Health Effects of Ambulance Desert*

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Abstract

Using detailed county-level data on ambulance service establishments, we show that loss of access to ambulance services reduces deaths due to external causes. The decline in deaths is driven by assaults and accidental injury deaths. The reduced mortality is concentrated in whites without a college degree. Our results are robust to a battery of empirical checks including accounting for staggered treatment adoption and bundling of hospital closure along with ambulance services loss.

JEL Classifications: I11, L91, R40

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1 Introduction

In the realm of emergency medical services, timely access to ambulance services is a critical component. However, the availability of ambulance services varies considerably in the United States, with notable gaps in certain regions. This uneven distribution of ambulance services raises concerns about the equitable delivery of emergency healthcare and its potential impact on health outcomes. In England, more than 43,000 people had already been pronounced dead when an ambulance arrived between 2022 and 2023 [1]. In the United States (US), average response time for emergency medical service (EMS) units to a 911 call is 7 minutes. In rural areas, the median time rises to more than 14 minutes, with roughly one in ten contacts necessitating a nearly 30-minute wait for EMS staff. Poorer outcomes for trauma victims have been linked to longer EMS response times. Even little delays can be fatal in some, albeit uncommon, emergencies such as cardiac arrest, acute bleeding, and airway obstruction (Mell et al., 2017).

Ambulance deserts are places where people live more than 25 minutes from the nearest station. According to Jonk et al. (2023), data in 41 states shows that 4.5 million people reside in these deserts, and six out of 10 live in the US South. The nearest surviving facilities are several minutes' drive away, implying that ambulance coverage is scarce. Delayed emergency medical response can have significant negative health effects on the affected individuals and their communities. This has put residents needing medical emergencies in an increasingly precarious situation in these areas. In ambulance deserts, there is often a market failure where the private sector may need help finding it economically viable to provide ambulance services due to low population density and the high cost of maintaining ambulance fleets. In many cases, governments step in to address this market failure by providing publicly funded ambulance services in rural areas or by reimbursing private providers for rendering their services.

In this paper, we study the mortality and health effects of living in an ambulance desert across various subpopulations. Apriori, it is unclear if losing access to ambulance services worsens health outcomes. Reduced medical transportation opportunities in the wake of ambulance service provider closure may

[1] More on this at https://www.dailymail.co.uk/news/article-11996389/More-43-000-people-declared-dead-time-ambulance-arrived-year.html

worsen health outcomes. This may happen if the patient cannot receive timely care, increasing the chances of developing medical complications. If a hospital closure accompanies the closing of ambulance services, it is also possible that the remaining hospitals, albeit further away, provide better quality care. This might lead to better health outcomes due to improved care quality. At the same time, residents of counties without access to ambulance services may be incentivized to undertake private actions to reduce their risk of acute medical emergencies. Thus, depending on the context, lost access to ambulance services may positively or negatively affect health outcomes.

Using detailed county-level data on establishments providing ambulance services together with restricted data on multiple causes of death, we examine if losing access to ambulance services in the residence county affects mortality due to various causes of death. Our empirical strategy relies on comparing counties that lose access to ambulance services and those that don't after accounting for time-invariant unobservable characteristics at the county-level and time-varying shocks that are common across counties with different levels of urbanization. We use inverse probability weighting to ensure that treatment and control counties are balanced along the observable characteristics. We also establish that our conclusions are not driven by counties losing access to ambulance services at different times during the sample period by making use of modern estimators allowing for staggered treatment adoption and dynamic heterogeneous treatment effects.

We find that after the county loses access to ambulance services, there is a decline in the number of deaths due to external causes. In particular, there are approximately five fewer deaths annually due to external causes, amounting to an 18% decline over the pre-treatment mean for the counties that ever lose access to ambulance services. The decline in deaths gradually emerges after the county lost access to ambulance services and persists for more than nine years. We establish that the reduced deaths due to external causes are not driven by loss of access to hospitals. Our estimates are not sensitive to including additional counties or accounting for shocks that are time-varying and common across all counties in a state.

The reduced deaths due to external causes are driven by the reduction in deaths due to assault and accidental injury. We find that the reduction in deaths becomes less pronounced as we move across the age distribution. The decline in deaths is concentrated among the whites who do not have a college degree.

With this work, we contribute to multiple strands of literature. We contribute to an emerging literature on the health effects of losing access to medical services (Avdic et al., Forthcoming; Battaglia, Forthcoming; Fischer et al., 2024). This literature also relates to a wider literature on the role of place in health outcomes (Deryugina and Molitor, 2021; Finkelstein et al., 2016; Molitor, 2018; Skinner, 2011). We add to this literature by identifying the role of delayed access to medical transport facilities on mortality due to acute causes. Most of the existing literature documents the reasons for the emergence of the ambulance desert. Booker et al. (2015) reviews this literature, while Mikolaizak et al. (2013) provides a systematic review of limited but promising evidence showing that appropriate interventions can improve the health outcomes of older people. While the effect of living in an ambulance desert might be more pronounced for older subpopulations, we show that in our context young and working age adults experience an improvement in their mortality outcomes when their residence county loses access to ambulance services.

2 Background

Ambulance services primarily involve transporting patients to medical facilities, but their role extends beyond mere transportation. They also include air medical transport, emergency medical dispatch, and non-transporting ambulance services.[2] As ambulance services traditionally provided ground-based transport and emergency medical assistance, they have been governed and regulated by the National Highway Traffic Safety (NHTSA) housed within the United States Department of Transportation (DOT). Historically, ambulance services have relied on funding from community resources and goodwill donations for their continued operation. Before 1969, a multitude of organizations provided ambulance services. These included fire departments, hospitals, funeral homes, towing companies, and

[2]Establishment level data from CBP that we use preclude us from identifying the exact service type of ambulance services.

volunteers.[3]

With the passing of the Emergency Medical Services (EMS) Act of 1973, the federal government was the chief funder of EMS up until the 1980s when the federal support for EMS declined significantly (on the Future of Emergency Care in the US Health System and others, 2006). Despite the federal support, differences in local needs, characteristics, and concerns lead to a system where EMS differs significantly across states and regions. Furthermore, the late 1970s also saw coordination problems between the Department of Health and Human Services and DOT. With the passage of the Omnibus Budget Reconciliation Act (OBRA), categorical federal support to states for EMS was eliminated. With greater discretion on the allocation of block grants, states significantly reduced their expenditures on EMS. States further allowed cities and counties to develop their own EMS systems. As the involvement of local agencies increased, the extent and quality of EMS differed significantly across areas often due to the economic conditions of such areas. During this period national volunteer EMS organizations took an important role in providing such services across the nation.

Contemporaneously EMS are provided by the local governments who are responsible for their management and financing. These local EMS systems are under the oversight of state EMS agencies. Local EMS providers include community nonprofit organizations, fire departments, other government departments, hospitals, and private non-hospital organizations. Unsurprisingly, the quality of services rendered by these different entities differs significantly. For rural areas, EMS providers are relatively more heavily dependent on volunteers than their urban counterparts.[4] Problems surrounding volunteer recruitment and retention in these areas are a perennial issue that EMS providers are faced with.

Jonk et al. (2023) argue that more than three-quarters of existing ambulance agencies in 2020 serve rural areas. As the demand for ambulance service use in rural areas is sporadic, ambulance services are exceedingly unable to meet their operating costs. As the medical equipment required for the successful operation of ambulance services has become costly, many rural areas have either lost or are at an

[3]Cincinnati, Ohio established the first civilian ambulance service in 1865 after the Union Army's Ambulance Corps saved many lives during the Civil War.

[4]Approximately half of all the revenue for rural providers is appropriated through Medicare payments (Chaudhary et al., 2019).

increasing risk of losing access to ambulance services. Furthermore, the reimbursement for the services rendered by the ambulance services takes place only if the patient is transported. Reduced revenue and increasing costs have led to mean that ambulance establishments exiting the counties altogether. This can be seen clearly in Figure 1. In this figure, we present the fraction of counties without an ambulance service establishment during our sample period. From this figure, we conclude that the share of counties that are ambulance deserts has been increasing over time. At the same time, we also observe that deaths due to external causes per-capita progressively increase over time during the sample period.

Using data on ambulance service locations, Jonk et al. (2023) find that almost 4.5 million reside in ambulance deserts. They define ambulance deserts as areas where that are beyond the 25-minute travel time away from transporting ambulance service locations.[5] These authors also find that of those who reside within ambulance deserts, more than half reside in rural counties. Furthermore, the extent of the population residing within the ambulance desert differs significantly across regions and states. As we leverage within county variation in the access to ambulance services, it is reassuring that using a different measure Jonk et al. (2023) find substantial within county variation in the population residing within the ambulance desert.

Ambulance services are often provided by the hospitals. As has been well documented, rural counties are seeing increasing hospital closures (Alexander and Richards, 2023; Battaglia, Forthcoming; Fischer et al., 2024). As a result, residents in such counties may have to wait longer as ambulance services see increased response times in the wake of hospital closures. For acute illnesses, this increased response time might be fatal. In our empirical strategy, we explicitly account for the hospital access at the county-level.[6] Therefore, our estimates should be interpreted as the marginal effects of losing ambulance services after purging out the effects of hospital closures.

[5]We highlight that our measure of ambulance desert differs from Jonk et al. (2023). Specifically, we treat counties without an establishment that provides ambulance services as an ambulance desert. Lack of access to the precise location of ambulance services, we are unable to replicate the measure in Jonk et al. (2023). Nevertheless, for counties in which the population is sparsely distributed we undercount the population that resides within an ambulance desert. Further, we also show that our main findings are not altered by dropping counties at the state border which might be serviced by the ambulance services from the counties in the neighboring state.

[6]Using the CBP establishment-level data, we construct a count measure of hospitals in the county for each sample year.

3 Data

In this section, we discuss various data sources that we use to examine the effect of reduced ambulance service access on mortality. The ideal data to study the effect of restricted ambulance services access will contain information on the availability of such services along with individual-level information on mortality. While these data are not available to us, we combine data from multiple sources to come closer to the ideal data. We combine county-level mortality data from the restricted version of death certificates with the number of establishments in the county rendering ambulance services. We also combine these data with various time-varying county-level variables. Each data source is discussed in detail in the following subsections.

3.1 Mortality Data

For our outcomes of interest, we use multiple cause of death (MCOD) mortality files data from the National Vital Statistics System (NVSS). We use the restricted version of these data. The restricted version allows us to obtain information on the county of residence and death of the deceased person at the time of death. The geographic identification of the residence county is crucial for us to construct access to ambulance services measures, details of which are provided in Section 3.2.

MCOD data are the universe of deaths reported in the United States of America (USA). MCOD data provides information on the single underlying cause of death. Additionally, information on up to 20 more causes of death is available. The causes of death, including the underlying cause, are provided as four-digit International Classification of Diseases, Tenth Revision (ICD-10) codes. MCOD data also provide limited demographic information. Specifically, we observe age, race, ethnicity, and education level for each registered death. We also observe the month and the year of death. Furthermore, MCOD data provides information on whether the death occurs due to injury at work. We can also ascertain if the death occurs due to an accident. The information on demographics and circumstances related to the death aids us in uncovering potential heterogeneities and mechanisms driving changes in mortality due to reduced access to ambulance services.

Finally, we are also able to observe the activity that might have led to the death. While we mainly focus on all-cause mortality, we expect reduced access to ambulance services to exert more influence on mortality occurring due to acute reasons like accidents or injuries. Therefore, in Section 3.4, we discuss how we leverage information in the MCOD data to construct mortality measures that are driven by deaths due to acute causes. In particular, we focus on deaths related to external causes.

External causes include injuries, suicides, homicides, and various types of accidents including motor vehicles. Some of these causes of death have been used in existing work examining the effect of hospital closure on health outcomes (Avdic, 2016; Buchmueller et al., 2006). As a placebo check, we also examine response of “all deaths" to assuage concerns that the effect of losing access to ambulance services might be spurious as deaths due to these causes are unlikely to be impacted by the travel time to receive medical care.

3.2 County-level Ambulance Services Data

We rely on County Business Pattern (CBP) establishment-level data to construct the measures of ambulance service access for each county in our 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 et al., 2022a,b). 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 us from constructing our measure of access to ambulance services before 1998. We, therefore, restrict our 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 ambulance services access, we use a single six-digit NAICS code, 621910. For each county-year pair, we measure ambulance services using the number of establishments in that pair that have the NAICS code 621910. NAICS description for this six-digit code is "Ambulance services". For our main specifications, we use contemporaneous ambulance service access measures. We establish the robustness of our main results using one period lag of whether the county has any ambulance service establishment. We lag ambulance service access measures to allow the establishment to be fully operational (Bondurant et al., 2018; Bradford and Maclean, 2023; Deza et al., 2022a,b; Swensen, 2015).[7] Our measure of ambulance service access does not fully capture all the aspects of access to ambulance services care. Access to such services depends on, among other things, communication skills, patience, and telephone connectivity. Nonetheless, a larger presence of providers might be the most important aspect of access to such services.

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, we note some potential reporting issues that might bias our estimates. We construct our measure of access to ambulance services using the reported six-digit NAICS code by the establishment. If this code is misreported by the establishments, then our estimates will be biased. Mis-attributing 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 correctly report their principle business code. 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 principle business code. Further, inaccurate reporting might attract fines and incarceration. Due to these reasons, we are confident that our measures of access to ambulance services are a fairly accurate reflection of actual access.

[7] In Figure 2, we show that when the ambulance service access measure is lagged by one period there is no statistically significant change in the estimates.

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

3.3 Other Data

As counties across the USA that experience changes in ambulance services access are likely to be different than counties that do not, we use data from various sources to account for potential confounding factors associated with ambulance services access and mortality changes. We derive information on time-varying county-level covariates from the National Institute for Health Surveillance, Epidemiology and End Results (SEER) Program (Surveillance, Epidemiology, and End Results , SEER) and from the Regional Economic Information System (REIS) (Bureau of Economic Analysis , BEA). From REIS, we obtain personal income for each county in the analytical sample. In particular, we 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 us 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, we also use 1993 rural-urban continuum codes obtained from 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

Our main analytical sample consists of counties in the continental United States. We drop counties in Alaska, Hawaii, D.C., and Virginia. This is either due to the unique geographical characteristics of these states or because county borders frequently change in these states (Fischer et al., 2024). Further, for our main analytical sample, we also drop counties that lose or gain access over the sample period multiple times. In our sample, 752 counties lost access to ambulance services at some point during our sample period. Of these counties, 152 experienced a loss of ambulance services without a subsequent resumption of such services. We also drop counties that never have access to ambulance services (987 counties) and also those counties that only gained access to ambulance services during our sample period (51 counties) as this paper focuses on reduced access to such services. In a robustness check later, we establish the robustness of our main finding to the inclusion of these counties. Our analytical sample consists of 991 counties with 152 of these counties losing access to ambulance services in some year during our sample period.

We measure access to ambulance services both on the extensive and intensive margin. For the extensive margin measure, we designate a county in a given year to have ambulance services if there is any establishment that render ambulance services in that county in that year. For the intensive margin measure, we count the number of establishments that provide ambulance services. Since our main empirical specification controls for the count of the population, our intensive margin measure might be interpreted as number of establishments that provide ambulance services in the county per-capita.

4 Empirical Strategy

This section discusses the empirical framework we use to examine the health effects of losing access to ambulance services. We spell out the main empirical specifications that we estimate. We then investigate the plausibility of the identifying assumptions needed to interpret our estimates as causal. Finally, we detail the steps we take to alleviate potential violations of identifying assumptions of our empirical setup.

Our main empirical specification derives from a difference-in-differences (DD) research design. We estimate this specification using the following two-way fixed-effects (TWFE) specification.

$$M_{c,t} = \alpha_c + \alpha_{u,t} + \beta AmbulanceService_{c,t} + \mathbf{X}^{'}_{c,t}\gamma + \varepsilon_{c,t} \tag{1}$$

In Equation (1), the outcome variable $M_{c,t}$ is the count of deaths in the residence county c in year t. Our variable of interest is $AmbulanceService_{c,t}$. This variable measures the extent to which a county has access to ambulance services in a given year. We measure access to ambulance services both on the extensive and intensive margin. For the extensive margin measure, we designate a county in a given year to have ambulance services access if any establishment renders ambulance services in that county in that year. Thus, for specifications where we are interested in the extensive margin effects of ambulance services access on health outcomes, $AmbulanceService_{c,t}$ is an indicator variable. This indicator variable takes a value of one if a county has any establishment providing ambulance services in a given year. For the intensive margin measure, $AmbulanceService_{c,t}$ counts the number of establishments that provide ambulance services.

$\mathbf{X}_{c,t}$ is a vector of time-varying county-level covariates. As we outlined in Section 3.3, these covariates are derived from the National Institute for Health Surveillance, Epidemiology and End Results (SEER) Program (Surveillance, Epidemiology, and End Results) and the Regional Economic Information System (REIS) (Regional Economic Information System). In the time-varying county covariates vector, we include population shares for multi-year age bands, per-capita personal income, per-capita government transfers, employment-population ratio, and the population density. α_c are county fixed-effects. These fixed-effects control for time-invariant county-level characteristics that may affect the mortality rate and level of ambulance services in the county. Following Bailey and Goodman-Bacon (2015), we also include urban group-by-year fixed-effects. Given that most counties that experience loss in access to ambulance services are rural, the secular shocks are unlikely to be common across rural and urban counties. We use 1993 Rural-urban continuum codes. We do not want the rural county designation affected by endogenous demographic shifts. Therefore, we use a designation determined before our sample period. These rural-urban continuum codes classify counties into nine groups by distinguishing metropolitan counties by size and nonmetropolitan counties by degree of urbanization and proximity to metro areas. We cluster standard errors at the county-level as that corresponds to our level of treatment (Abadie et al., 2022).

The parallel trend assumption must be satisfied for β in Equation 1 to be interpreted as the causal effect of losing access to ambulance services on outcome variables. For our context, this parallel trend assumption requires that all time-varying unobservables that affect mortality are uncorrelated with the event of the county losing access to ambulance services. However, it is unlikely that the loss of ambulance services is randomly assigned across space. In Table 1, we show that the counties that experience loss of ambulance services have smaller populations and are less urbanized relative to the counties that do not experience loss of access to ambulance services. By controlling for county fixed-effects we can account for time-invariant differences across counties. Nonetheless, we cannot fully control for all the factors that might induce differential trends in mortality between the counties experiencing a loss of ambulance services and counties that do not. In what follows, we detail how we address this concern in addition to controlling for urban group-by-year fixed-effects. The urban group-by-year fixed-effects account for time-varying shocks to mortality that are common across counties at similar levels of urbanization in a given year.

First, we address the potential imbalance between the treated (loss of access to ambulance services) and untreated (no loss of access to ambulance services) counties by reweighting control observations. The weights are determined with a logit estimation of a specification to determine if the county ever experience a loss of ambulance services access based on cross-sectional differences across counties in their observable characteristics in the first year of the sample, 1999. We then reweight control observations by $\frac{\hat{p}}{1-\hat{p}}$, where $\hat{p}$ is the predicted probability of a county ever experiencing a loss of access to ambulance services. Note that this weighting scheme assigns a weight of one to treated counties. This reweighting approach assigns more weight to rural counties and nearly zero weight to highly dense urban counties that are part of the control group. Later, in a robustness check, we show that there is essentially no difference between the estimates from weighted and unweighted specifications. Therefore, potential imbalance across treated and untreated counties is inconsequential for our estimates. Second, we estimate a richer version of the specification in Equation 1 by replacing urban group-by-year fixed-effects with state-by-year fixed-effects. Our estimates do not differ with this modification of the estimating specification.

Finally, we reckon that the treatment we examine immediately affects mortality. To alleviate concerns that our estimates may be plagued by the long-term trends that we cannot fully account for, we estimate event-study based specifications. Specifically, we estimate the following specification.

$$M_{c,t} = \alpha_c + \alpha_{u,t} + \sum_{i=-6, i\neq -1}^{9} \beta_i AmbulanceService_{c,t,i} + \mathbf{X}_{c,t}^{'} \gamma + \varepsilon_{c,t} \tag{2}$$

The specification in Equation 2 is the same as that in Equation (1) except that we replace the single post-treatment indicator variable ($AmbulanceService_{c,t}$) with 16 indicator variables for the time relative to treatment, $AmbulanceService_{c,t,i}$. We omit the indicator for one year before treatment as the reference group. We, thus, report estimates for six years pre- and nine years post-treatment.

Since counties in our main empirical specification are treated over time, we show that our results are robust to using estimators that account for negative weights in staggered treatment settings (de Chaisemartin and D'Haultfœuille, 2022; Roth et al., 2023). These negative weights arise because some later-treated units are compared to earlier-treated ones. Since we have multiple counties that are never treated in our setting, i.e., never lose access to ambulance services, this concern is not overarching.[8] For our specifications with the treatment variable being an indicator for whether the county has an operational ambulance service establishment or not, we present estimates by using estimators proposed by Borusyak et al. (2023) in addition to our TWFE estimates. For our specifications with treatment variable as the count of establishments in the county that provide ambulance services, we present estimates from the estimator proposed by de Chaisemartin and D'Haultfoeuille (2023a) alongside our TWFE estimates.

[8] Using an approach outlined in de Chaisemartin and D'Haultfoeuille (2023b), we find two-by-two DD comparisons that receive negative weight in the specification with only county and year fixed-effects where the outcome is the external causes of deaths are 13.69% of all two-by-two DD comparisons. Further, these negative weights sum to -0.024, thus, receiving weight close to zero in aggregate.

4.1 Summary Statistics

Table 1 presents the descriptive statistics of the county characteristics for our analytical sample categorized into three groups: all counties, counties that have lost ambulance services access ("Lost Access Counties"), and counties that have not lost ambulance services access ("Non-Lost Access Counties"). For counties that have lost access to ambulance services, the average population is lower, suggesting that smaller counties may be more affected by the loss of ambulance services access.

In comparison, non-lost access counties have a higher unweighted average population, indicating they are larger on average. Lost access counties have a lower population growth rate on average, which may indicate declining populations or slower development, while non-lost access counties have a slightly higher growth rate than the overall average, suggesting they may be more economically vibrant or attractive for residents.

Similarly, Lost access counties have lower average earnings per capita, which could be related to lower economic opportunities or could influence the sustainability of ambulance services. Non-lost access counties have slightly higher earnings per capita, which suggests a slightly better economic situation for these counties. Lost access counties receive a similar amount in terms of transfers per capita relative to the overall average. However, it is slightly higher than the overall average.

Non-lost access counties also receive a similar amount of transfers per capita, very close to the overall average, indicating that there is little difference between the lost access counties and non-lost access counties in terms of transfers per capita. For lost access counties, employment to population ratio is lower, suggesting fewer employed people relative to the population size, which may reflect weaker economic conditions that could impact healthcare services, like ambulance availability. Non-lost access counties have a slightly higher employment-to-population ratio compared to the overall average, potentially indicative of stronger employment conditions as well as the availability of ambulance services.

The table further reveals that the number of deaths in the counties that lost access to ambulance services is lower than in the non-lost access counties. A suggestive evidence that, on average, the count of deaths is lower in rural areas relative to urban areas. Therefore, the demand for ambulance services in these areas is potentially lower. The lower demand for ambulance services might be one of the reasons why firms operating in this industry are exiting these areas as it is not profitable for them to continue their operations. By weighting the non-lost access counties using the inverse probability weights, the non-lost access counties look more similar to those that lose access to ambulance services.

5 Results

5.1 Main Results

We begin by examining how loss of access to ambulance services in the county affects deaths related to external causes. To this end, we report estimates from the specification in Equation 2 in Figure 3. The estimates from the periods before the county experienced loss of ambulance services access show that relative to counties without such a loss of access to ambulance services, loss of access to ambulance services counties are trending similarly. For the period after the loss of access to ambulance services, there is a marked decline in deaths due to external causes. The reduced deaths due to external causes persist for almost the entirety of the post-loss of ambulance services access period. The estimates in Table 3 show that when we aggregate all the post-treatment periods, there are four lower deaths due to external causes in counties that experience loss of access to ambulance services relative to the counties without such a loss of access to ambulance services in the post-treatment compared to pre-treatment period. Relative to the mean in the periods before the loss of access to ambulance services in counties that experience loss of access to ambulance services, the reduced death count is approximately 18%.

As the counties do not experience loss of access to ambulance services all at the same time, we show that our conclusions are unaltered when we use estimators that account for staggered treatment timings and dynamic heterogeneous treatment effects. The estimates from the estimator proposed in Borusyak et al. (2024) are reported in Figure 4. We also establish that our estimates are not confounded by the loss of access to ambulance services being correlated with the loss of hospital establishments. In Figure 5, we establish that the correlation between the extent of ambulance services and hospital establishments is low for our sample of counties. This is also borne out for extensive margin measure of access to these two distinct establishment types, estimates for which are reported in Table 4. Indeed, when we control for the count of hospital establishment in the specification in Equation 2, our estimates (see Figure 6) are extremely similar to the baseline specification.[9]

When we examine if deaths due to all causes are affected by whether the deceased person's residence county has access to ambulance services, we find that access to ambulance services impacts total deaths in the county (see Figure 9[10]). When we aggregate all post-treatment estimates for deaths due to all causes, the estimate is only marginally significant. The absence of statistical precision for deaths due to all causes suggests that deaths due to acute causes could be disproportionately affected by the loss of ambulance service access in the county. We explore in detail this possibility in Section 5.2.

The estimates from modifying the specification in Equation 2 by including state-year fixed-effects are presented in Figure 7. The decline in deaths due to external causes is unaltered when the estimating specification controls for state-level time-varying unobservables by including state-year fixed-effects. We reach the same conclusion when we include the counties that only gained or never had access to ambulance services during the sample period. These estimates are reported in Figure 8. While being qualitatively similar to weighted estimates, unweighted estimates are larger in magnitude suggesting that counties that lose access to ambulance services differ across observable characteristics (see Table 5).

Estimates in Table 6 suggest that each additional establishment rendering ambulance services does not affect the deaths due to external causes. If medical emergencies are not lumped together temporally, it's plausible that having extra establishments is unlikely to influence deaths due to external causes. The intensive margin estimates support this conclusion.

[9]The corresponding estimates from specification in Equation 1 are reported in Table 5

[10]The estimates from specification in Equation 1 with deaths due to all causes as the dependent variable are reported in Table 3.

5.2 Heterogeneity

We examine the heterogeneous effects of losing access to ambulance services on deaths due to external causes across various demographic groups, including those based on deceased person's age, education, and race. Figure 10 to Figure 13 report event-study estimates from these heterogeneity analyses. The corresponding estimates from the specification in Equation 1 are reported in Table 7 to Table 9.

Our analysis reveals distinct patterns across different subgroups. The most notable effects are observed among white individuals with a high school education or less, particularly those aged 35 to 49. For this subgroup, the loss of access to ambulance services is associated with reduction in deaths due to external causes.

Table 9 quantifies these effects. Statistically significant decline in deaths due to external causes is found for whites with high school or some college education. However, we observe no statistically significant effects for Black individuals and other racial groups, or those with bachelor's degrees or higher (see Table 8).

These results indicate that the impact of losing access to ambulance services varies considerably across different demographic subgroups, with the most pronounced effects observed among specific segments of the white population, particularly those with lower levels of educational attainment and mid-aged.

6 Conclusion

This study examines the effect of losing access to ambulatory services on mortality, focusing on external causes of death. We assess the impact of losing access to ambulance services on mortality while controlling for potential confounding factors such as hospital closures.

The results consistently indicate a decline in deaths due to external causes following the loss of access to ambulance services. The estimated effects are robust to including various controls and the number of hospital establishments, suggesting that hospital closures do not confound the impact of ambulance service availability.

Moreover, our findings reveal notable heterogeneity in the effects across demographic groups, with significant improvements in mortality primarily seen among white individuals with lower levels of educational attainment and mid-aged.

References

Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey M Wooldridge, "When Should You Adjust Standard Errors for Clustering?," *The Quarterly Journal of Economics*, 10 2022, *138* (1), 1–35.

Alexander, Diane and Michael R. Richards, "Economic consequences of hospital closures," *Journal of Public Economics*, 2023, *221*, 104821.

Avdic, Daniel, "Improving efficiency or impairing access? Health care consolidation and quality of care: Evidence from emergency hospital closures in Sweden," *Journal of Health Economics*, 2016, *48*, 44–60.

__ , Petter Lundborg, and Johan Vikström, "Does Healthcare Consolidation Harm Patients? Evidence from Maternity Ward Closures," *American Economic Journal: Economic Policy*, Forthcoming.

Bailey, Martha J. and Andrew Goodman-Bacon, "The War on Poverty's Experiment in Public Medicine: Community Health Centers and the Mortality of Older Americans," *American Economic Review*, March 2015, *105* (3), 1067–1104.

Battaglia, Emily, "The Effect of Hospital Maternity Ward Closures on Maternal and Infant Health," *American Journal of Health Economics*, Forthcoming, pp. 1–57.

Bondurant, Samuel R., Jason M. Lindo, and Isaac D. Swensen, "Substance abuse treatment centers and local crime," *Journal of Urban Economics*, 2018, *104*, 124–133.

Booker, Matthew J, Ali RG Shaw, and Sarah Purdy, "Why do patients with 'primary care sensitive'problems access ambulance services? A systematic mapping review of the literature," *BMJ open*, 2015, *5* (5), e007726.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess, "Revisiting Event Study Designs: Robust and Efficient Estimation," 2023.

__ , __ , and __ , "Revisiting Event-Study Designs: Robust and Efficient Estimation," *The Review of Economic Studies*, 02 2024, p. rdae007.

Bradford, Ashley C. and Johanna Catherine Maclean, "Evictions and psychiatric treatment," *Journal of Policy Analysis and Management*, 2023, *n/a* (n/a).

Buchmueller, Thomas C., Mireille Jacobson, and Cheryl Wold, "How far to the hospital?: The effect of hospital closures on access to care," *Journal of Health Economics*, 2006, *25* (4), 740–761.

Bureau of Economic Analysis (BEA), "Regional Economic Accounts," https://www.bea.gov/data/economic-accounts/regional November 2023. Accessed: 2024-10-01.

Cattaneo, Matias D., Richard K. Crump, Max H. Farrell, and Yingjie Feng, "Binscatter Regressions," 2023.

Chaudhary, Sookti, Kenneth R. Troske, Suzanne Troske, and Alison F. Davis, "Ambulance Service Ownership and Management: How It Affects Quality of Service Delivery for Medicare Patients," 2019.

de Chaisemartin, Clément and Xavier D'Haultfoeuille, "Difference-in-Differences Estimators of Intertemporal Treatment Effects," 2023.

— and — , "Two-way fixed effects and differences-in-differences estimators with several treatments," *Journal of Econometrics*, 2023, *236* (2), 105480.

Deryugina, Tatyana and David Molitor, "The Causal Effects of Place on Health and Longevity," *Journal of Economic Perspectives*, November 2021, *35* (4), 147–70.

Deza, Monica, Johanna Catherine Maclean, and Keisha Solomon, "Local access to mental healthcare and crime," *Journal of Urban Economics*, 2022, *129*, 103410.

— , Thanh Lu, and Johanna Catherine Maclean, "Office-based mental healthcare and juvenile arrests," *Health Economics*, 2022, *31* (S2), 69–91.

de Chaisemartin, Clément and Xavier D'Haultfœuille, "Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: a survey," *The Econometrics Journal*, 06 2022, *26* (3), C1–C30.

Eckert, Fabian, Teresa C Fort, Peter K Schott, and Natalie J Yang, "Imputing Missing Values in the US Census Bureau's County Business Patterns," Working Paper 26632, National Bureau of Economic Research January 2020.

Finkelstein, Amy, Matthew Gentzkow, and Heidi Williams, "Sources of Geographic Variation in Health Care: Evidence From Patient Migration*," *The Quarterly Journal of Economics*, 07 2016, *131* (4), 1681–1726.

Fischer, Stefanie, Heather Royer, and Corey White, "Health Care Centralization: The Health Impacts of Obstetric Unit Closures in the United States," *American Economic Journal: Applied Economics*, July 2024, *16* (3), 113–41.

Jonk, Yvonne, Carly Milkowski, Zachariah Croll, and Karen Pearson, "Ambulance Deserts: Geographic Disparities in the Provision of Ambulance Services [Chartbook]," 2023.

Mell, Howard K, Shannon N Mumma, Brian Hiestand, Brendan G Carr, Tara Holland, and Jason Stopyra, "Emergency medical services response times in rural, suburban, and urban areas," *JAMA surgery*, 2017, *152* (10), 983–984.

Mikolaizak, A Stefanie, Paul M Simpson, Anne Tiedemann, Stephen R Lord, and Jacqueline CT Close, "Systematic review of non-transportation rates and outcomes for older people who have fallen after ambulance service call-out," *Australasian journal on ageing*, 2013, *32* (3), 147–157.

Molitor, David, "The Evolution of Physician Practice Styles: Evidence from Cardiologist Migration," *American Economic Journal: Economic Policy*, February 2018, *10* (1), 326–56.

on the Future of Emergency Care in the US Health System, Committee and Institute of Medicine others, "Emergency medical services at the crossroads," *Washington: DC*, 2006.

Roth, Jonathan, Pedro H.C. Sant'Anna, Alyssa Bilinski, and John Poe, "What's trending in difference-in-differences? A synthesis of the recent econometrics literature," *Journal of Econometrics*, 2023, *235* (2), 2218–2244.

Skinner, Jonathan, "Chapter Two - Causes and Consequences of Regional Variations in Health Care," in Mark V. Pauly, Thomas G. Mcguire, and Pedro P. Barros, eds., *Handbook of Health Economics*, Vol. 2 of Handbook of Health Economics, Elsevier, 2011, pp. 45–93.

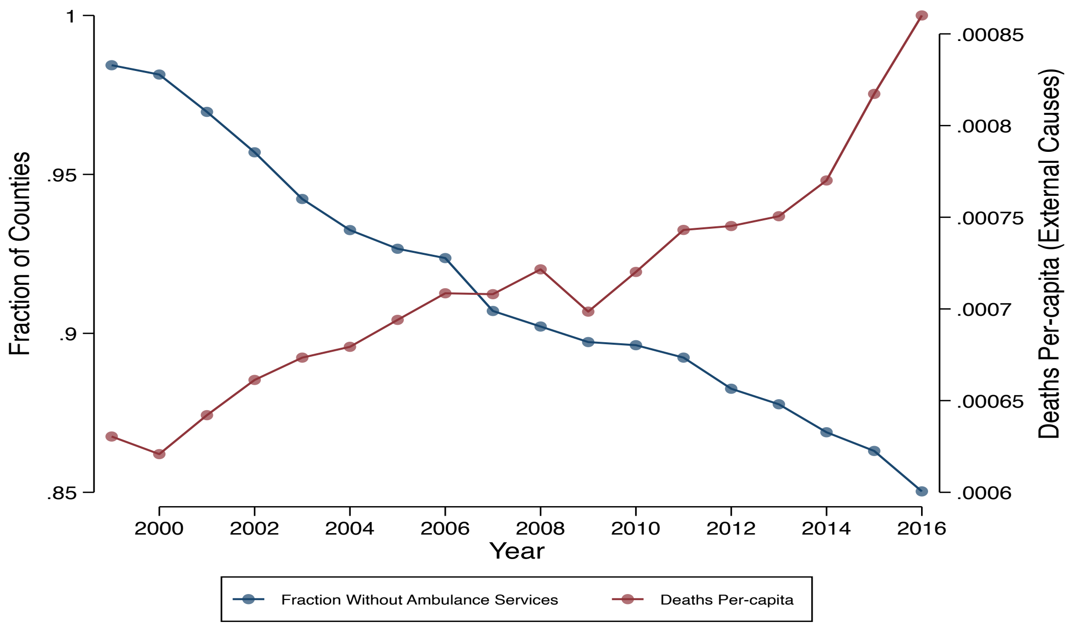
Surveillance, Epidemiology, and End Results (SEER) Program, "Surveillance, Epidemiology, and End Results (SEER) Program," https://seer.cancer.gov/data/ April 2023. Accessed: 2024-10-01.

Swensen, Isaac D., "Substance-abuse treatment and mortality," *Journal of Public Economics*, 2015, *122*, 13–30.

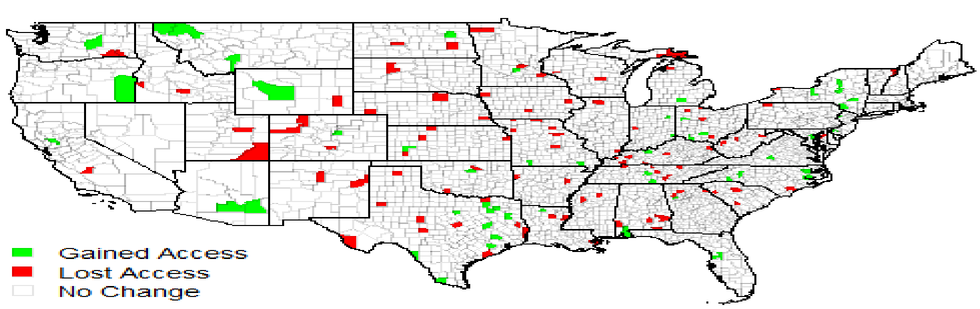
U.S. Census Bureau, "County Business Patterns (CBP)," https://www.census.gov/programs-surveys/cbp/data.html November 2023. Accessed: 2024-10-01.

Figure 1: Temporal and Spatial Variation in Access to Ambulance Services and Deaths Due to External Causes Per-capita

(a) Trend in Access to Ambulance Services and Deaths Due to External Causes Per-capita

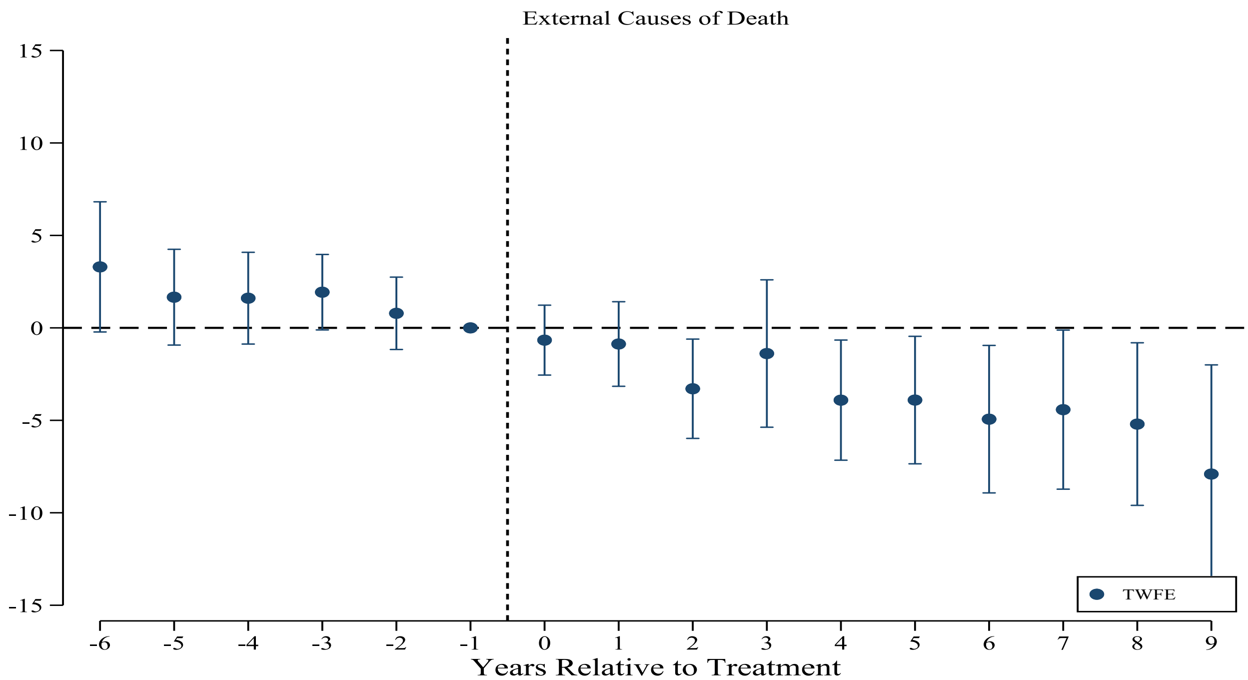


(b) Ambulance Services Access Loss and Gain



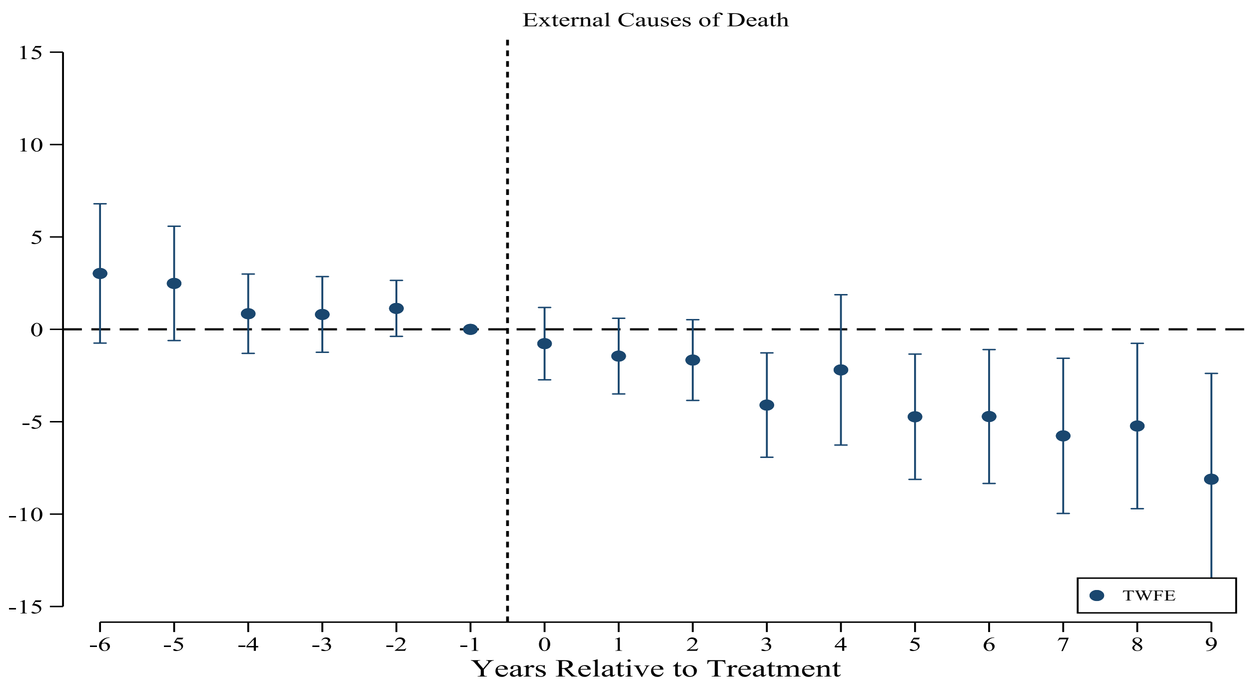
Note: Data on the county's access to ambulance services comes from the County Business Patterns (CBP). A county is designated as having access to ambulance services if it has any establishment that provides these services in a given year. The sample is restricted to 1999-2016. Section 3.2 provides more information on these data. Data on deaths are derived from restricted death certificate files from the National Vital Statistics System of the Centers for Disease Control and Prevention (CDC). The top panel displays the share of counties with at least one establishment providing ambulance services. External causes of death are derived from ICD-10 Version:2019. In the bottom panel, counties are shaded by their status of having access to ambulance services. A county is designated as having "lost access" if it goes from having at least one establishment providing ambulance services to having none for the rest of the sample period. "Gained access" is defined as the opposite of "lost access". County shapefiles are derived from the US Census Bureau.

Figure 2: Robustness Check: Lag Treatment by One Period



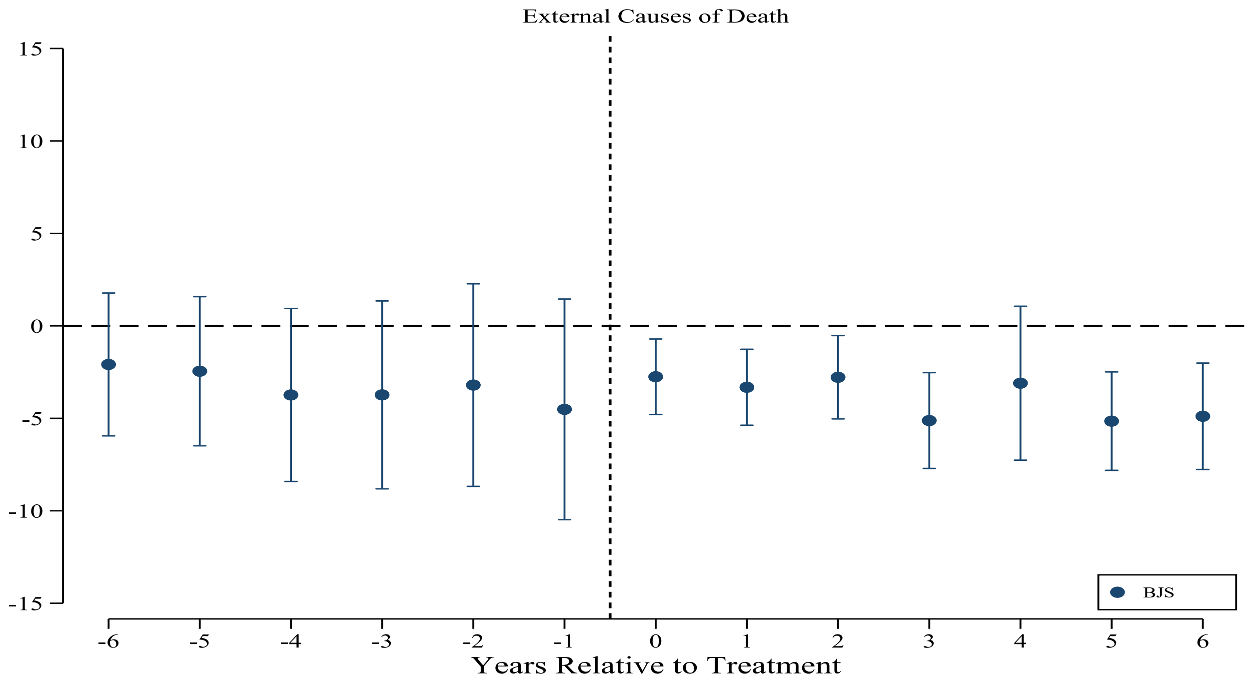
Note: Heteroskedasticity robust standard errors clustered by the county are reported. 99% confidence intervals are plotted along with the point estimates. All estimates are relative to the year immediately before the county loses access to ambulance services. The estimates are from the estimation of specification in Equation 2, except that the ambulance service measure is lagged by one period. The estimated specification also includes time-varying county variables. These variables are population shares for various age groups, earnings per-capita, transfers per-capita, employment-population ratio, and population density. Data on ambulance services establishment are derived from County Business Patterns (CBP). Data on deaths are derived from restricted death certificate files from the National Vital Statistics System of the Centers for Disease Control and Prevention (CDC). Time-varying county-level variables are derived from the Regional Economic Information System (REIS) and Surveillance, Epidemiology, and End Results (SEER). The sample is restricted to 1999-2016. External causes of death are derived from ICD-10 Version:2019.

Figure 3: Does Loss of Access to Ambulance Services Worsen Mortality Due to External Causes of Deaths?



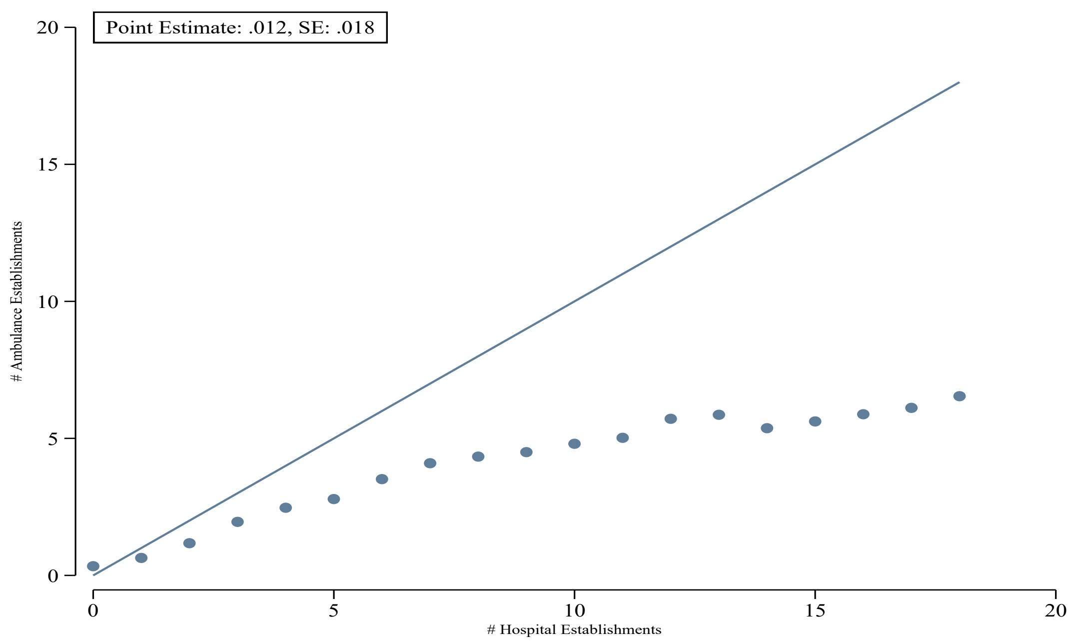
Note: Heteroskedasticity robust standard errors clustered by the county are reported. 99% confidence intervals are plotted along with the point estimates. All estimates are relative to the year immediately before the county loses access to ambulance services. The estimates are from the estimation of specification in Equation 2. The estimated specification also includes time-varying county variables. These variables are population shares for various age groups, earnings per-capita, transfers per-capita, employment-population ratio, and population density. Data on ambulance services establishment are derived from County Business Patterns (CBP). Data on deaths are derived from restricted death certificate files from the National Vital Statistics System of the Centers for Disease Control and Prevention (CDC). Time-varying county-level variables are derived from the Regional Economic Information System (REIS) and Surveillance, Epidemiology, and End Results (SEER). The sample is restricted to 1999-2016. External causes of deaths are derived from ICD-10 Version:2019.

Figure 4: Borusyak et al. (2024) Estimation



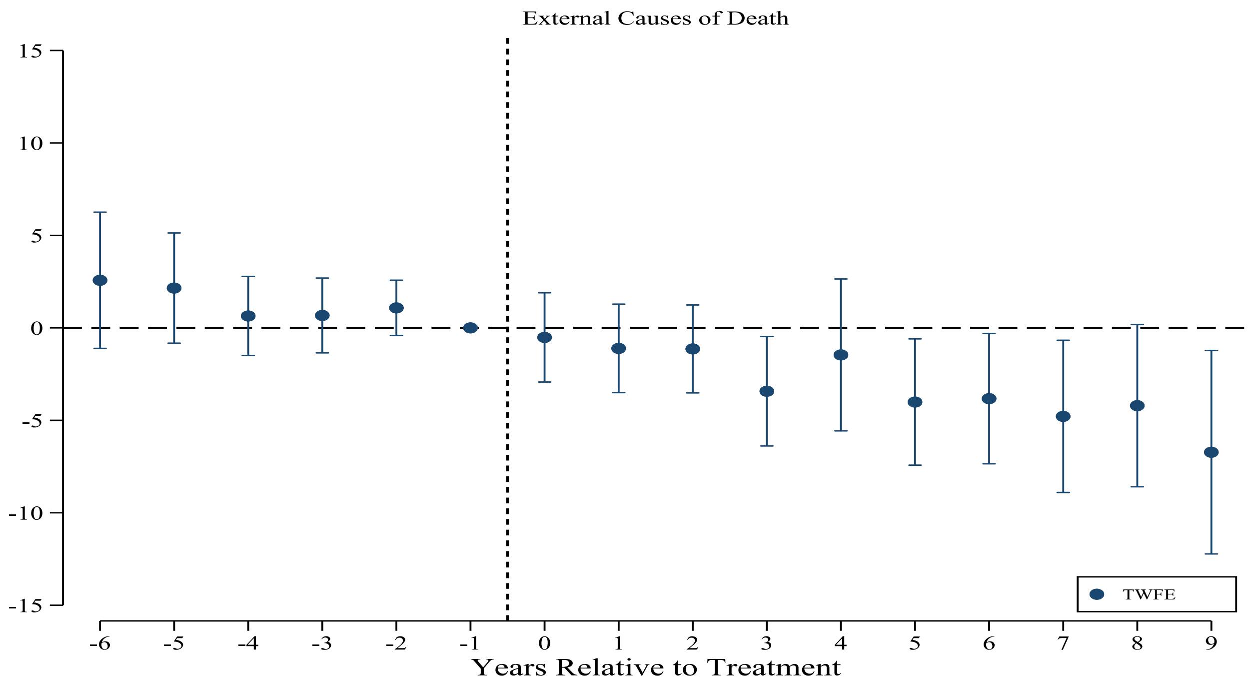
Note: Heteroskedasticity robust standard errors clustered by the county are reported. 99% confidence intervals are plotted along with the point estimates. All estimates are relative to the year immediately before the county loses access to ambulance services. The estimates are from the estimation of specification in Equation 2. The specification is estimated using the estimator proposed in Borusyak et al. (2024). The estimated specification also includes time-varying county variables. These variables are population shares for various age groups, earnings per-capita, transfers per-capita, employment-population ratio, and population density. Data on ambulance services establishment are derived from County Business Patterns (CBP). Data on deaths are derived from restricted death certificate files from the National Vital Statistics System of the Centers for Disease Control and Prevention (CDC). Time-varying county-level variables are derived from the Regional Economic Information System (REIS) and Surveillance, Epidemiology, and End Results (SEER). The sample is restricted to 1999-2016. External causes of death are derived from ICD-10 Version:2019.

Figure 5: Ambulance Services and Hospital Establishment Correlation



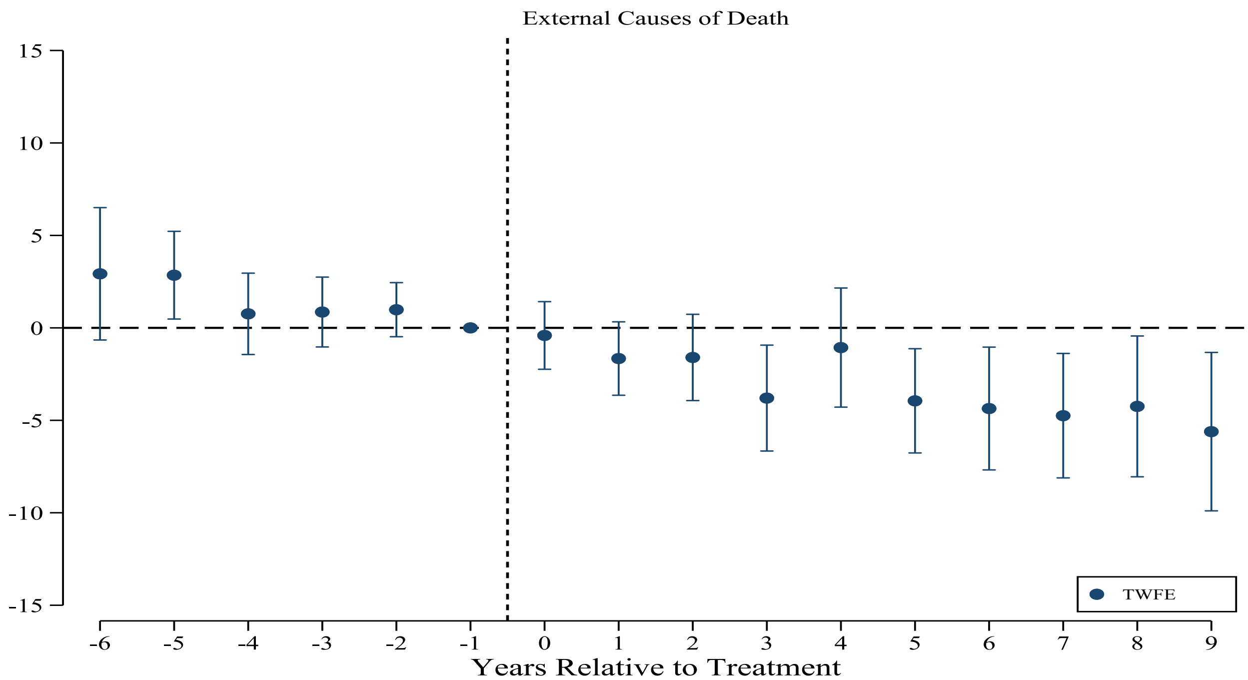
Note: Data on the county's access to ambulance services and hospitals comes from the County Business Patterns (CBP). The sample is restricted to 1999-2016. The scatter plot is from the approach in Cattaneo et al. (2023) with default options. The solid line is at an angle of 45 degrees. The estimates at the top left are from the specification where the dependent variable is an indicator variable for whether the county has any establishment rendering ambulance services and the independent variable is a similar indicator variable for any hospital establishment in the county. This specification also controls for county and state-year fixed-effects. The standard errors are clustered at the county-level. These estimates are also reported in Table 4.

Figure 6: Controlling for Access to Hospital Establishments



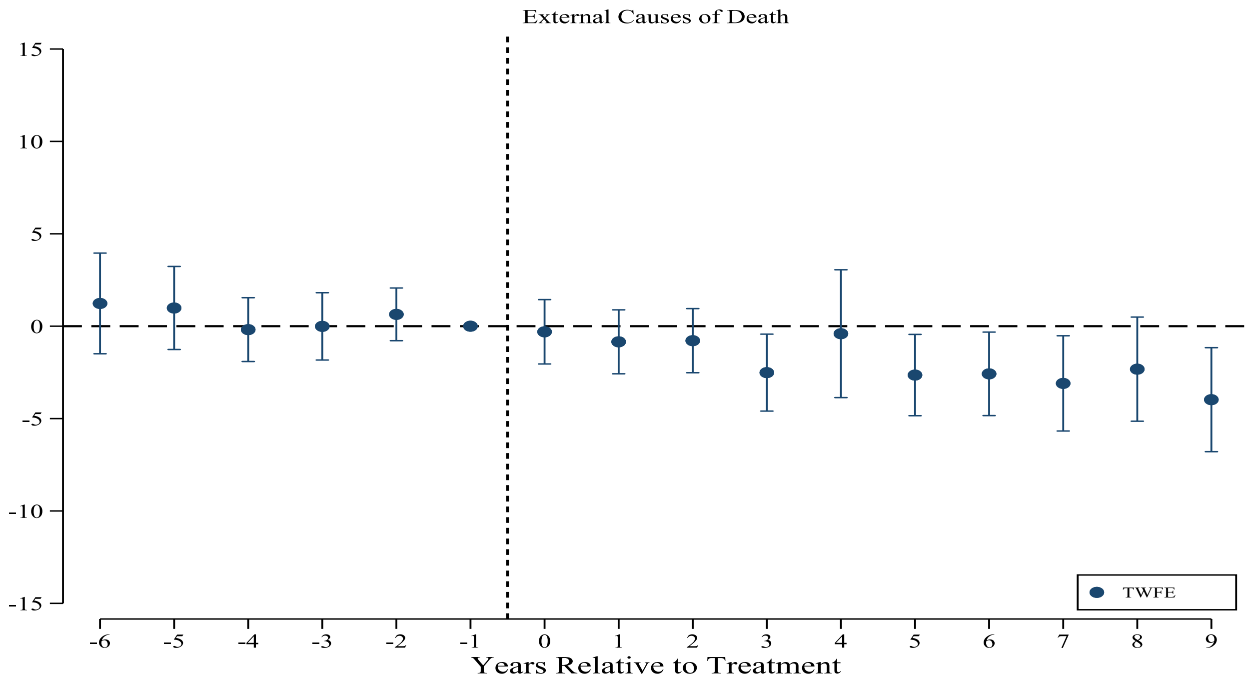
Note: Heteroskedasticity robust standard errors clustered by the county are reported. 99% confidence intervals are plotted along with the point estimates. All estimates are relative to the year immediately before the county loses access to ambulance services. The estimates are from the estimation of specification in Equation 2. The estimated specification also includes time-varying county variables. These variables are population shares for various age groups, earnings per-capita, transfers per-capita, employment-population ratio, and population density. Additionally, the estimated specification also controls for the number of hospital establishments in the county. Data on ambulance services and hospital establishments are derived from County Business Patterns (CBP). Data on deaths are derived from restricted death certificate files from the National Vital Statistics System of the Centers for Disease Control and Prevention (CDC). Time-varying county-level variables are derived from the Regional Economic Information System (REIS) and Surveillance, Epidemiology, and End Results (SEER). The sample is restricted to 1999-2016. External causes of deaths are derived from ICD-10 Version:2019.

Figure 7: Robustness Check: Include State-Year Fixed-effects



Note: Heteroskedasticity robust standard errors clustered by the county are reported. 95% confidence intervals are plotted along with the point estimates. All estimates are relative to the year immediately before the county loses access to ambulance services. The estimates are from the estimation of specification in Equation 2. The estimated specification also includes time-varying county variables. These variables are population shares for various age groups, earnings per-capita, transfers per-capita, employment-population ratio, and population density. Additionally, the estimated specification also includes state-year fixed-effects. Data on ambulance services are derived from County Business Patterns (CBP). Data on deaths are derived from restricted death certificate files from the National Vital Statistics System of the Centers for Disease Control and Prevention (CDC). Time-varying county-level variables are derived from the Regional Economic Information System (REIS) and Surveillance, Epidemiology, and End Results (SEER). The sample is restricted to 1999-2016. External causes of deaths are derived from ICD-10 Version:2019.

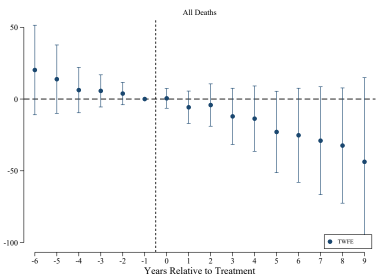
Figure 8: Robustness Check: Include All Counties



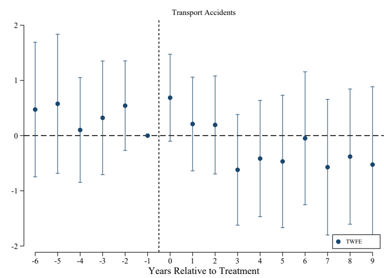
Note: Heteroskedasticity robust standard errors clustered by the county are reported. 99% confidence intervals are plotted along with the point estimates. All estimates are relative to the year immediately before the county loses access to ambulance services. The estimates are from the estimation of specification in Equation 2. The estimated specification also includes time-varying county variables. These variables are population shares for various age groups, earnings per-capita, transfers per-capita, employment-population ratio, and population density. Additionally, the estimation sample also includes counties that never have or only gained access to ambulance services during the sample period. Data on ambulance services are derived from County Business Patterns (CBP). Data on deaths are derived from restricted death certificate files from the National Vital Statistics System of the Centers for Disease Control and Prevention (CDC). Time-varying county-level variables are derived from the Regional Economic Information System (REIS) and Surveillance, Epidemiology, and End Results (SEER). The sample is restricted to 1999-2016. External causes of death are derived from ICD-10 Version:2019.

Figure 9: All Causes of Deaths and Individual External Causes of Deaths

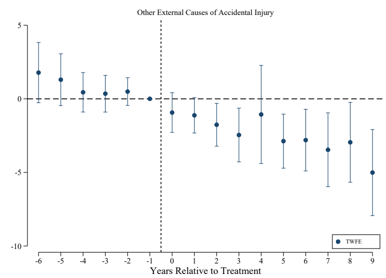
(a) All Deaths



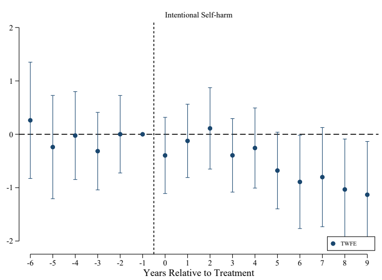
(b) Transport Accidents



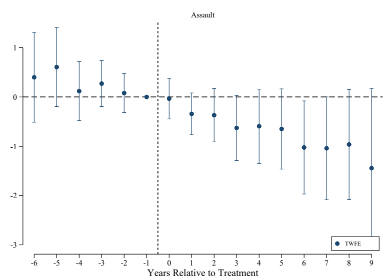
(c) Other External Causes of Accidental Injury



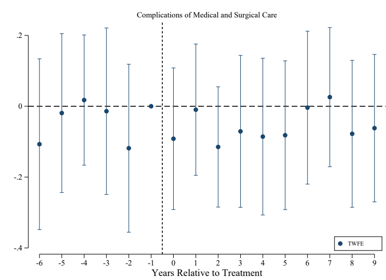
(d) Intentional Self-harm



(e) Assault



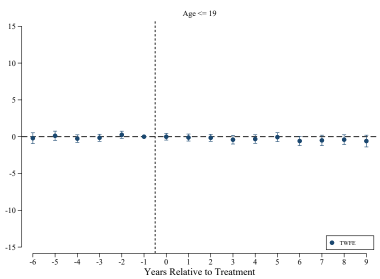
(f) Complications of Medical and Surgical Care



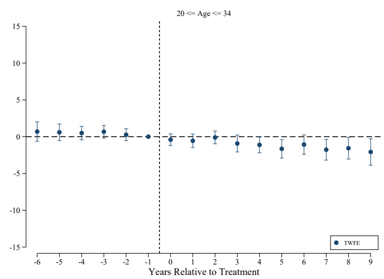
Note: Heteroskedasticity robust standard errors clustered by the county are reported. 99% confidence intervals are plotted along with the point estimates. All estimates are relative to the year immediately before the county loses access to ambulance services. The estimates are from the estimation of specification in Equation 2. The estimated specification also includes time-varying county variables. These variables are population shares for various age groups, earnings per-capita, transfers per-capita, employment-population ratio, and population density. Data on ambulance services establishment are derived from County Business Patterns (CBP). Data on deaths are derived from restricted death certificate files from the National Vital Statistics System of the Centers for Disease Control and Prevention (CDC). Time-varying county-level variables are derived from the Regional Economic Information System (REIS) and Surveillance, Epidemiology, and End Results (SEER). The sample is restricted to 1999-2016. External causes of deaths are derived from ICD-10 Version:2019.

Figure 10: Heterogeneity: Age

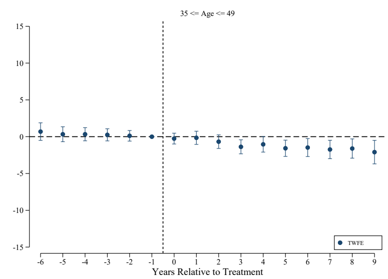
(a) Under 19



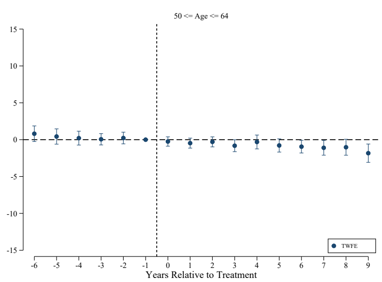
(b) 20 - 34



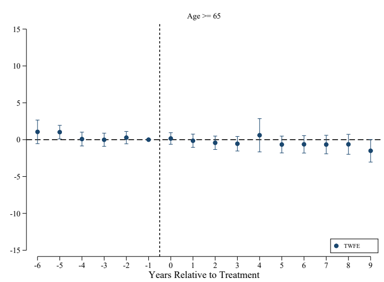
(c) 35 - 49



(d) 50 - 64



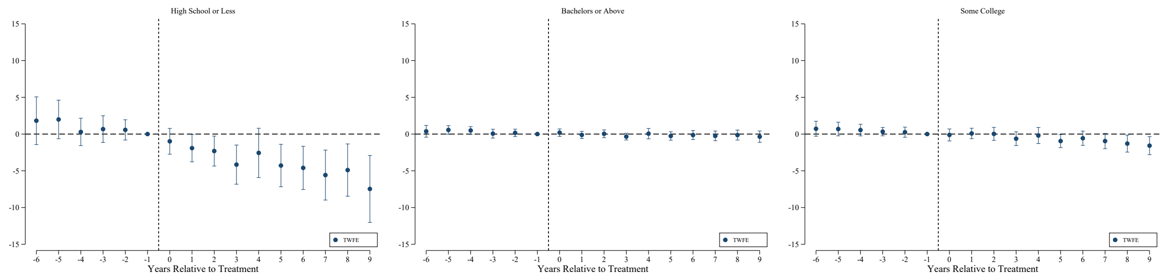
(e) Over 65



Note: Heteroskedasticity robust standard errors clustered by the county are reported. 99% confidence intervals are plotted along with the point estimates. All estimates are relative to the year immediately before the county loses access to ambulance services. The estimates are from the estimation of specification in Equation 2. The estimated specification also includes time-varying county variables. These variables are population shares for various age groups, earnings per-capita, transfers per-capita, employment-population ratio, and population density. Data on ambulance services establishment are derived from County Business Patterns (CBP). Data on deaths are derived from restricted death certificate files from the National Vital Statistics System of the Centers for Disease Control and Prevention (CDC). Time-varying county-level variables are derived from the Regional Economic Information System (REIS) and Surveillance, Epidemiology, and End Results (SEER). The sample is restricted to 1999-2016. External causes of death are derived from ICD-10 Version:2019. Subfigure captions denote the age category that constitutes the estimation sample.

Figure 11: Heterogeneity: Education

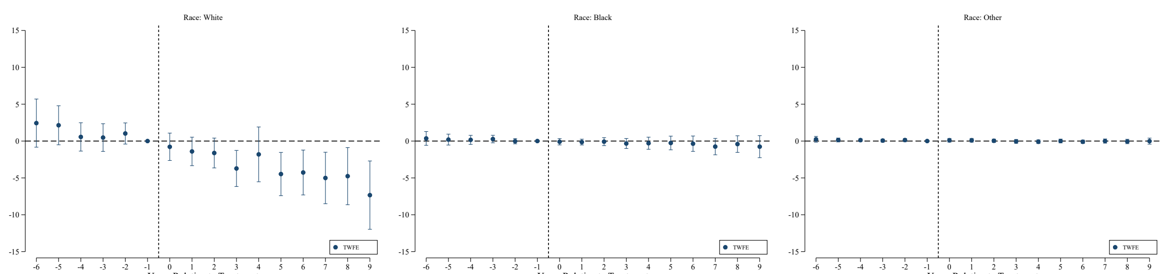
(a) High School or Less (b) Bachelors or Above (c) Some College



Note: Heteroskedasticity robust standard errors clustered by the county are reported. 99% confidence intervals are plotted along with the point estimates. All estimates are relative to the year immediately before the county loses access to ambulance services. The estimates are from the estimation of specification in Equation 2. The estimated specification also includes time-varying county variables. These variables are population shares for various age groups, earnings per-capita, transfers per-capita, employment-population ratio, and population density. Data on ambulance services establishment are derived from County Business Patterns (CBP). Data on deaths are derived from restricted death certificate files from the National Vital Statistics System of the Centers for Disease Control and Prevention (CDC). Time-varying county-level variables are derived from the Regional Economic Information System (REIS) and Surveillance, Epidemiology, and End Results (SEER). The sample is restricted to 1999-2016. External causes of death are derived from ICD-10 Version:2019. Subfigure captions denote the education category that constitutes the estimation sample.

Figure 12: Heterogeneity: Race

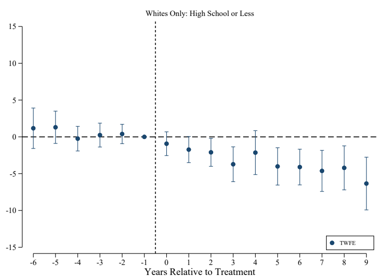
(a) White (b) Black (c) Other



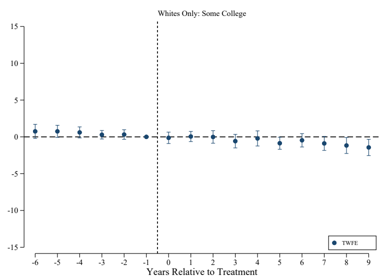
Note: Heteroskedasticity robust standard errors clustered by the county are reported. 99% confidence intervals are plotted along with the point estimates. All estimates are relative to the year immediately before the county loses access to ambulance services. The estimates are from the estimation of specification in Equation 2. The estimated specification also includes time-varying county variables. These variables are population shares for various age groups, earnings per-capita, transfers per-capita, employment-population ratio, and population density. Data on ambulance services establishment are derived from County Business Patterns (CBP). Data on deaths are derived from restricted death certificate files from the National Vital Statistics System of the Centers for Disease Control and Prevention (CDC). Time-varying county-level variables are derived from the Regional Economic Information System (REIS) and Surveillance, Epidemiology, and End Results (SEER). The sample is restricted to 1999-2016. External causes of death are derived from ICD-10 Version:2019. Subfigure captions denote the race category that constitutes the estimation sample.

Figure 13: Heterogeneity: Education Only for White

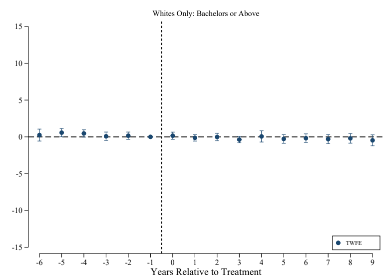
(a) High School or Less



(b) Some College



(c) Bachelors or Above



Note: Heteroskedasticity robust standard errors clustered by the county are reported. 99% confidence intervals are plotted along with the point estimates. All estimates are relative to the year immediately before the county loses access to ambulance services. The estimates are from the estimation of specification in Equation 2. The estimated specification also includes time-varying county variables. These variables are population shares for various age groups, earnings per-capita, transfers per-capita, employment-population ratio, and population density. Data on ambulance services establishment are derived from County Business Patterns (CBP). Data on deaths are derived from restricted death certificate files from the National Vital Statistics System of the Centers for Disease Control and Prevention (CDC). Time-varying county-level variables are derived from the Regional Economic Information System (REIS) and Surveillance, Epidemiology, and End Results (SEER). The sample is restricted to 1999-2016. External causes of death are derived from ICD-10 Version:2019. Subfigure captions denote the education category that constitutes the estimation sample. In all subfigures estimation sample is restricted to deaths where the race of the deceased person is reported to be White.

Table 1: Summary Statistics: County Characteristics

	All Counties	Lost Access Counties	Non-Lost Access Counties Unweighted	Non-Lost Access Counties P-Weighted
Population	105,989	33,349	110,606	60,527
Population Growth Rate	0.3060	0.2671	0.3084	0.3487
Earnings Per Capita	19,645	18,587	19,712	18,981
Transfers Per Capita	6,694	6,781	6,689	6,709
Empl./Pop.	0.518	0.481	0.520	0.497
Rural County	0.732	0.843	0.725	0.723
No. of Deaths (External Causes)	62.240	22.204	64.737	39.113
# Ambulance Service Establishments	1.510			
$\mathbb{1}$(Ambulance Service Establishments)	0.469			
Number of Counties	2,606	153	2,453	2,453

Notes: Author's calculations. More information on the variable construction and data sources is presented in Section 3.3.

Table 2: Lost Access Probit Regression Estimates

	Estimate (SE)
Empl./Pop. Ratio	-0.519**
	(0.211)
Earnings Per-Capita	0.000
	(0.000)
Transfers Per-Capita	0.000
	(0.000)
Pop. Share 0-19	0.955
	(1.266)
Pop. Share 20-34	5.462***
	(1.052)
Pop. Share 35-49	0.785
	(1.677)
Pop. Share 50-64	5.253**
	(2.297)
Total Population	-0.000***
	(0.000)
Pop. Density	0.000***
	(0.000)
Rural County	-0.288***
	(0.079)
Pseudo R2	0.033
N	2,967

Notes: * p<.10 ** p<.05 *** p<.01. Estimates are from a cross-sectional probit regression where the outcome is an indicator for a county ever experiencing a loss of ambulance services. Regressors represent county characteristics in the first year of the sample (1999). See Section 3 for more details on the construction of the variables and data sources.

Table 3: Effect of Loss of Ambulance Services Access on Mortality

	External Causes of Deaths	All Causes of Deaths	Transport Accidents	Other External Causes of Accidental Injury	Intentional Self-harm	Assault	Complications of Medical and Surgical Care	Cardiovascular
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}\{Treat_c\} \times \mathbb{1}\{Post_y\}$	-4.91957***	-22.76692*	-0.37694	-3.22771***	-0.37240	-0.91612**	-0.00817	-2.79806
	(1.40530)	(13.35065)	(0.33590)	(0.77046)	(0.27520)	(0.36715)	(0.03667)	(3.65934)
	[-17.96]	[-6.15]	[-4.58]	[-30.98]	[-6.49]	[-63.14]	[-2.03]	[-4.35]
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Urban Year Group FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.988	0.995	0.972	0.973	0.985	0.973	0.800	0.989
N	17,374	17,374	17,374	17,374	17,374	17,374	17,374	17,374

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 pre-treatment mean for the treated group is in square brackets. Each cell is a separate estimation of Equation 1. The estimated specification also includes time-varying county variables. These variables are population shares for various age groups, earnings per-capita, transfers per-capita, employment-population ratio, and population density. See Section 3 for more details on the construction of the variables and data sources. The sample is restricted to 1999-2016.

Table 4: Does Loss of Access to Hospitals Predict Loss of Access to Ambulance Services?

	Any Ambulance Services Establishments (1)	# Ambulance Services Establishments (2)
$\mathbb{1}$(Any Hospital Establishment)	0.01191	
	(0.01847)	
	[98.02]	
# Hospital Establishments		0.21695
		(0.17830)
		[65.21]
County FEs	Yes	Yes
State-Year FEs	Yes	Yes
Adj. R^2	0.723	0.892
N	60,612	60,612

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 sample mean is in square brackets. Each cell is a separate estimation of a specification with the county and state-year fixed-effects. Data comes from CBP. The sample is restricted to 1999-2016.

Table 5: Robustness Checks

	Baseline	Add Hospital Count	Unweighted
	(1)	(2)	(3)
$\mathbb{1}\{Treat_c\} \times$	-4.91957***	-4.95072***	-10.03267***
$\mathbb{1}\{Post_y\}$	(1.40530)	(1.50158)	(1.50697)
	[-17.96]	[-18.08]	[-36.63]
County FEs	Yes	Yes	Yes
Urban Year Group FEs	Yes	Yes	Yes
# Hospital Establisments	No	Yes	No
Adj. R^2	0.988	0.988	0.984
N	17,374	17,374	17,374

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 pre-treatment mean for the treated group is in square brackets. Each cell is a separate estimation of Equation 1. The estimated specification also includes time-varying county variables. These variables are population shares for various age groups, earnings per-capita, transfers per-capita, employment-population ratio, and population density. See Section 3 for more details on the construction of the variables and data sources. The sample is restricted to 1999-2016.

Table 6: Intensive Margin

	Baseline (1)	Intensive Margin (2)
$\mathbb{1}\{Treat_c\} \times$ $\mathbb{1}\{Post_y\}$	-4.91957*** (1.40530) [-17.96]	
# Establishments		0.01614 (0.39677) [0.06]
County FEs	Yes	Yes
Urban Year Group FEs	Yes	Yes
Adj. R^2	0.988	0.988
N	17,374	17,374

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 pre-treatment mean for the treated group is in square brackets. Each cell is a separate estimation of Equation 1. The estimated specification also includes time-varying county variables. These variables are population shares for various age groups, earnings per-capita, transfers per-capita, employment-population ratio, and population density. In column (2), the indicator variable for whether the county has at least one establishment rendering ambulance services is replaced with the count of such establishments. See Section 3 for more details on the construction of the variables and data sources. The sample is restricted to 1999-2016.

Table 7: Age Heterogeneity

	Age $\leq$ 19 (1)	20 $\leq$ Age $\leq$ 34 (2)	35 $\leq$ Age $\leq$ 49 (3)	50 $\leq$ Age $\leq$ 64 (4)	Age $\geq$ 65 (5)
$\mathbb{1}\{Treat_c\} \times$	-0.26432	-1.47796***	-1.25477***	-1.04263***	-0.88575**
$\mathbb{1}\{Post_y\}$	(0.17695)	(0.43548)	(0.37818)	(0.30503)	(0.39006)
	[-9.65]	[-25.69]	[-19.39]	[-21.34]	[-11.76]
County FEs	Yes	Yes	Yes	Yes	Yes
Urban Year Group FEs	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.965	0.978	0.979	0.978	0.977
N	17,374	17,374	17,374	17,374	17,374

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 pre-treatment mean for the treated group is in square brackets. Each cell is a separate estimation of Equation 1. The estimated specification also includes time-varying county variables. These variables are population shares for various age groups, earnings per-capita, transfers per-capita, employment-population ratio, and population density. See Section 3 for more details on the construction of the variables and data sources. The sample is restricted to 1999-2016. Column headers denote the age category that constitutes the estimation sample.

Table 8: Race and Education Heterogeneity

	White	Black	Other	High School or Less	Some College	Bachelors and Above
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}\{Treat_c\} \times \mathbb{1}\{Post_y\}$	-4.38407***	-0.44173	-0.09378	-4.45792***	-0.91482***	-0.32870
	(1.14218)	(0.36168)	(0.10087)	(1.08647)	(0.32298)	(0.22002)
	[-17.54]	[-24.89]	[-15.16]	[-24.90]	[-20.07]	[-11.43]
County FEs	Yes	Yes	Yes	Yes	Yes	Yes
Urban Year Group FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.987	0.979	0.975	0.981	0.977	0.977
N	17,374	17,374	17,374	17,374	17,374	17,374

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 pre-treatment mean for the treated group is in square brackets. Each cell is a separate estimation of Equation 1. The estimated specification also includes time-varying county variables. These variables are population shares for various age groups, earnings per-capita, transfers per-capita, employment-population ratio, and population density. See Section 3 for more details on the construction of the variables and data sources. The sample is restricted to 1999-2016. Column headers denote the race and education category that constitutes the estimation sample.

Table 9: Education Heterogeneity Whites Only

	High School or Less	Some College	Bachelors and Above
	(1)	(2)	(3)
$\mathbb{1}\{Treat_c\} \times \mathbb{1}\{Post_y\}$	-3.60576***	-0.87902***	-0.36715
	(0.81974)	(0.29156)	(0.23053)
	[-22.32]	[-20.78]	[-13.38]
County FEs	Yes	Yes	Yes
Urban Year Group FEs	Yes	Yes	Yes
Adj. R^2	0.980	0.973	0.973
N	17,374	17,374	17,374

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 pre-treatment mean for the treated group is in square brackets. Each cell is a separate estimation of Equation 1. The estimated specification also includes time-varying county variables. These variables are population shares for various age groups, earnings per-capita, transfers per-capita, employment-population ratio, and population density. See Section 3 for more details on the construction of the variables and data sources. The sample is restricted to 1999-2016. Column header denote the education category that constitutes the estimation sample. In all columns estimation sample is restricted to deaths where the race of the deceased person is reported to be White.