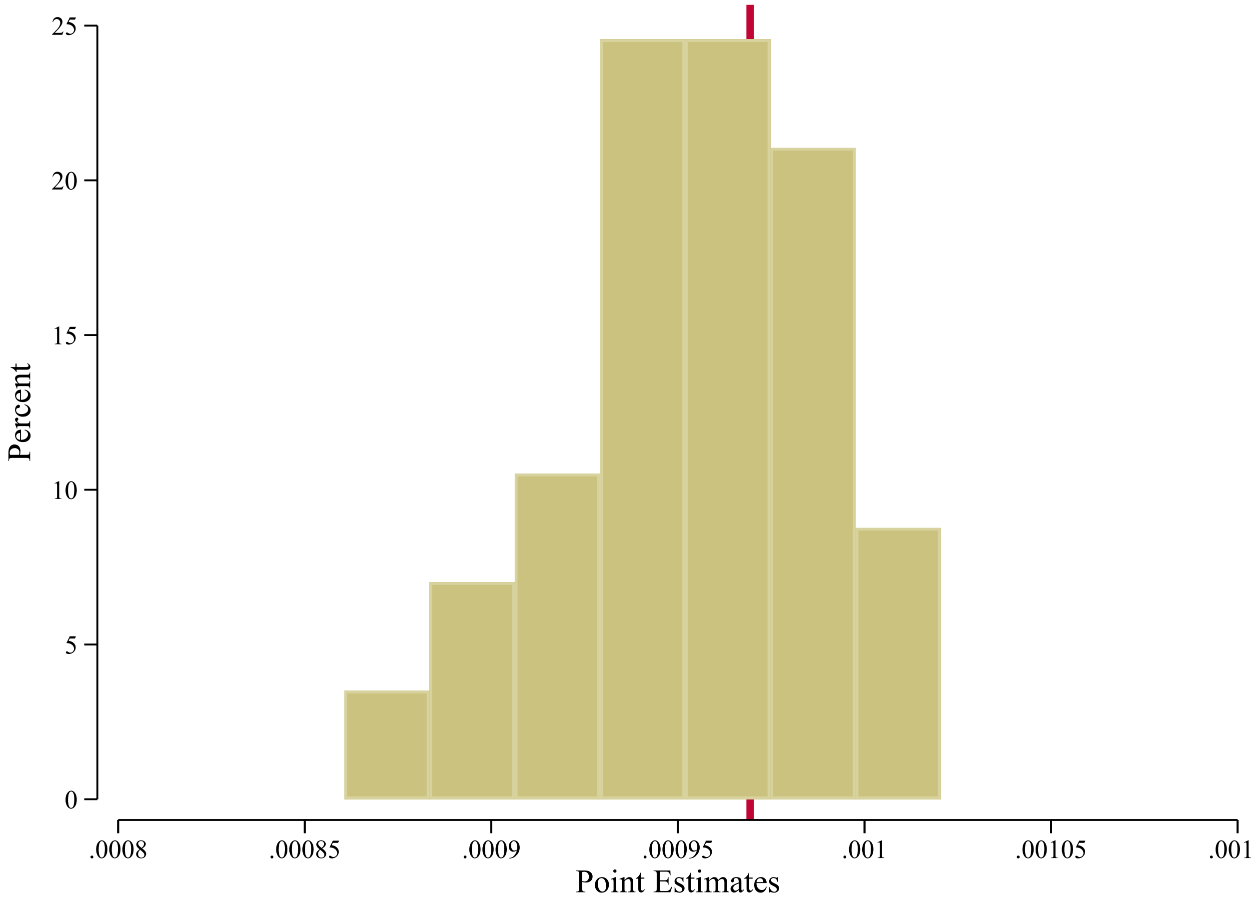
(b) At least 25% MA Penetration



Notes: 90% confidence intervals shown.
Average cumulative (total) effect per treatment unit: 0.012
Test of joint nullity of the pre-treatment coefficients: p-value = 0.005
Test of joint nullity of the post-treatment coefficients: p-value = 0.439

Note: Data on MA penetration are derived from the Centers for Medicare & Medicaid Services's Medicare Advantage/Part D Contract and Enrollment Data series. MA enrollment counts are suppressed if there are fewer than 10 eligible beneficiaries enrolled. For such counts, I top code the missing data with 10. Month-year counts are averaged across the year.

Figure 7: Robustness Check: Drop One Treatment County at a Time from the Analytical Sample.



Note: Estimates from the specification in Equation 1 are reported. Refer to Section 4 for more details. Standard errors are clustered at the county-level. Red vertical line denotes the estimate in column (1) of Table 2.

Table 1: Summary Statistics: County Characteristics

	All Counties	No Hospital Counties	Hospital Counties
Population	120,626	20,067	123,121
Population Growth Rate	0.5186	-0.0742	0.5333
Earnings Per-Capita	20,663	19,016	20,704
Transfers Per-Capita	7,086	9,279	7,032
Empl./Pop.	0.536	0.450	0.538
Rural County	0.703	0.877	0.698
# Hospital Establishments	2.842		
$\mathbb{1}$(No Hospital Establishment)	0.024		
MA Penetration (%)	14.669	20.848	14.514
Number of Counties	2,354	57	2,297

Notes: Author's calculations. More information on the variable construction and data sources is presented in Section 3.4. For counties labeled "No Hospital Counties", the data are from the year immediately preceding the year the county lost all the hospital establishments. In contrast, for counties labeled "Hospital Counties", the data are from 2008.

Table 2: Effect of Medicare Advantage (MA) Penetration on Hospital Establishment Availability

	No Hospital Establishment (1)	Number of Hospital Establishment (2)
$MAPenetration_{ct}$	0.00097***	0.00079
	(0.00030)	(0.00242)
County FEs	Yes	Yes
Year FEs	Yes	Yes
$\frac{\text{Coefficient}}{\text{Pre-treatment Mean in Treatment Group}} \times 100$		0.1
Adj. R^2	0.515	0.978
N	20,571	20,571

Notes: Heteroskedasticity robust standard errors clustered by the county in parentheses. (* p<.10 ** p<.05 *** p<.01). The ratio of point estimate in each cell and mean of the outcome variable for the counties that lost all hospital establishments during the sample period in the year immediately before the loss of hospital establishments is in square brackets. Each cell is a separate estimation of Equation 1. The estimated specification also includes county and year fixed-effects. See Section 3 for more details on the construction of the variables and data sources. The sample is restricted to 2008-2016.

Table 3: Poisson pseudo-maximum likelihood (PPML) Estimation

	OLS	PPML
	(1)	(2)
$MAPenetration_{ct}$	0.00079	0.00079
	(0.00242)	(0.00269)
County FEs	Yes	Yes
Year FEs	Yes	Yes
$\frac{\text{Coefficient}}{\text{Pre-treatment Mean in Treatment Group}} \times 100$	0.1	0.1
Adj. R^2	0.978	
N	20,571	20,571

Notes: Heteroskedasticity robust standard errors clustered by the county in parentheses. (* p<.10 ** p<.05 *** p<.01). The ratio of point estimate in each cell and mean of the outcome variable for the counties that lost all hospital establishments during the sample period in the year immediately before the loss of hospital establishments is in square brackets. Each cell is a separate estimation of Equation 1. The estimated specification also includes county and year fixed-effects. See Section 3 for more details on the construction of the variables and data sources. The sample is restricted to 2008-2016.

Table 4: Robustness Checks: No Hospital Establishment

	Baseline	Include Urban Group × Year FEs	Include All Counties	Lead Penetration Measure
	(1)	(2)	(3)	(4)
$MAPenetration_{ct}$	0.00097***	0.00112***	0.00076***	0.00107***
	(0.00030)	(0.00032)	(0.00027)	(0.00033)
County FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	Yes
Urban Group × Year FEs	No	Yes	No	No
Adj. R^2	0.515	0.517	0.958	0.587
N	20,571	20,571	25,155	18,285

Notes: Heteroskedasticity robust standard errors clustered by the county in parentheses. (* p<.10 ** p<.05 *** p<.01). The ratio of the point estimate in each cell and mean of the outcome variable for the counties that lost all hospital establishments during the sample period in the year immediately before the loss of hospital establishments is in square brackets. Each cell is a separate estimation of Equation 1. The estimated specification also includes county and year fixed-effects, except in column (2), where the year fixed-effects are replaced by urban group times year fixed-effects. In column (3), all counties that never had access to a hospital establishment and those counties that only gained hospital establishment are also included. In column (4), the Medicare Advantage (MA) penetration measure is led by one year. See Section 3 for more details on the construction of the variables and data sources. The sample is restricted to 2008-2016.