Insurance Expansion and Emergency Medical Service Establishments: Evidence from the Affordable Care Act*

Olanrewaju Yusuff†

Georgia State University

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Abstract

This paper examines how health insurance expansion affects the availability of emergency medical services across local markets. Using county-level variation in pre-ACA uninsured rates and state decisions on Medicaid expansion, I find heterogeneous effects of insurance expansion on ambulance service establishments. While difference-in-differences estimates show that Medicaid expansion states experienced a 3.8 percentage point average decrease in ambulance establishments, triple-difference estimates reveal that counties with higher pre-expansion uninsured rates saw significant increases in service availability. At the mean pre-treatment uninsured rate of 18.6 percent, Medicaid expansion led to an 8.6 percentage point increase in ambulance service establishments. These effects persist in event study analyses and are robust to various specifications, including propensity score weighting and state-by-year fixed effects. The results suggest that insurance expansion's impact on emergency medical infrastructure varies systematically with local market conditions, highlighting the importance of considering pre-existing insurance coverage when evaluating healthcare policy effects. These findings contribute to understanding how insurance expansion shapes the spatial distribution of emergency medical services.

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†oyusuff4@student.gsu.edu

1 Introduction

Ambulance services are critical for emergency medical care and patient survival. Recent evidence suggests concerning trends in emergency medical service availability across the United States, with some areas experiencing reduced access to these vital services (Jonk et al., 2023).[1] While extensive research has examined how insurance expansion affects healthcare utilization and outcomes (Baicker et al., 2014; Courtemanche et al., 2017; Carey et al., 2020). Less is known about its impact on the spatial distribution of emergency medical infrastructure, particularly ambulance services.

The effect of insurance expansion on ambulance service availability is theoretically ambiguous. On one hand, increased insurance coverage through the Affordable Care Act (ACA) may improve the financial viability of emergency medical services in previously underserved areas by ensuring payment for services rendered (Garthwaite et al., 2017). This *coverage effect* could lead to market entry or expansion of ambulance services, particularly in areas with high pre-expansion uninsured rates. On the other hand, improved access to preventive care through insurance expansion may reduce emergency service utilization Simon et al. (2017). Potentially affecting the market structure of ambulance services (McInerney et al., 2017). This *preventive care effect* aligns with evidence that increased access to alternative transportation services reduces ambulance utilization (Moskatel and Slusky, 2019).

This paper provides new evidence on how insurance expansion shapes the spatial distribution of emergency medical services. Using county-level variation in pre-ACA uninsured rates and state decisions on Medicaid expansion.[2] I find that Medicaid expansion led to an average 3.8 percentage point decrease in ambulance establishments. However, this average effect masks important heterogeneity. Triple-difference estimates reveal that counties with higher pre-expansion uninsured rates experienced significant increases in ambulance service availability. At the mean pre-treatment uninsured rate of 18.6 percent, Medicaid expansion increased the likelihood of ambulance service presence by 8.6 percentage points. These contrasting findings suggest that local market conditions, particularly pre-existing insurance coverage, play a crucial role in determining how insurance expansion affects healthcare infrastructure.[3]

The results are robust to a variety of specification checks and alternative research designs. Event study analyses confirm parallel pre-trends and show persistent effects post-expansion. The findings remain

[1] Emergency medical service response times are critical for survival. According to recent reports, ambulance response times exceeding 25 minutes significantly reduce survival rates for cardiac arrests and other life-threatening conditions. Media coverage has highlighted growing concerns about “ambulance deserts" - for example, The New York Times reported in 2023 that over 4.5 million Americans live in areas with dangerously long ambulance response times.

[2] The County Business Patterns (CBP) data used in this study provides comprehensive information on ambulance establishments at the county level. An ambulance establishment is defined as a physical location primarily engaged in providing emergency medical transportation services. The Small Area Health Insurance Estimates (SAHIE) data provides county-level uninsurance rates.

[3] My identification strategy leverages both cross-sectional variation in pre-ACA county-level uninsured rates and temporal variation from state decisions on Medicaid expansion. This allows me to identify how local market conditions mediate the effects of insurance expansion.

stable when accounting for potential selection through propensity score weighting, controlling for demographic and economic characteristics, and including state-by-year fixed effects.

These findings contribute to several strands of literature. First, they extend research on how insurance expansion affects healthcare markets (Baicker et al., 2014; Courtemanche et al., 2017; Garthwaite et al., 2017) by showing heterogeneous effects on emergency medical infrastructure. Second, they complement studies on geographic access to healthcare (Buchmueller et al., 2006) by demonstrating how policy changes can reshape the spatial distribution of emergency services. Third, they add to our understanding of healthcare market structure (Cutler and Morton, 2013; Dafny et al., 2012) by revealing how local market conditions mediate the effects of coverage expansion.

The results have important implications for health policy design. The heterogeneous effects suggest that insurance expansion's impact on healthcare infrastructure depends crucially on local market conditions, particularly pre-existing insurance coverage. This pattern aligns with recent evidence on how local market characteristics shape the effects of healthcare policy reforms (Carey et al., 2020). These findings imply that policies aimed at expanding coverage may need to consider complementary interventions in areas with different baseline characteristics to ensure equitable access to emergency medical services.

2 Literature Review

This paper connects to several strands of literature examining the effects of insurance expansion on healthcare markets. The first strand focuses on how insurance coverage affects healthcare access and utilization. Buchmueller et al. (2015) provide a comprehensive analysis of Medicaid expansion effects on insurance coverage. Courtemanche et al. (2017) find that at average pre-treatment uninsured rates, the ACA increased insurance coverage by 5.9 percentage points, with larger effects in Medicaid expansion states. Frean et al. (2017) decompose these coverage gains, finding that exchange premium subsidies and Medicaid expansion contributed 40% and 60%, respectively.

A second strand examines how insurance expansion affects healthcare infrastructure and market structure. [4] Most closely related to my study, Duggan et al. (2022) and Lindrooth et al. (2018) show that Medicaid expansion substantially increased hospital revenue and reduced uncompensated care, strengthening hospitals' financial positions. However, Carroll et al. (2023) finds that improved performance led to hospital consolidation in some markets, highlighting how insurance expansion can reshape local healthcare infrastructure. This tension between market entry and exit mirrors my findings on ambulance services, where effects vary by local market conditions.

[4] Recent work has highlighted the importance of understanding how policy changes affect healthcare market structure. For instance, Bond and White (2013) examines market responses to Massachusetts health reform, while Garthwaite (2012) studies provider responses to public insurance expansion.

A third strand investigates the spillover effects of insurance expansion on healthcare delivery. [5] Prior work demonstrates both positive and negative spillovers. On preventive care, Simon et al. (2017) find that Medicaid expansion increased the utilization of preventive services. Wherry and Miller (2016) document improved quality of coverage and increased healthcare utilization among low-income adults. These findings support my mechanism that improved preventive care access may reduce emergency service demand in some areas.

Finally, my work relates to the literature on geographic access to healthcare services.[6] Buchmueller et al. (2016) show that coverage gains varied geographically, with larger improvements in Medicaid expansion states. Gruber and Sommers (2019) find that insurance expansion improved healthcare access, though effects varied by local market conditions. These spatial patterns echo my finding that pre-existing local insurance coverage mediates the impact of expansion on emergency medical infrastructure.

My paper extends this literature in several ways. First, while prior work focuses primarily on insurance coverage effects or hospital market structure, I examine impacts on emergency medical services - a crucial but understudied component of healthcare infrastructure. Second, I show how local market conditions, particularly pre-existing uninsurance rates, mediate policy effects on healthcare provision. Third, my findings on heterogeneous effects contribute to understanding how insurance expansion reshapes the spatial distribution of healthcare services.[7]

3 Background

3.1 The ACA and Ambulance Service Reimbursement

The Affordable Care Act (ACA) represents one of the largest healthcare coverage expansions in U.S. history. While its primary goal was expanding insurance coverage, the policy's effects extended to healthcare delivery systems, including emergency medical services. This section outlines the institutional framework governing ambulance services under the ACA and explains how insurance expansion might affect ambulance service provision.[8]

[5] The spillover effects of insurance expansion have been documented across various healthcare settings. A growing body of work examines both supply-side responses (e.g., provider behavior) and demand-side impact (e.g., utilization patterns).

[6] Geographic variation in healthcare access remains a critical policy concern. Recent media coverage has highlighted growing disparities in emergency medical service availability across rural and urban areas (Wall Street Journal, 2023

[7] While several studies examine healthcare market structure, this paper is the first to comprehensively analyze how insurance expansion affects the spatial distribution of emergency medical services using detailed county-level data on ambulance establishments.

[8] The ACA's implementation varied significantly across states, with some choosing to expand Medicaid coverage while others did not. As of 2016, the end of my study period, 32 states (including the District of Columbia) had adopted Medicaid expansion. These states chose to expand Medicaid eligibility to adults with incomes up to 138% of the federal poverty level (FPL), as allowed under the ACA.

Emergency medical services, including ambulance transport, are classified as Essential Health Benefits (EHB) under the ACA.[9] However, the reimbursement structure for these services creates unique market dynamics. Medicare Part B, which covers ambulance services, operates through both the Physician Fee Schedule and the Hospital Outpatient Prospective Payment System (OPPS).[10] Reimbursement rates vary by geographic classification—urban, rural, or super-rural—reflecting different cost structures and market conditions across locations.

A key feature of the current reimbursement system is its transportation-centric nature. Providers can only submit claims for reimbursement when patients are physically transported, regardless of the level of care delivered at the scene.[11] This creates potential tensions between service provision and financial viability. As Lyon et al. (2014) note, improved access to preventive care through the ACA might reduce transport needs while emergency response obligations remain constant.

The reimbursement structure varies across coverage types. Traditional Medicare (Parts A and B) covers inpatient and outpatient services, while Part C covers Medicare Advantage Plans, and Part D covers prescription drugs. For ambulance services specifically, Medicare reimburses providers through the Physician Fee Schedule or OPPS using Ambulatory Payment Classifications (APCs)—a set of comparable services based on clinical criteria and pricing.[12]

These institutional features create competing effects on ambulance service provision. On one hand, expanded insurance coverage through the ACA increases the insured population that can access and pay for emergency medical services. On the other hand, improved access to preventive care might reduce emergency service utilization, while the transportation-based reimbursement model may not fully compensate providers for all services rendered. Understanding these competing forces is crucial for interpreting the heterogeneous effects of insurance expansion on ambulance service availability.[13]

3.2 Abulance Service and Ambulance Deserts in the United States

Emergency medical services (EMS) in the United States have evolved from a patchwork system of local providers to a more structured, though still heterogeneous, network of services. While ambulance services primarily involve patient transportation, they encompass broader services, including air medical

[9] Essential Health Benefits represent the minimum set of healthcare services that must be covered by insurance plans under the ACA. Emergency services were included to ensure access to critical care.

[10] The geographic variation in reimbursement rates reflects Congress's recognition of the unique challenges faced by rural emergency medical services, as documented in various Medicare Payment Advisory Commission reports.

[11] https://www.cms.gov/medicare/payment/fee-schedules/ambulance

[12] https://revcycleintelligence.com/features/the-difference-between-medicare-and-medicaid-reimbursement

[13] The relationship between insurance coverage and emergency medical service provision remains debated. Industry reports and academic studies suggest that while insurance expansion improves access to care, its effects on emergency service utilization and provider viability vary by market characteristics.

transport, emergency medical dispatch, and non-transporting medical support.[14]

The institutional evolution of ambulance services provides an important context for understanding current market dynamics. Before 1969, diverse organizations including fire departments, hospitals, funeral homes, and volunteers provided ambulance services.[15] The Emergency Medical Services Act of 1973 established significant federal funding, but support declined in the 1980s following the Omnibus Budget Reconciliation Act, which eliminated categorical federal support and increased state discretion through block grants (on the Future of Emergency Care in the US Health System and others, 2006). This devolution of authority led to substantial variation in EMS quality and availability across regions.

Contemporary EMS provision reflects this historical fragmentation. Local governments manage and finance services under state EMS agency oversight, with providers including community nonprofits, fire departments, hospitals, and private organizations. Rural areas face particular challenges, relying more heavily on volunteers and Medicare payments than urban counterparts (Chaudhary et al., 2019).[16] This geographic disparity in service provision creates vulnerability to market exits.

Recent evidence suggests growing concerns about ambulance service availability. Jonk et al. (2023) find that over three-quarters of ambulance agencies serve rural areas, where sporadic demand and rising equipment costs challenge financial viability. The transportation-based reimbursement model, which only compensates providers for patient transport, further strains service sustainability. Figure (1a) documents the increasing fraction of counties without ambulance establishments during my sample period.

The emergence of “ambulance deserts" - areas with limited emergency medical service access - represents a critical policy concern. Figure (1b) shows the spatial distribution of these changes, highlighting counties that have gained or lost ambulance services over the sample period. Jonk et al. (2023) estimate that 4.5 million Americans reside in areas more than 25 minutes from ambulance services.[17] This access problem disproportionately affects rural areas, where over half of the population in ambulance deserts resides. The challenge is compounded by rural hospital closures (Alexander and Richards, 2023; Battaglia, Forthcoming; Fischer et al., 2022).

[14] County Business Patterns data used in this study capture establishment-level information but do not distinguish between specific types of ambulance services.

[15] The first civilian ambulance service was established in Cincinnati, Ohio, in 1865, inspired by the Union Army’s Ambulance Corps’ success during the Civil War.

[16] Approximately half of rural providers’ revenue comes from Medicare payments, highlighting the importance of public insurance for service sustainability.

[17] While this paper defines ambulance deserts at the county level based on establishment presence, Jonk et al. (2023) use more granular location data. Though methodologies differ, both approaches reveal significant within-county variation in ambulance service access.

4 Data

The ideal data to uncover the causal effect of ACA on ambulance deserts would be firm-level data that includes specific reasons for market entry and exit. Such data would allow direct testing of whether health improvements from the ACA reduce ambulance service demand or whether increased insurance coverage drives market entry. In the absence of such ideal data, I construct a comprehensive county-level panel using five main data sources.[18]

4.1 Primary Data Sources

4.2 County Business Patterns (CBP) Data

My primary measure of ambulance service availability comes from the County Business Patterns (CBP) establishment-level data. These data have been widely used in healthcare access studies (Bradford and Maclean, 2023; Deza et al., 2022a,b) and provide annual information on establishments with paid employees for every U.S. county at detailed industry levels.[19]

I identify ambulance service establishments using the six-digit North American Industry Classification System (NAICS) code 621910.[20] I measure ambulance service availability for each county-year observation through the number of establishments with this NAICS code. While this measure may not capture all dimensions of ambulance service access (such as response times or service quality), it provides a consistent measure of physical service availability across counties.

The CBP data come from annual tax filings with the Internal Revenue Service (IRS), lending credibility to their accuracy.[21] However, three important data features affect my analysis. First, the Census Bureau suppresses exact establishment counts in some counties for privacy protection. Second, employment data are noise-infused in more than half of the observations.[22] Third, starting in 2017, the Census Bureau only publishes cells containing three or more establishments.

Given these constraints, I restrict my analysis to 1999-2016.[23] The start date ensures consistent NAICS

[18] While these data sources do not directly observe firm decision-making, their combination allows me to examine how local market conditions affect ambulance service availability.

[19] The CBP defines an establishment as a “single physical location at which business is conducted, or services or industrial operations are performed."

[20] Prior to 1998, CBP data were only available at the four-digit Standard Industrial Classification (SIC) level, precluding consistent measurement of ambulance services in earlier years.

[21] Establishments face increased audit risk and potential penalties for misreporting their principal business code, providing strong incentives for accurate NAICS reporting.

[22] In robustness checks, I use imputed establishment-level employment data from Eckert et al. (2020), who develop a linear programming approach leveraging the hierarchical nature of CBP data to address missing employment information.

[23] This sample period allows me to observe market structure changes before and after the ACA’s implementation while

coding across years, while the end date avoids misclassifying counties with 1-2 establishments as lacking service availability under the post-2016 reporting rules. This timeframe encompasses the pre-ACA period and the initial years of implementation, allowing me to examine both the immediate and medium-term effects of insurance expansion on ambulance service availability.

4.3 Small Area Health Insurance Estimates (SAHIE)

A crucial component of my identification strategy relies on pre-ACA county-level insurance coverage data from the Small Area Health Insurance Estimates (SAHIE) program. SAHIE, administered by the U.S. Census Bureau, provides the only source of single-year health insurance coverage estimates for all U.S. counties, making it uniquely suited for analyzing local variation in insurance markets.[24]

The SAHIE program combines multiple data sources to generate its estimates, including administrative records, population estimates, and survey data. This methodology produces detailed estimates of insurance coverage rates across various demographic and economic characteristics.[25] For my analysis, I focus on the overall county-level uninsured rates in the pre-ACA period, which serve as a key source of identifying variation in my triple-difference framework.

SAHIE data are particularly valuable for three reasons. First, they provide consistent measurement of insurance coverage across all counties, including rural areas that are often underrepresented in survey data. Second, the estimates account for local economic and demographic factors that might affect insurance coverage. Third, the pre-ACA estimates capture baseline market conditions that could influence how insurance expansion affects healthcare infrastructure.[26]

I use the 2019 release of the SAHIE data, which underwent extensive quality control and validation.[27] This release provides consistent historical estimates that allow me to measure pre-treatment uninsured rates with precision, a critical feature for my empirical strategy.[28]

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maintaining consistent measurement of ambulance service availability.

[24] Unlike other insurance coverage data sources, SAHIE provides consistent coverage for all counties, including those with small populations where survey-based estimates might be unreliable.

[25] The program produces estimates by age, sex, race/ethnicity, and income levels, though my primary specifications focus on overall county rates to capture market-level effects.

[26] The variation in pre-ACA uninsured rates (ranging from under 5% to over 40% across counties) provides substantial identifying variation for estimating the heterogeneous effects of insurance expansion.

[27] https://www.census.gov/data

[28] Quality metrics from the Census Bureau indicate that SAHIE estimates have particularly high precision for the pre-ACA period, which is crucial for my identification strategy.

4.3.1 Regional Economic Information System (REIS)

The Bureau of Economic Analysis's REIS data provide detailed county-level economic indicators. I extract four key measures: population counts, per capita earnings, per capita transfer receipts, and total employment. From these, I construct the employment-to-population ratio, an important control for local economic conditions.[29]

4.3.2 Surveillance, Epidemiology, and End Results (SEER)

The SEER data provide detailed demographic information at the county level. These data are particularly valuable for constructing population-based controls and accounting for demographic shifts that might affect ambulance service demand.[30]

4.4 Analytical Sample Construction

My analytical sample spans 1999-2016 and focuses on counties in the continental United States. Following Fischer et al. (2022), I exclude Alaska, Hawaii, D.C., and Virginia due to unique geographic characteristics or frequent changes in county borders. The sample construction prioritizes clean identification of the effects of insurance expansion on ambulance service availability.

Using NAICS code 621910, I track ambulance service establishments at both extensive and intensive margins. The extensive margin captures whether a county has any ambulance service establishment, while the intensive margin counts the number of establishments. To allow for operational adjustment periods, I follow recent literature (Bondurant et al., 2018; Bradford and Maclean, 2023; Deza et al., 2022a,b; Swensen, 2015) and use lagged measures in my robustness checks. While this approach may not capture all dimensions of access, such as response times or service quality, it consistently measures physical service availability across counties and over time.

I incorporate a rich set of county-level controls to account for local market conditions that might affect both insurance coverage and ambulance service provision. REIS economic indicators capture local market conditions through employment-population ratios, per capita earnings, and transfer payments. Demographic characteristics from SEER data include age distributions and population composition. I also control for pre-existing health market features, including baseline uninsured rates and hospital presence. Robustness checks confirm that the main results are not sensitive to including previously excluded

[29] The REIS variables are coded as follows: - Population (linecode 100): Number of persons - Per capita earnings (linecode 120): Dollars - Per capita transfer receipts (linecode 130): Dollars - Total employment (linecode 240): Number of jobs

[30] The SEER data complement the REIS demographic information and help control for population characteristics that might correlate with both insurance coverage and ambulance service demand.

counties or using alternative lag structures.

4.5 Mortality Data

To explore the mechanisms behind the negative average effect found in my difference-in-differences analysis, I examine mortality outcomes using CDC WONDER data, a public version of the National Vital Statistics System (NVSS). These data provide comprehensive death records with county-level identifiers that allow me to link mortality outcomes to local ambulance service measures.

CDC WONDER offers detailed cause-of-death information through International Classification of Diseases, Tenth Revision (ICD-10) codes, recording both the underlying cause and up to 20 contributing causes. The data include rich demographic information (age, race, ethnicity, education) and temporal details (month and year of death), as well as contextual factors such as work-related injuries and accidental deaths.[31]

My mechanism analysis focuses mainly on external causes of death - including injuries, suicides, homicides, motor vehicle accidents, and other accidents. This focus follows Avdic (2016) and Buchmueller et al. (2006), who examine similar outcomes in studies of hospital closure effects. External causes are especially relevant for explaining the DD results, as they typically require immediate emergency response and may be most affected by changes in preventive care access under insurance expansion.[32] The CDC WONDER data's comprehensive coverage of these acute events helps illuminate how improved preventive care through insurance expansion might reduce emergency service demand in some areas.

4.6 Summary Statistics

Table 1 presents baseline differences between Medicaid expansion and non-expansion states before the ACA implementation. Expansion states had a higher fraction of counties with ambulance services, suggesting systematically different pre-existing emergency medical infrastructure. Figure 1 provides two perspectives on these differences: Panel 1a shows a secular decline in ambulance service availability from 1999-2016, while Panel 1b reveals the spatial distribution of service changes, with substantial variation in both gains and losses across counties.

The concentration of ambulance services also varies considerably across locations. Figure 2 shows that in both pre- and post-ACA periods, Harris County, TX, maintained the highest concentration of estab-

[31] While the data include various causes of death, I concentrate on external causes due to their clear connection to emergency medical service response times and preventive care effects.

[32] Due to data limitations in CDC WONDER, I cannot examine acute respiratory causes of death, which might also help explain the relationship between insurance expansion and ambulance service availability.

lishments. However, after the implementation of the ACA, the number decreased from 200 to about 100 establishments. Other high-concentration areas, primarily major metropolitan counties, also experienced changes in service levels, suggesting market restructuring following insurance expansion.

Figure 3 explores these changes more systematically. Panel 3a shows divergent trends between expansion and non-expansion states after 2014, with non-expansion states experiencing steeper declines in service availability. However, Panel 3b reveals that this average effect masks important heterogeneity based on pre-ACA uninsured rates. Areas with high baseline uninsurance in expansion states show relative improvements in service availability post-ACA, while similar areas in non-expansion states experience the steepest declines.[33]

This heterogeneity becomes visually apparent in Figure 4, which maps the evolution of service availability from 2013 to 2016. Panel 4a shows the baseline distribution, while Panels 4b through 4d track the emergence of new services (yellow) against the backdrop of existing services (blue) and areas without service (white). The pattern suggests that insurance expansion helped maintain or improve service availability, particularly in areas with high pre-existing uninsurance rates.

5 Empirical Strategy

5.1 Medicaid Expansion and Ambulance Deserts Event Study Specification

To examine how Medicaid expansion affects ambulance service availability and how these effects vary with local market conditions, I implement a multi-step empirical approach. I begin with an event study specification that examines average effects:

$$Y_{dcst} = \beta_s + \beta_t + X'_{dcst}\beta + Expansion_s \times \left[\sum_{y=-6}^{-2} \beta_y I(t - t_s^* = y) + \sum_{y=0}^{1} \beta_y I(t - t_s^* = y) \right] + \varepsilon_{dcst} \quad (1)$$

Where Y_{dcst} represents ambulance service measures for desert status d in county c, state s, and year t. I examine both extensive margin (binary indicator for service presence) and intensive margin (establishment count) outcomes. The vector X_{dcst} includes time-varying county characteristics: economic conditions from REIS data, demographic composition from SEER data, and healthcare market features.[34]

The variable $Expansion_s$ equals 1 for the 24 states that expanded Medicaid eligibility in 2014 or 2015. The term $I(t - t_s^* = y)$ indicates time relative to expansion implementation in state s, with t_s^* denoting

[33] Appendix Figures A1 and A2 provide additional evidence of this heterogeneity through box plots and density distributions of establishment counts, showing substantial within-group variation both with and without the Harris County outlier.

[34] Standard errors are clustered at the county level to account for serial correlation in outcomes.

the expansion date. Following Carey et al. (2020), I combine y = -6 and y = -7 since only three states expanding in 2015 have non-zero values for y = -7.

The coefficients β_y measure the evolution of ambulance service availability in expansion versus non-expansion states, with the year before expansion as the reference period. Pre-expansion coefficients (β_{-6} through β_{-2}) test the parallel trends assumption. Post-expansion coefficients (β_0 and β_1) capture average policy effects, which I later decompose through triple-difference analysis to examine heterogeneity based on pre-expansion market conditions.[35]

5.2 DD Specification

Building on the event study analysis, I estimate a difference-in-differences specification that measures the average treatment effect:

$$Y_{dcst} = \beta_0 + \beta_1 \mathbb{1}(Post_t) + \beta_2 \mathbb{1}(Medicaid\ Expansion\ State_s)\mathbb{1}(Post_t) + X'_{dcst}\beta_3 + \gamma_s + \theta_t + \varepsilon_{dcst} \quad (2)$$

where Y_{dcst} represents ambulance service outcomes as defined previously, and $\mathbb{1}(Post_t)$ indicates the post-2014 period. The vector X_{dcst} contains the same county-level controls as in the event study specification.[36]

Following Courtemanche et al. (2017), β_1 captures the effect of non-Medicaid ACA components (insurance market reforms, individual mandates, subsidies, exchanges), while β_2 isolates the Medicaid expansion effect. Their sum, $\beta_1 + \beta_2$, represents the full ACA impact on ambulance service availability.[37]

This specification differs from the event study approach by estimating the aggregate treatment effect - comparing mean outcomes between entire pre- and post-intervention periods across expansion and non-expansion states rather than examining year-by-year changes relative to implementation.

[35] This initial specification establishes baseline effects before examining how local insurance market conditions mediate policy impacts.

[36] State fixed effects (γ_s) absorb the main impact of Medicaid expansion, making a separate expansion indicator redundant.

[37] The causal interpretation relies on the assumption that conditional on controls, changes in outcomes would have been similar across expansion and non-expansion states absent the policy change.

5.3 DDD Specification

To address potential concerns with the two-way fixed effects model and exploit additional variation in treatment intensity, I implement a triple-difference (DDD) specification that leverages pre-ACA uninsured rates across counties:

$$\begin{aligned} Y_{dcst} = \alpha_0 &+ \alpha_1(\text{Uninsured}_{cs} \times \mathbb{1}(\text{Post}_t)) \\ &+ \alpha_2(\mathbb{1}(\text{Medicaid Expansion State}) \times \mathbb{1}(\text{Post}_t)) \\ &+ \alpha_3(\mathbb{1}(\text{Medicaid Expansion State}) \times \text{Uninsured}_{cs} \times \mathbb{1}(\text{Post}_t)) \\ &+ X'_{dcst}\beta + \gamma_s + \theta_t + \varepsilon_{dcst} \end{aligned} \tag{3}$$

Where Uninsured_{cs} represents the 2013 pre-treatment uninsured rate in county c in state s. Following Courtemanche et al. (2017), this specification assumes treatment intensity varies proportionally with baseline uninsured rates.[38]

The coefficient α_1 captures how the non-Medicaid ACA components affect areas with different baseline uninsurance rates, while α_3 measures how Medicaid expansion impacts vary with local uninsured rates. Since Medicaid expansion should not affect areas with zero baseline uninsurance, α_2 likely captures unobserved confounders rather than causal effects.[39]

This specification's key identifying assumption is weaker than the DD model - requiring only that differences in outcomes between high and low uninsured areas in expansion states would have evolved similarly to these differences in non-expansion states absent the ACA.[40] The model includes the same controls X_{dcst} as previous specifications, though main effects of Post_t, expansion status, and uninsured rates are absorbed by fixed effects.

[38] This approach follows Finkelstein (2007) and Miller (2012)'s studies of Medicare introduction and Massachusetts health reform.

[39] At the mean pre-treatment uninsured rate, the full effect of Medicaid expansion is $\alpha_3 \times \overline{\text{Uninsured}}$.

[40] The model's validity is supported by evidence that pre-ACA uninsured rates are not systematically related to state expansion decisions or other concurrent policy changes.

6 Results

6.1 Event Study Results

To examine whether counties in states that underwent Medicaid expansion experienced differential changes in ambulance service availability. I first present the event study results from Equation 1.

Figure 5a, 5b, and 5c displays the event study coefficient estimates of Equation 1. Figure 5a and 5b present the event study at the extensive and intensive margin, respectively. Figure 5c presents the Poisson Pseudo Maximum Likelihood (PPML) at the intensive margin of the effect of ACA on ambulance deserts. The result reveals suggestive evidence that expansion and non-expansion states followed parallel trends in the pre-period. However, I observe a divergence following the implementation period, with expansion states experiencing a decline in ambulance services relative to non-expansion states.

6.2 DD Results

I report the difference-in-difference coefficients in Table 2. I find a statistically significant decrease in ambulance service availability in expansion relative to non-expansion states of approximately 3.8 percentage points ($p<0.01$). This effect is robust across different specifications, including county- and state-fixed effects. When adding economic and demographic controls, the estimated effect increases slightly to 4.1 percentage points.

The consistency of these estimates across specifications suggests that concurrent changes in local economic conditions or demographics do not drive the observed relationship between Medicaid expansion and ambulance service availability. This provides suggestive evidence that beneficiaries who lived in these states were receiving timely healthcare that prevented chronic health cases involving ambulance services. However, these average effects may mask important heterogeneity based on local market conditions, particularly pre-existing levels of insurance coverage.

6.3 DDD Results

To investigate whether the effects of Medicaid expansion vary with local market conditions, I estimate triple-difference specifications that interact the basic DD terms with county-level pre-treatment uninsured rates. This approach allows me to test whether areas with greater potential for insurance expansion – as measured by higher baseline uninsured rates – experienced different effects on ambulance service availability.

I present the DDD results from Equation 3. My preferred specification in Table 3. Following Courtemanche et al. (2017), for the DDD specifications, the estimated effects of the private portion, Medicaid portion, and the full ACA at the mean are $\alpha_1 \times \overline{\text{UNINSURED}}$, $\alpha_3 \times \overline{\text{UNINSURED}}$, and $(\alpha_1 + \alpha_3) \times \overline{\text{UNINSURED}}$, respectively, where $\overline{\text{UNINSURED}} = 0.1859$ or 18.6%. I present the coefficient estimates for the key interaction terms in Panel A. Panel B uses these estimates to compute the implied effects of the private (non-Medicaid expansion) and Medicaid expansion components at the sample mean pre-treatment uninsured rate.

The DDD specification reveals several significant findings. First, the coefficient on the triple interaction term (Medicaid Expansion State $\times$ Uninsured$_{cs} \times$ Post$_t$) is positive and statistically significant at the 5 percent level, with magnitudes of 0.4637 and 0.4906 in my baseline and controlled specifications, respectively. This suggests that counties in Medicaid expansion states with higher pre-treatment uninsured rates experienced larger increases in ambulance establishment presence following the expansion.

The positive and significant triple interaction coefficient reveals an important source of heterogeneity in the effects of Medicaid expansion. While the average impact across all counties is negative (as shown in the DD results), areas with higher pre-treatment uninsured rates experienced increases in ambulance establishment presence. This pattern is consistent with the improved financial viability of emergency medical services in previously underserved areas, where expansion increased the insured population.

At the mean pre-treatment uninsured rate of 18.59 percent, my estimates indicate that Medicaid expansion led to an 8.62 percentage point increase in ambulance establishment presence (Panel B). This effect remains stable at 9.12 percentage points when including my full set of economic and demographic controls. Both estimates are statistically significant at the 5 percent level. Interestingly, I find no evidence of significant private market effects – the estimated impact of non-Medicaid expansion components is small (-0.42 to -0.90 percentage points) and statistically insignificant.

The full implementation of the ACA (including both private and Medicaid expansion components) is estimated to increase ambulance establishment presence by approximately 8.20-8.22 percentage points in counties with mean pre-treatment uninsured rates. This effect is primarily driven by the Medicaid expansion component, suggesting that expanding public insurance coverage affected the emergency medical services market structure.

My results are robust in including various controls and fixed effects, as demonstrated by the similar magnitudes and statistical significance across specifications. Adding economic and demographic controls in Column (2) slightly increases the magnitude of the Medicaid expansion effect while maintaining statistical significance, lending credibility to my main findings.

These findings provides suggestive evidence that the impact of Medicaid expansion on emergency medical services varies systematically with local market conditions. The negative average effect found in the

DD analysis appears to be driven by areas with lower pre-treatment uninsured rates, while areas with higher uninsured rates saw increases in service availability. This heterogeneity highlights the importance of considering local market conditions when evaluating the effects of insurance expansion policies on healthcare infrastructure.

7 Robustness & Mechanism

7.1 DD: Baseline Effects Under Alternative Specifications

The DD result is robust across different specifications, including county- and state-fixed effects. When adding economic and demographic controls. The decline of ambulance services at the extensive and intensive margin holds consistently with different alternative specifications that include county fixed effects, year fixed effects, and for controlling for state time trends before and after the Medicaid Expansion. The result is also robust to different estimation techniques, such as the PPML, as there might be some concern about the skewness of the ambulance service data.

I show suggestive evidence that ambulance deserts in expansion states are increasing. One possible explanation is that health improves in expansion states as access to healthcare increases. This reduces the probability of needing an ambulance service for acute health issues at the end stage or last resort, as preventive health care visits prevent acute health issues.

As a mechanism to explain why ACA increases ambulance deserts, in Figure 6, the event study shows the difference in mortality rates between the treated group (counties that lost access to ambulance services) and the control group (counties that did not lose access to ambulance services) for four years before and four years after the event.

There was no significant pre-trend between the treated and control groups, as the event study shows that the mortality rate in the treated group was similar to the mortality rate in the control group, especially two years before the event of losing access to ambulance services. The mortality rate in the treated counties decreased significantly in the third year following the loss of access to ambulance services.

This shows some suggestive evidence that this is the case, using the CDC Wonder mortality data to document the health effects of ambulance deserts. The result reveals that health proxy as mortality improves in counties where we have these ambulance deserts.

7.2 DDD: Market Structure and Local Conditions

To further validate my main findings, I conduct several additional specification checks presented in Table 4. While my baseline DDD results already demonstrate stability across basic control variations, I explore more demanding specifications that address potential threats to identification.

First, I account for potential selection into Medicaid expansion by weighting observations by propensity score (Column 1). The Medicaid expansion effect remains positive and significant at 11.12 percentage points, slightly larger than the baseline estimate but statistically indistinguishable from it. This suggests that the selection of observable state characteristics does not drive the main results.

In Columns 2-4, I isolate the role of different county characteristics. The Medicaid expansion effect remains stable when separately controlling for demographic composition (9.20 percentage points), economic conditions (9.26 percentage points), and age distribution (8.26 percentage points). This stability across specifications suggests that concurrent changes in county characteristics are unlikely to confound the estimated effect of Medicaid expansion.

Column 5 includes state-by-year fixed effects, which absorb all state-level annual variation and identify the impact solely from within-state differences in pre-expansion uninsured rates. While this reduces the magnitude of the full ACA effect to 3.25 percentage points, it remains statistically significant at the 10 percent level. The persistence of the positive effect under this demanding specification provides strong evidence that state-specific shocks or policies do not drive the relationship between pre-expansion uninsurance rates and post-expansion changes in ambulance services.

These robustness checks complement and extend the stability in the main analysis, providing additional confidence in the causal interpretation of the estimated effects. The consistent pattern of positive and significant effects across specifications suggests that the heterogeneous impact of Medicaid expansion based on local insurance market conditions represents a robust feature of the policy's effects on emergency medical services.

Dynamic Effects of Medicaid Expansion.—- I examine the dynamic effects of Medicaid expansion on ambulance establishments by estimating leads and lags of the triple-difference coefficient. Columns 1-3 present the lags (pre-treatment periods), while Columns 4-6 show the contemporaneous effect and leads (post-treatment periods). The lag coefficients are statistically insignificant and smaller in magnitude than the main effect, supporting the parallel trends assumption in my triple-difference framework. This suggests that counties with different pre-expansion uninsured rates were not experiencing differential trends in ambulance services prior to Medicaid expansion.

The positive effect of Medicaid expansion persists in the years following implementation. The contemporaneous effect (0.4637) remains similar to my main specification, and the coefficients for one and two

years after expansion (0.4776 and 0.4421) stay positive and significant.[41] This persistence suggests that the increase in ambulance establishments represents a sustained response to the change in local insurance coverage rather than a temporary adjustment. The stability of these coefficients also helps rule out anticipatory responses or delayed effects that could complicate the interpretation of the main results.

8 Discussion & Conclusion

This paper provides new evidence on how health insurance expansion affects the spatial distribution of emergency medical services. The results reveal important heterogeneity in how local markets respond to insurance expansion, with effects varying systematically based on pre-existing insurance coverage. While the average impact of Medicaid expansion is negative, suggesting a reduction in ambulance establishments, areas with higher pre-expansion uninsured rates experienced significant increases in service availability.

These findings contribute to our understanding of how healthcare policy shapes local market structure. The heterogeneous effects align with theoretical predictions about market entry and exit in response to changes in insurance coverage. In areas with low pre-expansion uninsured rates, the reduction in ambulance establishments may reflect improved population health and reduced emergency service demand, consistent with evidence on the preventive care effects of insurance expansion (Simon et al., 2017). However, in areas with high pre-expansion uninsured rates, the positive impact on ambulance establishments suggests that increased insurance coverage can enhance market viability for emergency services, particularly in previously underserved areas.

The results have important implications for health policy design. First, they suggest that the effects of insurance expansion on healthcare infrastructure depend crucially on local market conditions, particularly pre-existing insurance coverage. This heterogeneity implies that policies to expand insurance coverage may need to consider complementary interventions in areas with different baseline characteristics. Second, the findings highlight the complex relationship between insurance coverage and emergency medical service availability, adding to the literature on healthcare market structure (Cutler and Morton, 2013; Dafny et al., 2012).

These findings extend several strands of literature. While prior work has examined how insurance expansion affects healthcare utilization Baicker et al. (2014); Courtemanche et al. (2017) and provider behavior (Garthwaite et al., 2017), less attention has been paid to effects on market structure, partic-

[41] The lagged effects are consistent with recent evidence on establishment-level responses to policy changes in healthcare markets. Several studies document similar adjustment patterns, including Bondurant et al. (2018) for substance abuse treatment facilities, Bradford and Maclean (2023) for mental health services, and Deza et al. (2022a,b) for healthcare access more broadly. The positive and significant coefficient at $t-1$ likely reflects operational adjustments in CBP reporting, a pattern also noted by Swensen (2015).

ularly in emergency medical services. The results also contribute to our understanding of geographic access to healthcare Buchmueller et al. (2006), showing how insurance expansion can reshape the spatial distribution of emergency services.

References

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.

Baicker, Katherine, Amy Finkelstein, Jae Song, and Sarah Taubman, "The impact of Medicaid on labor market activity and program participation: evidence from the Oregon Health Insurance Experiment," *American Economic Review*, 2014, *104* (5), 322–328.

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

Bond, Amelia M and Chapin White, "Massachusetts coverage expansion associated with reduction in primary care utilization among Medicare beneficiaries," *Health Services Research*, 2013, *48* (6pt1), 1826–1839.

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.

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.

Buchmueller, Thomas C, Zachary M Levinson, Helen G Levy, and Barbara L Wolfe, "Effect of the Affordable Care Act on racial and ethnic disparities in health insurance coverage," *American journal of public health*, 2016, *106* (8), 1416–1421.

Buchmueller, Thomas, John C Ham, and Lara D Shore-Sheppard, "The medicaid program," *Economics of Means-Tested Transfer Programs in the United States, Volume 1*, 2015, pp. 21–136.

Carey, Colleen M., Sarah Miller, and Laura R. Wherry, "The Impact of Insurance Expansions on the Already Insured: The Affordable Care Act and Medicare," *American Economic Journal: Applied Economics*, October 2020, *12* (4), 288–318.

Carroll, Caitlin, Rhiannon Euhus, Nancy Beaulieu, and Michael E Chernew, "Hospital survival in rural markets: Closures, mergers, and profitability: Study examines rural market hospital closures, mergers, and profitability," *Health Affairs*, 2023, *42* (4), 498–507.

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.

Courtemanche, Charles, James Marton, Benjamin Ukert, Aaron Yelowitz, and Daniela Zapata, "Early Impacts of the Affordable Care Act on Health Insurance Coverage in Medicaid Expansion and Non-Expansion States," *Journal of Policy Analysis and Management*, 2017, *36* (1), 178–210.

Cutler, David M and Fiona Scott Morton, "Hospitals, market share, and consolidation," *Jama*, 2013, *310* (18), 1964–1970.

Dafny, Leemore, Mark Duggan, and Subramaniam Ramanarayanan, "Paying a premium on your premium? Consolidation in the US health insurance industry," *American Economic Review*, 2012, *102* (2), 1161–1185.

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.

Duggan, Mark, Atul Gupta, and Emilie Jackson, "The Impact of the Affordable Care Act: Evidence from California's Hospital Sector," *American Economic Journal: Economic Policy*, February 2022, *14* (1), 111–51.

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, "The Aggregate Effects of Health Insurance: Evidence from the Introduction of Medicare*," *The Quarterly Journal of Economics*, 02 2007, *122* (1), 1–37.

Fischer, Stefanie J, Heather Royer, and Corey D White, "Health Care Centralization: The Health Impacts of Obstetric Unit Closures in the US," Working Paper 30141, National Bureau of Economic Research June 2022.

Frean, Molly, Jonathan Gruber, and Benjamin D. Sommers, "Premium subsidies, the mandate, and Medicaid expansion: Coverage effects of the Affordable Care Act," *Journal of Health Economics*, 2017, *53*, 72–86.

Garthwaite, Craig L, "The doctor might see you now: The supply side effects of public health insurance expansions," *American Economic Journal: Economic Policy*, 2012, *4* (3), 190–215.

Garthwaite, Craig, Tal Gross, Matthew Notowidigdo, and John A Graves, "Insurance expansion and hospital emergency department access: evidence from the Affordable Care Act," *Annals of internal medicine*, 2017, *166* (3), 172–179.

Gruber, Jonathan and Benjamin D. Sommers, "THE AFFORDABLE CARE ACT'S EFFECTS ON PATIENTS, PROVIDERS, AND THE ECONOMY: WHAT WE'VE LEARNED SO FAR," *Journal of Policy Analysis and Management*, 2019, *38* (4), 1028–1052.

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

Lindrooth, Richard C., Marcelo C. Perraillon, Rose Y. Hardy, and Gregory J. Tung, "Understanding The Relationship Between Medicaid Expansions And Hospital Closures," *Health Affairs*, 2018, *37* (1), 111–120. PMID: 29309219.

Lyon, Sarah M, Ivor S Douglas, and Colin R Cooke, "Medicaid expansion under the Affordable Care Act. Implications for insurance-related disparities in pulmonary, critical care, and sleep," *Annals of the American Thoracic Society*, 2014, *11* (4), 661–667.

McInerney, Melissa, Jennifer M Mellor, and Lindsay M Sabik, "The effects of state Medicaid expansions for working-age adults on senior Medicare beneficiaries," *American Economic Journal: Economic Policy*, 2017, *9* (3), 408–438.

Miller, Sarah, "The effect of insurance on emergency room visits: An analysis of the 2006 Massachusetts health reform," *Journal of Public Economics*, 2012, *96* (11), 893–908. Fiscal Federalism.

— **and Laura R Wherry**, "Health and access to care during the first 2 years of the ACA Medicaid expansions," *New England Journal of Medicine*, 2017, *376* (10), 947–956.

Moskatel, Leon and David Slusky, "Did UberX reduce ambulance volume?," *Health Economics*, 2019, *28* (7), 817–829.

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.

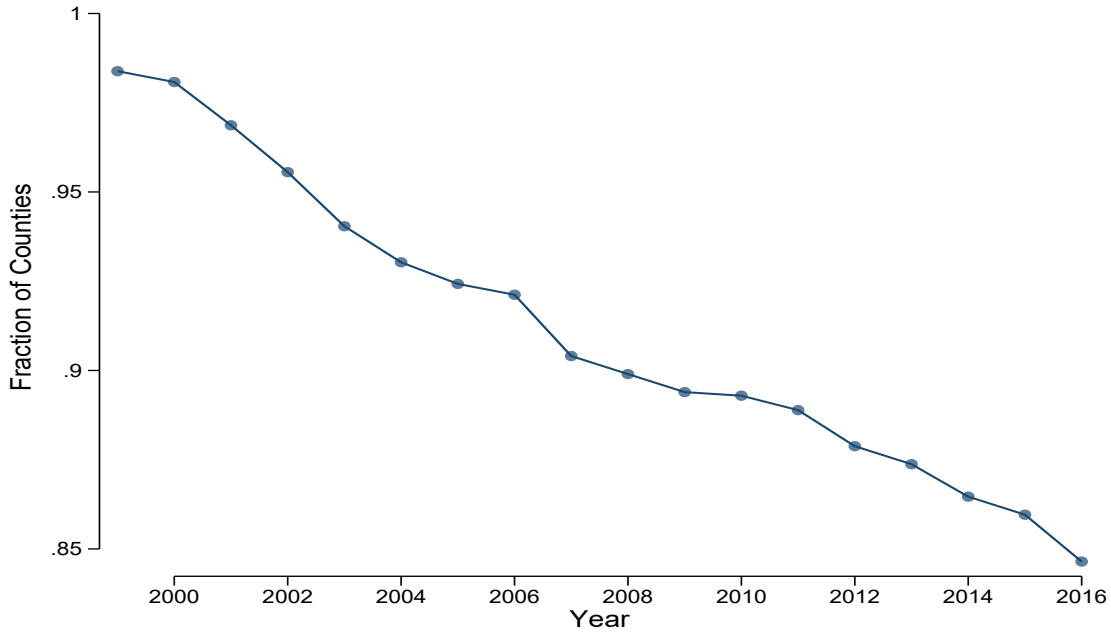
Simon, Kosali, Aparna Soni, and John Cawley, "The Impact of Health Insurance on Preventive Care and Health Behaviors: Evidence from the First Two Years of the ACA Medicaid Expansions," *Journal of Policy Analysis and Management*, 2017, *36* (2), 390–417.

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

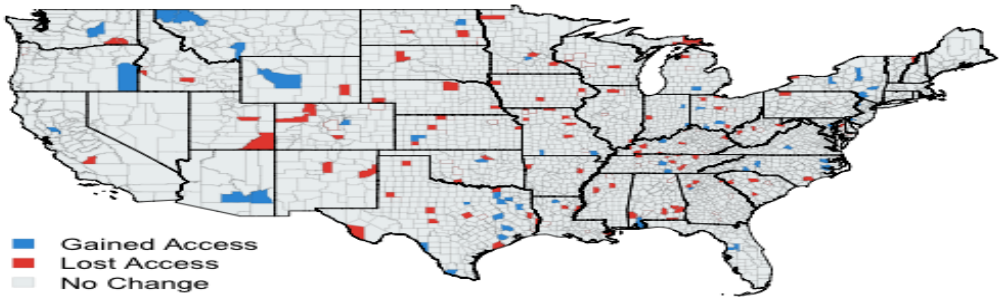
Wherry, Laura R and Sarah Miller, "Early coverage, access, utilization, and health effects associated with the Affordable Care Act Medicaid expansions: a quasi-experimental study," *Annals of internal medicine*, 2016, *164* (12), 795–803.

Figures

Figure 1: Temporal and Spatial Variation in Access to Ambulance Services



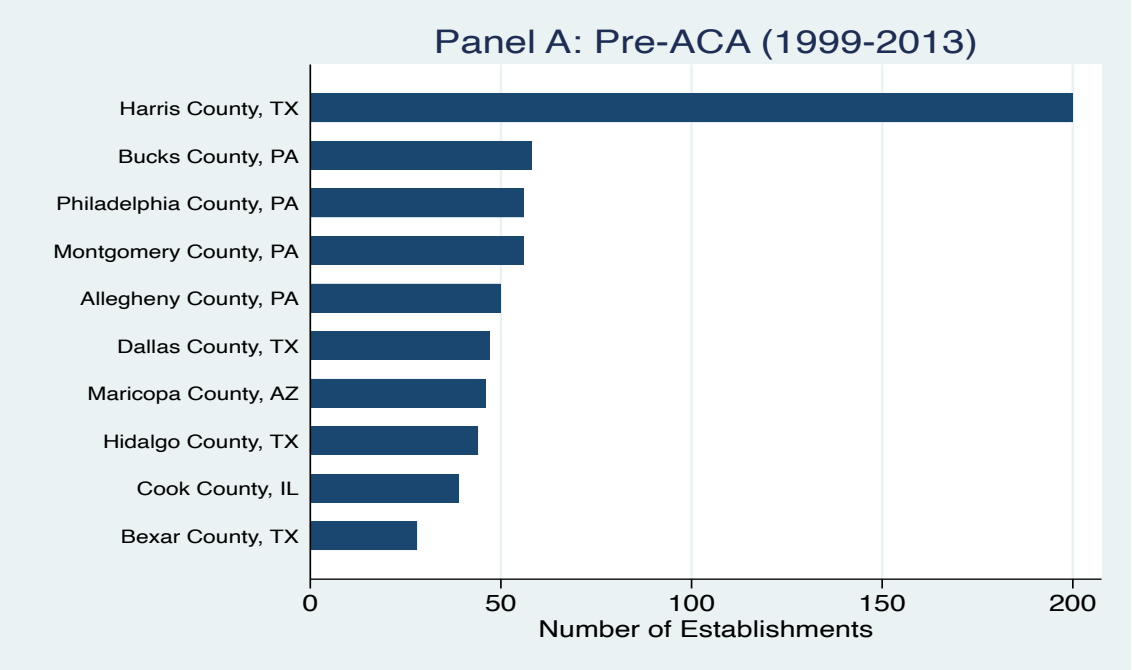
(a) Trend in Access to Ambulance Services



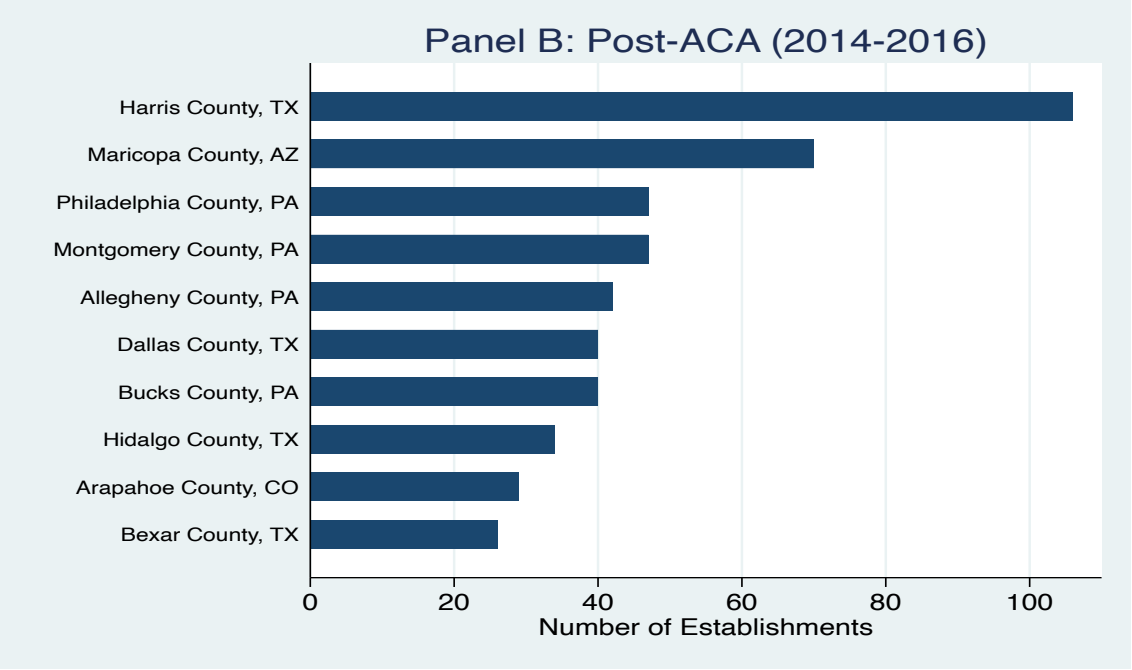
(b) Ambulance Services Access Loss and Gain

Note: Data on the county's access to ambulance services comes from the County Business Patterns. 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 4 presents more information on these data. The top panel displays the share of counties with at least one establishment providing ambulance services. 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".

Figure 2: Distribution of Ambulance Establishments Across Counties



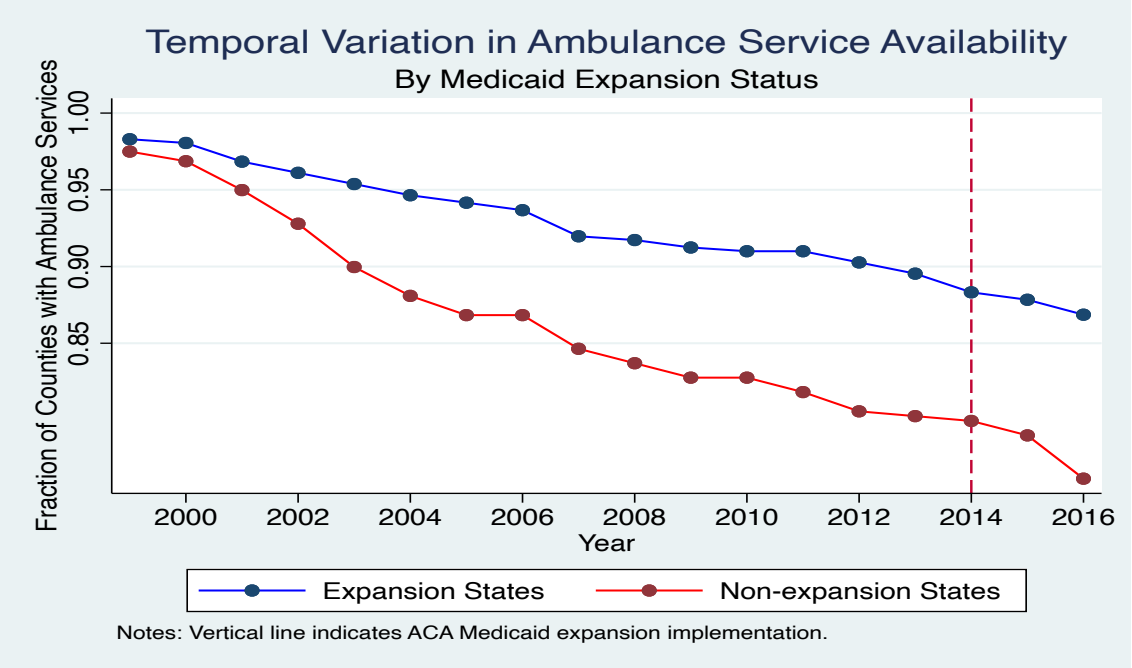
(a) Pre-ACA Period (1999-2013)



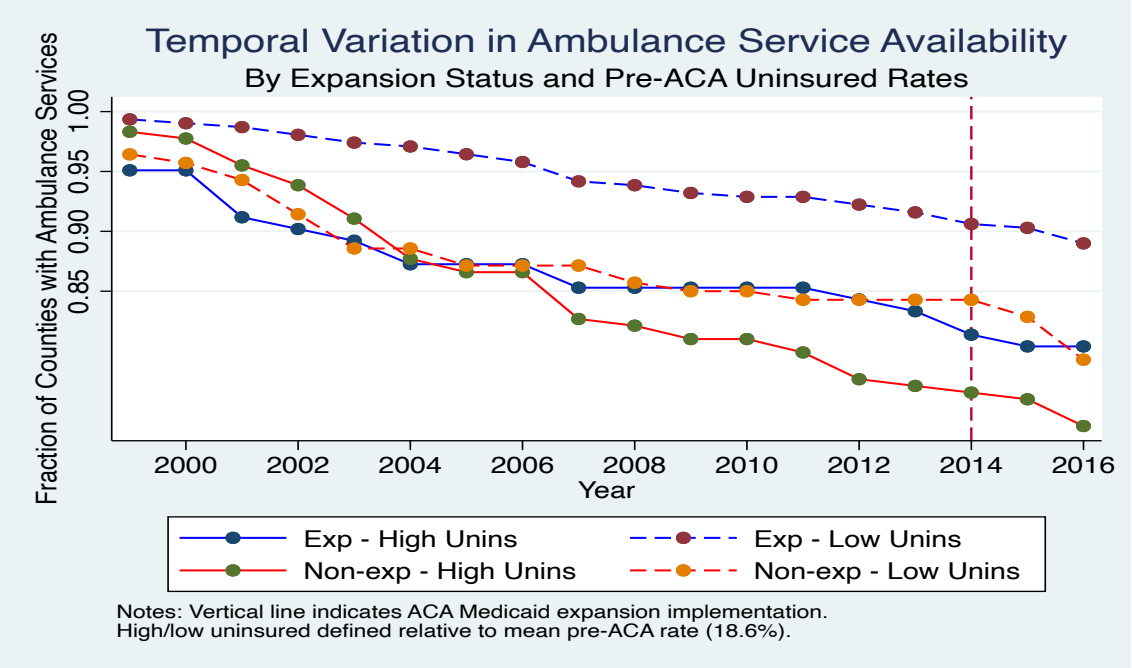
(b) Post-ACA Period (2014-2016)

Notes: Data from County Business Patterns. The figure shows the counties with highest concentration of ambulance establishments before and after ACA implementation.

Figure 3: Trends in Ambulance Service Availability by Medicaid Expansion Status



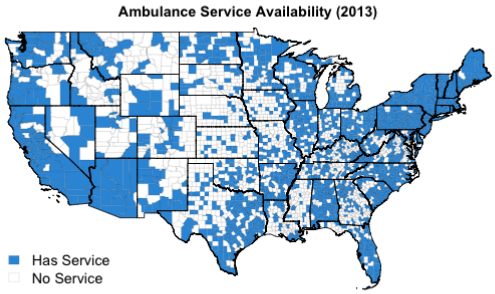
(a) Basic Expansion Effects



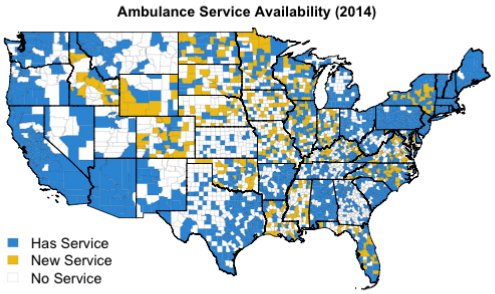
(b) Heterogeneity by Pre-ACA Uninsured Rates

Notes: Data from County Business Patterns, 1999-2016. Panel (a) shows differential trends in ambulance service availability between expansion and non-expansion states, motivating the DD analysis. Panel (b) reveals how these effects vary by pre-ACA uninsured rates, suggesting heterogeneous impacts that are explored in the DDD analysis. The vertical line indicates ACA Medicaid expansion implementation in 2014. High/low uninsured rates are defined relative to the mean pre-ACA rate of 18.6%. A county is designated as having ambulance service if it has at least one establishment providing these services in a given year.

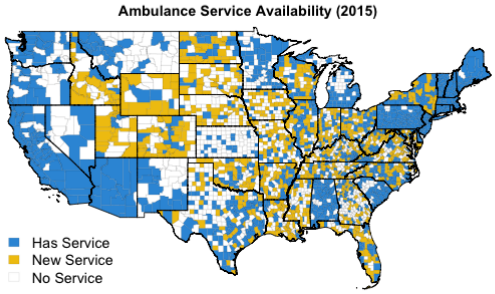
Figure 4: Evolution of Ambulance Service Availability (2013-2016)



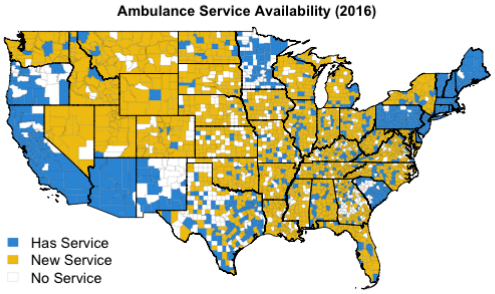
(a) Pre-ACA (2013)



(b) ACA Implementation (2014)



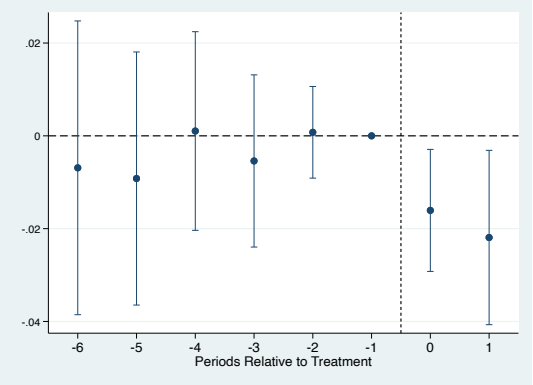
(c) Post-ACA Year 1 (2015)



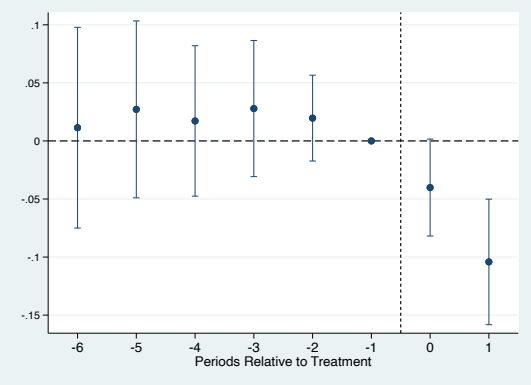
(d) Post-ACA Year 2 (2016)

Notes: Maps show the distribution of ambulance service establishments across U.S. counties. In the 2013 baseline map, blue indicates counties with at least one ambulance establishment, while white indicates counties with no establishments. In subsequent years (2014-2016), blue continues to indicate existing service, white indicates no service, and yellow highlights counties that gained service after 2013 (i.e., counties that transitioned from having no establishments in 2013 to having at least one establishment). Data source: County Business Patterns (CBP). Alaska, Hawaii, and U.S. territories are excluded from the analysis.

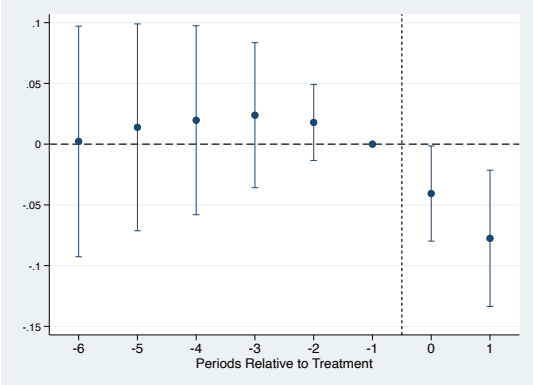
Figure 5: ACA and Ambulance Deserts



(a) Panel A: Extensive Margin



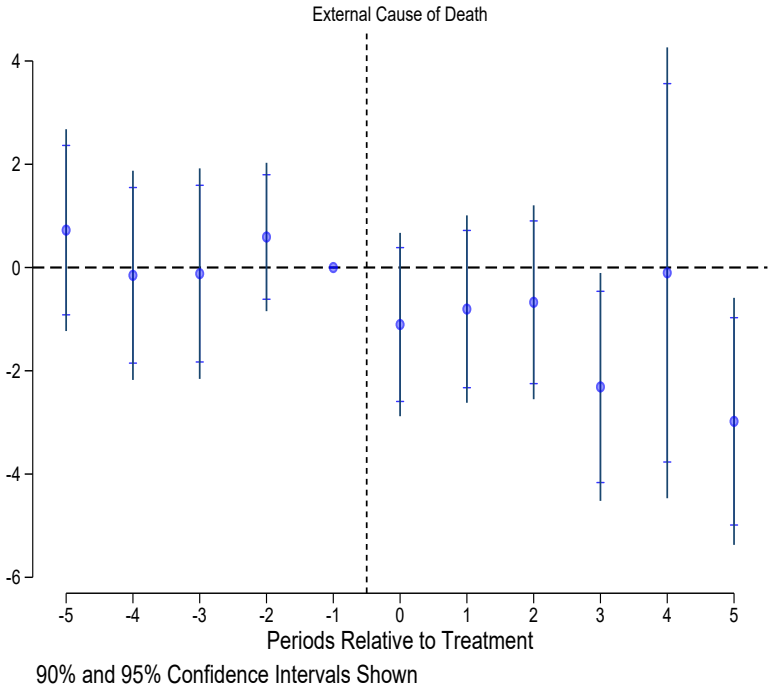
(b) Panel B: Intensive Margin



(c) Panel C: Poisson pseudo maximum likelihood Intensive Margin

Notes: Panel 5a, 5b, and 5c presents point estimates from the specification in Equation 1. In Figure 5a and 5c, the outcome variable is the indicator variable for whether the county has any ambulance services. In Figure 5b, the outcome variable is the count of ambulance services in the county. In Figure 5c, the estimates are from the Poisson Pseudo Maximum Likelihood (PPML) estimation. The outcome variable data is derived from the County Business Pattern (CBP). Economic controls (earnings per capita, employment-to-population ratio, and transfer payments) are from the Bureau of Economic Analysis Regional Economic Information System (REIS). Demographic controls (age distribution, population density) are from the Surveillance, Epidemiology, and End Results (SEER) Program. These data cover 2000 to 2016. The Affordable Care Act (ACA) is based on the author's calculations.

Figure 6: Ambulance Services Access Loss and Mortality(External Causes of Death)



Notes: The estimates are from the estimation of a specification where the outcome variable is the count of deaths in the county due to external causes. This specification has indicator variable for whether the county has any ambulance service establishment. Additionally, this specification also includes county and year fixed-effects. The observations in the estimation sample are weighted by the 1999 data on demographics at the county-level. The standard errors are clustered at the county-level. 90% and 95% confidence intervals are reported. The data is derived from County Business Patterns (CBP) and CDC-WONDER. These data are for the period from 2000 to 2016.

Tables

Table 1: Summary Statistics for Pre-Treatment Period

	ACA Non Expansion States			ACA Expansion States		
	Mean	Min	Max	Mean	Min	Max
County Characteristics						
_n Any Ambulance Establishment	0.384	0.000	1.000	0.555	0.000	1.000
Ambulance Establishment	0.890	0.000	200.000	1.718	0.000	58.000
Number of Counties	1,714			900		

Notes: Pre-treatment mean reported for counties in ACA expansion and non-expansion states. All states that expanded Medicaid either in 2014 or 2015 are classified in the treatment group. Data on ambulance establishment is derived from the County Business Patterns (CBP). The maximum of 200 establishments in non-expansion states is observed in Harris County, Texas, while the maximum of 58 establishments in expansion states is observed in Bucks County, Pennsylvania. The sample comprises years 1999 to 2016.

Table 2: Difference-in-Differences Results

	(1)	(2)	(3)
	County FE	State FE	Controls
$\mathbb{1}$(Medicaid Expansion State)$\times$			
$\mathbb{1}$(Post)	-0.0378***	-0.0378***	-0.0409***
	(0.0114)	(0.0114)	(0.0118)
Economic Controls			Yes
Demographic Controls			Yes
Observations	47,016	47,016	45,390
Adj. R2	0.713	0.713	0.712

Notes: Heteroskedasticity robust standard errors clustered by county are in parentheses. (* p<0.10 ** p<0.05 *** p<0.01). Column (1) includes county and year fixed effects. Column (2) adds state fixed effects. Column (3) includes economic controls (earnings per capita, transfer payments) from the Bureau of Economic Analysis Regional Economic Information System (REIS) and demographic controls (employment-to-population ratio, age distribution, population density) from the Surveillance, Epidemiology, and End Results (SEER) Program. The dependent variable is an indicator for whether the county has any ambulance establishment. Data on ambulance establishment is derived from the County Business Patterns (CBP). Data on county-level health uninsurance rate is derived from the Small Area Health Insurance Estimates (SAHIE). The sample comprises years 1999 to 2016.

Table 3: Main Triple Difference-in-Differences Results

	(1) Baseline	(2) Controls
Panel A: Triple Difference-in-Differences Estimates		
Uninsured_$cs \times \mathbb{1}$(Post_t)	-0.0226	-0.0485
	(0.1495)	(0.1514)
$\mathbb{1}$(Medicaid Expansion State) $\times \mathbb{1}$(Post_t)	-0.1170***	-0.1254***
	(0.0418)	(0.0422)
$\mathbb{1}$(Medicaid Expansion State) $\times$ Uninsured_$cs \times \mathbb{1}$(Post_t)	0.4637**	0.4906**
	(0.2262)	(0.2277)
N	46344	45390
Panel B: Implied Effects at Mean Pre-Treatment Uninsured Rate		
Sample Mean Pre-Treatment Uninsured Rate	0.1859	
Private (Non-Medicaid Expansion)	-0.0042	-0.0090
	(0.0278)	(0.0281)
Medicaid Expansion	0.0862**	0.0912**
	(0.0421)	(0.0423)
Full ACA (Private + Medicaid Expansion)	0.0820**	0.0822**
	(0.0504)	(0.0508)
Economic Controls	No	Yes
Demographic Controls	No	Yes
County Fixed Effects	Yes	Yes
State Fixed Effects	Yes	No
Year Fixed Effects	Yes	Yes
Observations	46344	45390
Adjusted R^2	0.710	0.712

Notes: Heteroskedasticity robust standard errors clustered by county are in parentheses. (* p<0.10 ** p<0.05 *** p<0.01). Column (1) includes county, state, and year fixed effects. Column (2) adds economic controls (earnings per capita) and demographic controls (employment-to-population ratio). The dependent variable is an indicator for whether the county has any ambulance establishment. Data on ambulance establishment is derived from the county business patterns (CBP). Data on county-level health uninsurance rate is derived from the small area health insurance estimates (SAHIE). The sample comprises years 1999 to 2016.

Table 4: Robustness Checks: Implied Effects of ACA at Mean Pre-Treatment Uninsured Rate

	(1) PS-Weight	(2) Demo. Controls	(3) Econ. Controls	(4) Age Controls	(5) State× Year FE
Sample Mean Pre-Treatment Uninsured Rate			0.1859		
Private (Non-Medicaid Expansion)	-0.0222	-0.0087	-0.0128	-0.0054	-0.0901**
	(0.0300)	(0.0282)	(0.0282)	(0.0278)	(0.0418)
Medicaid Expansion	0.1112**	0.0920**	0.0926**	0.0826*	0.1226*
	(0.0450)	(0.0423)	(0.0424)	(0.0428)	(0.0663)
Full ACA (Private + Medicaid Expansion)	0.0890**	0.0833**	0.0798**	0.0772*	0.0325*
	(0.0541)	(0.0509)	(0.0509)	(0.0511)	(0.0784)
Demographic Controls	No	Yes	No	No	No
Economic Controls	No	No	Yes	No	No
Age Controls	No	No	No	Yes	No
PS Weighting	Yes	No	No	No	No
County FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State × Year FE	No	No	No	No	Yes
Observations	45,252	45,390	45,390	46,308	46,344
Adjusted R^2	0.693	0.712	0.712	0.710	0.714

Notes: Heteroskedasticity robust standard errors clustered by county are in parentheses. (* p<0.10 ** p<0.05 *** p<0.01). All specifications include county and year fixed effects. Column (1) presents the propensity score weighting. Column (2) adds demographic controls (employment-to-population ratio). Column (3) adds economic controls (earnings per capita). Column (4) adds age distribution controls. Column (5) adds state-by-year fixed effects. The dependent variable is an indicator for whether the county has any ambulance establishment.

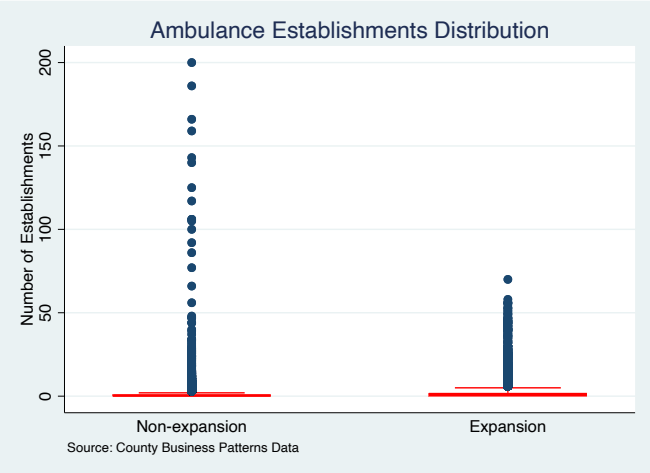
Table 5: Robustness by Leads and Lags of the Effect of ACA Medicaid Expansion on Ambulance Services Establishments

	(1) t-3	(2) t-2	(3) t-1	(4) t	(5) t+1	(6) t+2
$\mathbb{1}$ (Medicaid Expansion State) × Uninsured$_{cs}$ × $\mathbb{1}$ (Post$_t$)	0.3384	0.3523	0.4111*	0.4637**	0.4776**	0.4421*
	(0.2276)	(0.2353)	(0.2294)	(0.2262)	(0.2233)	(0.2316)
Observations	38,619	41,194	43,769	46,344	43,770	41,196
Adjusted R-squared	0.720	0.717	0.714	0.710	0.718	0.729
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

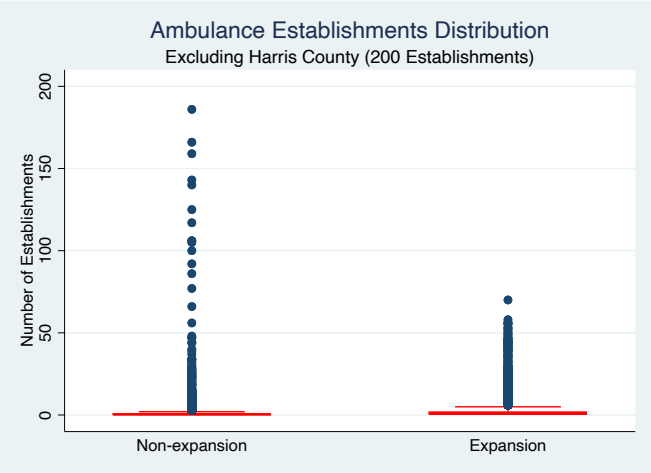
Notes: Heteroskedasticity-robust standard errors clustered at the county level are in parentheses. (* p<0.10, ** p<0.05, *** p<0.01). The dependent variable is an indicator for the presence of ambulance services establishments in a given county-year. Columns (1)-(3) report results for lags of the dependent variable, column (4) reports the baseline specification, and columns (5)-(6) report results for leads of the dependent variable. All specifications include county, state, and year fixed effects.

Appendix Figures

Figure A1: Box Plots of Establishments by Medicaid Expansion Status



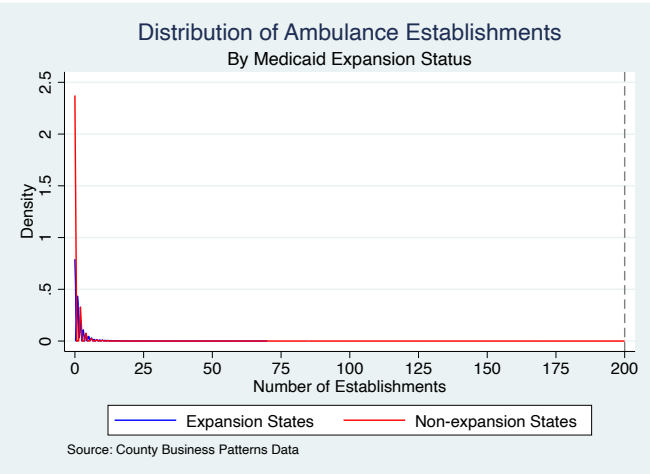
(a) Including All Counties



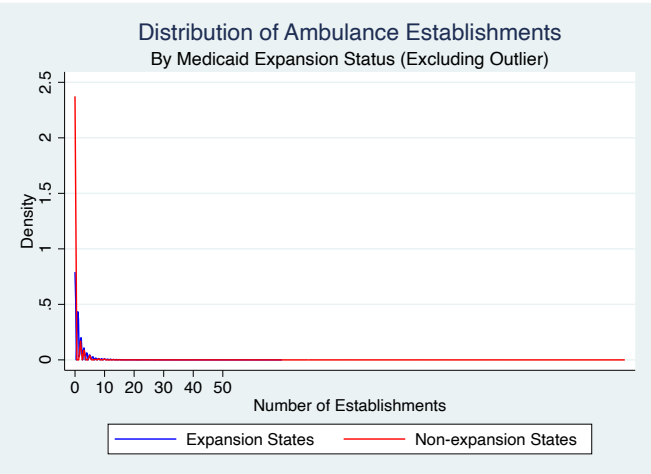
(b) Excluding Harris County, TX

Notes: The box plots show the distribution of ambulance establishments across counties, grouped by whether the state expanded Medicaid under the Affordable Care Act. The middle line represents the median, the box shows the interquartile range (IQR), and the whiskers extend to 1.5 times the IQR from the box. Panel (a) includes all counties, while panel (b) excludes Harris County, TX which is an outlier with 200 establishments. Data source: County Business Patterns. Alaska, Hawaii, and U.S. territories are excluded.

Figure A2: Density Plots of Establishments by Medicaid Expansion Status



(a) Including All Counties



(b) Excluding Harris County, TX

Notes: The density plots show the distribution of ambulance establishments across counties, grouped by whether the state expanded Medicaid under the Affordable Care Act. Panel (a) includes all counties, while panel (b) excludes Harris County, TX which is an outlier with 200 establishments. The vertical dashed line in panel (a) marks the Harris County value. Data source: County Business Patterns. Alaska, Hawaii, and U.S. territories are excluded.

Appendix Tables

Table A1: State Medicaid Expansion Status and Timing Under the ACA

State	Expansion Status	Implementation Date
Arizona	Expansion	January 2014
Arkansas	Expansion	January 2014
California	Expansion	January 2014
Colorado	Expansion	January 2014
Connecticut	Early Expansion	January 2014[a]
Delaware	Early Expansion	January 2014[a]
Hawaii	Expansion	January 2014
Illinois	Expansion	January 2014
Iowa	Expansion	January 2014
Kentucky	Expansion	January 2014
Maryland	Expansion	January 2014
Massachusetts	Early Expansion	January 2014[a]
Michigan	Expansion	January 2014
Minnesota	Expansion	January 2014
Nevada	Expansion	January 2014
New Hampshire	Expansion	January 2014
New Jersey	Expansion	January 2014
New Mexico	Expansion	January 2014
New York	Early Expansion	January 2014[a]
North Dakota	Expansion	January 2014
Ohio	Expansion	January 2014
Oregon	Expansion	January 2014
Rhode Island	Expansion	January 2014
Vermont	Early Expansion	January 2014[a]
Washington	Expansion	January 2014
West Virginia	Expansion	January 2014
Indiana	Expansion	February 2015
New Hampshire	Expansion	August 2015
Pennsylvania	Expansion	January 2015
Louisiana	Expansion	July 2016
Montana	Expansion	January 2016

[a] These states implemented early expansion under Section 1115 waivers prior to 2014.

Notes: This table shows the timing of Medicaid expansion adoption under the Affordable Care Act. Early expansion states implemented expansion through Section 1115 waivers prior to 2014. Large expansion states (California, Iowa, Minnesota, Hawaii, Indiana, Maryland, Connecticut, Wisconsin) experienced particularly large increases in Medicaid enrollment following expansion. Data sources: Medicaid expansion dates from Kaiser Family Foundation and state websites. Early expansion classification follows NEJM appendix Miller and Wherry (2017). Large expansion states identified following Carey et al. (2020).