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

Tejendra P. Singh[1] and Olanrewaju Yusuff[1]

[1]Georgia State University

July, 2025

Abstract

Access to ambulance services can mean the difference between life and death, yet many areas face limited emergency medical access. This paper examines how the Affordable Care Act's insurance expansion affected ambulance service availability. Using Poisson pseudo-maximum likelihood estimation of a triple-difference design that leverages county-level variation in pre-ACA uninsured rates and state Medicaid expansion decisions, we find that a one percentage point increase in pre-ACA uninsured rates amplifies the effects of Medicaid expansion on both the extensive and intensive margins. At a mean pre-treatment uninsured rate of 18.59 percent, Medicaid expansion increased the presence of ambulance services by 13.5 percentage points. Notably, the private marketplace components of the ACA had a substantial opposite effect, reducing service availability by 7.4 percentage points. Event studies confirm parallel pre-trends and strengthening impacts over time, while visual evidence shows clear geographic expansion in Medicaid expansion states. The results demonstrate that insurance expansion mechanisms and local market conditions fundamentally determine emergency medical infrastructure outcomes. This research informs targeted policy approaches for improving access to emergency care in underserved areas.

JEL Classifications: H70, I11, I31, I18, O1, P40,

Keywords: ACA, Ambulance Deserts, Emergency medical services, Healthcare access, Health policy and Local Markets.

*We are grateful to Lauren Hoehn-Velasco, James Marton, Ann DiGirolamo, and Keith Teltser for their valuable suggestions and comments. We also thank seminar participants at the 2024 Georgia State University Student Summer Symposium. Contact information: Singh: tpratapsingh1@student.gsu.edu and Yusuff: oyusuff4@student.gsu.edu.

1 Introduction

When every second counts in a medical emergency, access to ambulance services determines whether patients survive. Across the United States, over 4.5 million Americans live in what researchers term "ambulance deserts" where emergency medical transportation remains dangerously out of reach (Jonk et al., 2023).[1] This geographic inequality in emergency medical infrastructure represents a fundamental gap in the healthcare safety net that insurance expansion policies might address.

The Affordable Care Act created a large-scale natural experiment for understanding how coverage reforms affect healthcare markets. While extensive research documents how insurance expansion influences utilization and health outcomes (Baicker et al., 2014; Courtemanche et al., 2017; Miller et al., 2021), we know substantially less about its effects on the spatial distribution of healthcare infrastructure. This gap is particularly important for emergency medical services, where the location of providers directly determines access to life-saving care.

The theoretical effects of insurance expansion on ambulance service availability are ambiguous. Increased coverage may improve the financial viability of emergency medical services by reducing uncompensated care and ensuring payment for services rendered (Garthwaite et al., 2018). This coverage effect should be strongest in areas with high baseline uninsured rates, potentially driving both market entry and capacity expansion. Alternatively, improved access to preventive care through insurance expansion may reduce emergency service demand (Simon et al., 2017), affecting market structure and provider sustainability. A third possibility is that insurance expansion triggers market consolidation as providers adapt to changing reimbursement landscapes (Dafny et al., 2012; Fulton, 2017).

This paper presents new evidence on how insurance expansion affects emergency medical service availability, utilizing a triple-difference research design. We exploit county-level variation in pre-ACA uninsured rates and state decisions on Medicaid expansion to identify how local market conditions mediate the effects of coverage reform.[2] Following Courtemanche et al. (2017), we decompose ACA effects into Medicaid expansion and private marketplace components, revealing these mechanisms had starkly contrasting impacts on emergency medical infrastructure.

We employ Poisson pseudo-maximum likelihood estimation to properly account for the count nature of ambulance establishments, addressing concerns about zero outcomes and heteroskedasticity that plague linear models in this setting. To cleanly identify different economic margins, we separately examine

[1] Emergency medical service response times exceeding 25 minutes significantly reduce survival rates for cardiac arrests and other life-threatening conditions. Recent media reports have documented growing concerns about ambulance access disparities in both rural and urban areas.

[2] The County Business Patterns data provides comprehensive information on ambulance establishments at the county level, defined as physical locations primarily engaged in emergency medical transportation. The Small Area Health Insurance Estimates provide county-level uninsurance rates.

extensive margin effects (whether any ambulance service exists) and intensive margin effects (the number of establishments conditional on market presence). This distinction is crucial because entry decisions involve different costs and constraints than those associated with capacity expansion decisions.

The results demonstrate substantial positive effects of Medicaid expansion on the availability of ambulance services. For each percentage point increase in pre-ACA uninsured rates, Medicaid expansion increased the likelihood of having any ambulance establishment by 131 percent relative to the pre-treatment mean. On the intensive margin, properly conditioning counties with existing services, Medicaid expansion increased the number of establishments by 52 percent. At the sample mean pre-treatment uninsured rate of 18.59 percent, Medicaid expansion increased ambulance service presence by 13.5 percentage points and establishment counts by 29.7 percentage points among counties with existing service.

Notably, the private marketplace components of the ACA had opposite effects, reducing ambulance service availability by 7.4 percentage points on the extensive margin and 12.0 percentage points on the intensive margin. This divergence suggests that the expansion of public and private insurance operates through fundamentally different mechanisms. The positive effects of Medicaid likely reflect improved reimbursement certainty and reduced uncompensated care burdens, whereas the effects on the private marketplace may reflect increased administrative complexity and competitive pressures.

Event study analysis confirms these effects emerged immediately following ACA implementation and strengthened over time. The results survive extensive robustness checks, including alternative intensive margin specifications that model additional establishments beyond the first. Visual evidence from county-level maps shows clear geographic patterns of service expansion in Medicaid expansion states, particularly in previously underserved areas.

These findings make several contributions to the literature. First, we extend research on the effects of insurance expansion (Baicker et al., 2014; Garthwaite et al., 2018) by documenting heterogeneous impacts on emergency medical infrastructure and identifying the divergent roles of public versus private coverage expansion. Second, we contribute to the healthcare geography literature (Buchmueller et al., 2006; Jonk et al., 2023) by demonstrating how policy interventions can alter the spatial distribution of emergency services. Third, we add to the understanding of healthcare market dynamics (Cutler and Morton, 2013; Dafny et al., 2012) by revealing how local market conditions mediate policy effects.

The results carry important policy implications. The stark differences between Medicaid expansion and private marketplace effects highlight that the structure of coverage expansion matters fundamentally for healthcare infrastructure development. Areas with high baseline uninsured rates benefit substantially from Medicaid expansion through both new market entry and capacity expansion, while private marketplace components may generate consolidation pressures. This heterogeneity suggests that policies aimed at improving emergency medical access should consider local market conditions and the specific mechanisms of insurance expansion.

2 Literature Review

This paper contributes to several interconnected literatures examining how insurance expansion affects healthcare markets, provider behavior, and access to care. Understanding these connections is crucial for interpreting the mechanisms through which coverage reforms influence emergency medical infrastructure.

2.1 Insurance Access and Healthcare Utilization

A foundational literature documents how insurance coverage affects healthcare access and utilization patterns. The seminal Oregon Health Insurance Experiment (Baicker et al., 2014) established that Medicaid coverage increases healthcare utilization across multiple dimensions, including emergency department visits. Buchmueller et al. (2015) provide comprehensive evidence on Medicaid expansion effects, while Courtemanche et al. (2017) demonstrate that the ACA increased insurance coverage by 5.9 percentage points at average pre-treatment uninsured rates, with substantially larger effects in Medicaid expansion states.

The decomposition of ACA effects reveals important heterogeneity across coverage mechanisms. Frean et al. (2017) show that exchange premium subsidies and Medicaid expansion contributed 40 and 60 percent, respectively, to overall coverage gains. This distinction proves crucial for understanding differential impacts on healthcare infrastructure, as public and private insurance expansion may operate through fundamentally different channels affecting provider incentives and market structure.

Beyond the ACA context, earlier evidence from Massachusetts health reform provides additional insights. Miller (2012) demonstrates that insurance expansion significantly increased emergency department utilization, consistent with moral hazard effects. However, Kolstad and Kowalski (2016) show these utilization increases were accompanied by improvements in care quality and patient outcomes, suggesting that coverage expansion generates both demand and supply-side responses in healthcare markets.

2.2 Healthcare Infrastructure and Market Structure

A second strand examines how insurance expansion affects healthcare infrastructure and market dynamics. Recent work emphasizes that coverage reforms can reshape entire healthcare ecosystems beyond simple utilization effects. Duggan et al. (2022) and Lindrooth et al. (2018) demonstrate that Medicaid expansion substantially increased hospital revenue and reduced uncompensated care burdens, fundamentally altering the financial environment facing healthcare providers.

These financial improvements, however, do not uniformly translate into expanded access. Carroll et al. (2023) document that strengthened hospital finances often led to market consolidation rather than capacity expansion, highlighting how insurance expansion can reshape local healthcare infrastructure in complex ways. Similarly, Alexander and Richards (2023) show that rural hospital closures continue despite Medicaid expansion, suggesting that coverage effects on provider viability depend critically on local market conditions.

The market structure literature provides an important context for understanding these heterogeneous responses. Dafny et al. (2012) establish that insurance market concentration affects provider market outcomes, while Fulton (2017) documents widespread consolidation trends following healthcare reforms. These findings suggest that insurance expansion effects on healthcare infrastructure may vary substantially across markets with different baseline characteristics and competitive environments.

2.3 Emergency Medical Services and Geographic Access

Emergency medical services represent a unique component of healthcare infrastructure with distinct economic characteristics. Unlike other healthcare services, emergency medical care involves immediate geographic accessibility requirements and complex reimbursement structures that may respond differently to insurance expansion.

Jonk et al. (2023) provide the most comprehensive recent analysis of ambulance access disparities, documenting that over 4.5 million Americans live in areas with inadequate emergency medical transportation. This geographic inequality reflects both market failures in emergency medical service provision and historical underinvestment in rural healthcare infrastructure.

The relationship between insurance coverage and emergency service utilization has received attention primarily in the context of hospital emergency departments. Taubman et al. (2014) show that Medicaid coverage substantially increases emergency department visits, while Simon et al. (2017) demonstrate that improved access to preventive care through insurance expansion can reduce some types of emergency utilization. These potentially offsetting effects create ambiguous predictions for how coverage expansion affects demand for emergency medical transportation.

2.4 Broader Insurance Access Literature

The theoretical foundations for understanding the effects of insurance on healthcare markets draw from classic work on moral hazard and adverse selection. Einav and Finkelstein (2018) provides a comprehensive framework for understanding how insurance affects both the demand and supply sides of healthcare markets. Their analysis emphasizes that coverage expansion can simultaneously increase utilization (demand effects) and improve provider financial viability (supply effects), with net impacts depending on market-specific factors.

International evidence provides an additional perspective on the effects of insurance expansion. Hackmann et al. (2015) analyze German health insurance reforms and document substantial supply-side responses to coverage expansion, including provider entry and capacity investments. Card et al. (2008) examine Canadian healthcare reforms and show that universal coverage can significantly reshape healthcare delivery patterns, particularly in previously underserved areas.

The literature on healthcare financing mechanisms provides insights into why the expansion of public and private insurance might have different effects. Currie and Gruber (1996) establish that Medicaid reimbursement rates and administrative requirements substantially influence provider participation decisions. More recent work by Garthwaite et al. (2018) demonstrates that public insurance expansions can crowd in private sector healthcare investments, while Nikpay et al. (2020) shows that different insurance types generate varying provider responses.

2.5 Contribution and Positioning

This paper extends existing literature in several important dimensions. First, while prior research focuses primarily on insurance coverage effects or hospital market structure, we examine impacts on emergency medical services, a crucial but understudied component of healthcare infrastructure where provider location directly determines access to life-saving care.

Second, we contribute methodologically by employing appropriate econometric techniques for counting outcomes. The Poisson pseudo-maximum likelihood estimation addresses concerns about zero outcomes and heteroskedasticity that affect linear model estimates in healthcare provider studies. This methodological advancement allows for more credible identification of economically meaningful effect sizes.

Third, we demonstrate how local market conditions, particularly pre-existing uninsurance rates, mediate the effects of policy on healthcare provision. This finding extends the growing literature on geographic heterogeneity in policy effects, providing insights into which areas benefit most from different types of coverage expansion.

Finally, our decomposition of ACA effects into Medicaid expansion and private marketplace components reveals these mechanisms had fundamentally different impacts on emergency medical infrastructure. This finding contributes to understanding how different financing mechanisms influence healthcare market structure and suggests important considerations for future coverage expansion policies.

3 Background

3.1 The ACA and Emergency Medical Service Financing

The Affordable Care Act represents the most significant healthcare coverage expansion since Medicare and Medicaid's creation in 1965. While primarily designed to expand insurance coverage, the ACA fundamentally altered the financial landscape facing healthcare providers, including emergency medical services. Understanding these institutional changes is crucial for interpreting how coverage expansion affects ambulance service availability across different market contexts.

The ACA's implementation created substantial variation in coverage expansion across states and over time. Following the Supreme Court's decision in *National Federation of Independent Business v. Sebelius* (2012), states gained discretion over Medicaid expansion while the private marketplace components remained federally mandated. By 2016, 32 states had expanded Medicaid eligibility to adults with incomes up to 138 percent of the federal poverty level, creating a natural experimental variation that this study exploits.[3]

Emergency medical services occupy a unique position within the healthcare financing system established by the Affordable Care Act (ACA). Ambulance transport is classified as an Essential Health Benefit, requiring coverage by all ACA-compliant insurance plans. However, the reimbursement structure creates complex incentives that may generate heterogeneous responses to coverage expansion across different geographic areas and provider types.

Medicare reimbursement for ambulance services is administered through both the Physician Fee Schedule and the Hospital Outpatient Prospective Payment System, with rates varying by geographic classification to reflect the different cost structures in urban, rural, and super-rural areas. This geographic variation in reimbursement acknowledges the unique economic challenges facing rural emergency medical providers, who often serve large geographic areas with low population density and sporadic demand patterns.

A critical feature of ambulance service reimbursement is its transportation-centric structure. Providers receive payment only when patients are physically transported to medical facilities, regardless of the level of care provided at the scene. This creates potential tensions between clinical best practices and financial sustainability. As Lyon et al. (2014) note, improved access to preventive care through insurance expansion might reduce transportation needs while emergency response obligations remain constant, potentially affecting provider revenues despite increased insurance coverage.

The distinction between Medicaid expansion and private marketplace components of the ACA is partic-

[3] The staggered timing of expansion decisions, with most occurring in January 2014 but some states expanding earlier through Section 1115 waivers or later through 2015-2016, provides additional identifying variation for empirical analysis.

ularly important for understanding differential effects on ambulance services. Medicaid typically provides more predictable reimbursement and lower administrative burdens compared to private insurance plans, which may negotiate varying payment rates and impose different utilization review requirements. Additionally, Medicaid expansion directly targets low-income populations who historically generated substantial uncompensated care costs for emergency medical providers.

Recent research by Williams et al. (2001) demonstrates that ambulance services face distinct financial pressures compared to other healthcare providers, with high fixed costs for equipment and personnel combined with unpredictable demand patterns.[4] This economic structure suggests that the revenue effects of insurance expansion may be particularly pronounced for ambulance services, especially in areas with high baseline uninsured rates where coverage gains translate directly into reduced uncompensated care.

3.2 Emergency Medical Services Market Structure and Access Patterns

Emergency medical services in the United States operate within a complex institutional framework that reflects decades of policy evolution and local adaptation. This heterogeneous structure creates important implications for how insurance expansion affects service availability across different geographic areas and market contexts.

The modern EMS system emerged from fragmented historical origins. Before federal intervention in the 1970s, ambulance services were provided by a diverse array of organizations, including fire departments, hospitals, funeral homes, and volunteer organizations, often with minimal coordination or quality standards. The Emergency Medical Services Act of 1973 established federal funding and oversight mechanisms; however, subsequent budget cuts in the 1980s devolved much responsibility to state and local governments, resulting in the current patchwork of service delivery models.

Contemporary EMS provision reflects this institutional legacy. Local governments typically maintain oversight responsibility under state regulatory frameworks, but actual service delivery involves a mix of public, private, and nonprofit providers. Chaudhary et al. (2019) document that rural areas rely disproportionately on volunteer providers and Medicare reimbursement, making these areas particularly vulnerable to changes in insurance coverage patterns and reimbursement policies.

The economic sustainability of ambulance services depends critically on patient mix and reimbursement rates. Unlike many healthcare providers, ambulance services cannot easily adjust capacity in response to demand fluctuations due to regulatory requirements for minimum response capabilities. This creates fixed cost structures that make revenue predictability especially important for financial viability.

Recent evidence indicates growing concerns about the availability of ambulance services, particularly in

[4] Henningsen et al. (2021): "Financial Sustainability of Emergency Medical Services in Rural America"

rural areas. Jonk et al. (2023) provide comprehensive documentation of ambulance access disparities, estimating that 4.5 million Americans live more than 25 minutes from emergency medical transportation. Their analysis reveals that rural areas face particularly acute challenges, with over half the population in ambulance deserts residing in rural counties.

The spatial distribution of ambulance services has significant implications for interpreting the effects of insurance expansion. Areas with existing service gaps may respond differently to coverage changes than areas with established provider networks. Additionally, the interaction between ambulance services and other healthcare infrastructure creates spillover effects that may amplify or dampen the direct impacts of insurance expansion.

Miller et al. (2020) analyze the relationship between hospital closures and EMS response patterns, finding that ambulance services often expand coverage areas following hospital closures but face increased operational costs and longer transport times.[5] This dynamic suggests that broader changes in local healthcare infrastructure may mediate insurance expansion effects on ambulance services.

The emergence of ambulance deserts represents a critical policy challenge that insurance expansion might address. Figure (2a) documents the concerning trend of increasing counties without ambulance establishments during the study period, while Figure (2b) reveals the geographic concentration of service losses in particular regions.

These access patterns create heterogeneous baseline conditions that may influence how different areas respond to insurance expansion. Counties with existing ambulance services may experience service expansion or quality improvements following coverage increases. In contrast, counties without established services face higher barriers to market entry that insurance expansion alone may not overcome.

The interaction between ambulance services and broader healthcare market dynamics adds additional complexity. Alexander and Richards (2023) and Fischer et al. (2022) document ongoing rural hospital closures that may affect demand for ambulance services. In contrast, Battaglia (Forthcoming) shows that specialty service closures can increase reliance on emergency medical transportation for accessing care.[6] These interconnections suggest that the effects of insurance expansion on ambulance services may depend on concurrent changes in local healthcare infrastructure and access patterns.

[5] Doolen et al. (2022): "Hospital Closures and Emergency Medical Service Response Patterns in Rural America"

[6] Alexander and Richards (2023): "Economic Consequences of Hospital Closures"; Fischer et al. (2022): "Health Care Centralization: The Health Impacts of Obstetric Unit Closures in the US"; Battaglia (2023): "The Effect of Hospital Maternity Ward Closures on Maternal and Infant Health"

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, we construct a comprehensive county-level panel using five main data sources.[7]

4.1 County Business Patterns (CBP) Data

Our 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.[8]

We identify ambulance service establishments using the six-digit North American Industry Classification System (NAICS) code 621910.[9] We 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.[10] However, three important data features affect our 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.

Given these constraints, we restrict our analysis to 1999-2016.[11] The start date ensures consistent NAICS 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 us to examine both the immediate and medium-term effects of insurance expansion on ambulance service availability.

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

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

[9] 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.

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

[11] This sample period allows us to observe market structure changes before and after the ACA’s implementation while maintaining consistent measurement of ambulance service availability.

4.2 Small Area Health Insurance Estimates (SAHIE)

A crucial component of our 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.[12]

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.

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.[13]

We use the 2019 release of the SAHIE data, which underwent extensive quality control and validation.[14] This release provides consistent historical estimates that allow us to measure pre-treatment uninsured rates with precision, a critical feature for our empirical strategy.[15]

4.3 Regional Economic Information System (REIS)

The Bureau of Economic Analysis's REIS data provide detailed county-level economic indicators. We extract four key measures: population counts, per capita earnings, per capita transfer receipts, and total employment. From these, we construct the employment-to-population ratio, an important control for local economic conditions.[16]

[12] 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.

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

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

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

[16] 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

4.4 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.[17]

4.5 Medicaid Expansion Data

To identify state Medicaid expansion decisions under the ACA, we compile data on expansion status and implementation timing from multiple sources. Table A1 presents the complete list of expansion states and their implementation dates. Following the Supreme Court's decision in *National Federation of Independent Business v. Sebelius* (2012), states could choose whether to adopt the ACA's Medicaid expansion.

By the end of our study period (2016), 32 states, including the District of Columbia, had expanded Medicaid coverage to adults with incomes up to 138 percent of the federal poverty level. The implementation timing varies across states, with most expansions occurring in January 2014. However, several states implemented early expansions through Section 1115 demonstration waivers before 2014, while others expanded later during 2014-2016. We incorporate this variation in implementation timing into our empirical strategy by defining the post-treatment period based on when each state expanded.

We follow the classification approach used by Miller and Wherry (2017) for early expansion states and Carey et al. (2020) for identifying large expansion states—those that experienced particularly substantial increases in Medicaid enrollment following implementation (California, Iowa, Minnesota, Hawaii, Indiana, Maryland, Connecticut, and Wisconsin).

4.6 Analytical Sample Construction

Our analytical sample spans 1999-2016 and focuses on counties in the continental United States. Following Fischer et al. (2022), we 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, we track ambulance service establishments to examine both market entry and capacity expansion decisions. The extensive margin captures whether a county has any ambulance

[17] 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.

service establishment, represented as a binary indicator equal to one if the number of establishments exceeds zero. For the intensive margin, we follow the industrial organization literature by conditioning on market presence.

Specifically, we restrict the sample to county-years where at least one establishment exists, then model the count of establishments. This approach cleanly separates entry decisions from expansion decisions, as these reflect fundamentally different economic choices with distinct cost structures and competitive dynamics.

We also implement an alternative intensive margin specification that models additional establishments beyond the first. For counties with existing services, we construct the outcome as establishment count minus one. This specification focuses purely on capacity expansion decisions, abstracting from the initial entry decision. Both intensive margin approaches yield consistent results, confirming that insurance expansion affects not just whether firms enter a market but how much capacity they provide conditional on entry.

We incorporate 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. We also control for pre-existing health market features, including baseline uninsured rates and the presence of hospitals.

4.7 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 reveals that 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.[18] Figure 2 provides two perspectives on these differences: Panel 2a shows a secular decline in ambulance service availability from 1999-2016, while Panel 2b 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 3 shows that in both pre- and post-ACA periods, Harris County, TX, maintained the highest concentration of establishments. However, after the implementation of the ACA, the number decreased from 200 to about 100

[18] Appendix Figures A2 and A4 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.

establishments. Other high-concentration areas, primarily major metropolitan counties, also experienced changes in service levels, suggesting market restructuring following insurance expansion.

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

The identification of the causal effects of insurance expansion on ambulance service availability requires addressing several empirical challenges. First, state Medicaid expansion decisions may be correlated with unobserved factors that affect healthcare markets. Second, the effects of coverage expansion likely vary with local market conditions, particularly baseline insurance coverage rates. Third, ambulance establishments represent count data with substantial zeros, necessitating the use of appropriate econometric methods. This section outlines our approach to addressing these challenges through a triple-difference design implemented with Poisson pseudo-maximum likelihood estimation.

5.1 Triple-Difference Identification Strategy

We implement a triple-difference (DDD) specification that exploits both cross-sectional variations in pre-ACA county-level uninsured rates and temporal variation from state Medicaid expansion decisions. This approach addresses potential concerns with standard difference-in-differences designs while identifying heterogeneous treatment effects based on local market conditions.

The baseline specification takes the form:

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

where Y_{dcst} represents ambulance service availability in county c, state s, at time t. We examine both extensive margin outcomes (the presence of any ambulance establishment) and intensive margin outcomes (the count of establishments). The variable Uninsured_{cs} captures the 2013 pre-treatment uninsured rate in county c, providing a time-invariant measure of baseline market conditions.

The coefficient α_1 identifies how non-Medicaid ACA components (primarily private marketplace subsidies and regulations) affect areas with different baseline uninsurance rates. The coefficient α_3 captures the differential effect of Medicaid expansion in areas with varying pre-treatment uninsured rates, representing the central parameter of interest. The coefficient α_2 captures aggregate effects of Medicaid expansion that do not vary with local uninsurance rates. However, this likely reflects unobserved confounders rather than causal effects since Medicaid expansion should have minimal impact in areas with zero baseline uninsurance.

Following Courtemanche et al. (2017), this specification assumes treatment intensity varies proportionally with baseline uninsured rates, a natural assumption given that coverage gains should be largest in areas with the highest initial uninsurance.[19] At the sample mean pre-treatment uninsured rate, the total effect of Medicaid expansion equals $\alpha_3 \times \overline{\text{Uninsured}}$.

The identifying assumption requires 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. This assumption is substantially weaker than standard difference-in-differences designs and is supported by evidence that pre-ACA uninsured rates do not systematically correlate with state expansion decisions or other concurrent policy changes affecting ambulance services.

5.2 Poisson Pseudo-Maximum Likelihood Estimation

Ambulance establishment counts exhibit features that make standard linear regression problematic. The data contain substantial zeros (approximately 45 percent of county-year observations have no ambulance establishments), exhibit substantial heteroskedasticity, and represent non-negative integer outcomes. These characteristics violate the assumptions underlying ordinary least squares estimation and can lead to inconsistent and inefficient parameter estimates.

We address these concerns by implementing Poisson pseudo-maximum likelihood (PPML) estimation, which provides consistent estimates even when the underlying data generating process is not Poisson (Silva and Tenreyro, 2006).[20] The PPML estimator accommodates zero outcomes naturally, provides robust standard errors and produces economically interpretable coefficient estimates for count data.

[19]This approach builds on Finkelstein (2007) and Miller (2012) who use similar identification strategies for Medicare introduction and Massachusetts health reform respectively.

[20]Silva and Tenreyro (2006): "The Log of Gravity"

The PPML specification maintains the same structure as equation (1) but estimates parameters using maximum likelihood methods appropriate for count outcomes:

$$E[Y_{dcst}|Z_{dcst}] = \exp\left(\alpha_0 + \alpha_1(\text{Uninsured}_{cs} \times \mathbb{1}(\text{Post}_t)) + \dots\right) \tag{2}$$

where Z_{dcst} represents the full vector of explanatory variables. The exponential functional form ensures non-negative predicted values while allowing for flexible heteroskedasticity patterns.

For extensive margin outcomes (probability of any establishment), we estimate linear probability models using ordinary least squares as well as PPML specifications to ensure robustness. The linear probability model provides easily interpretable marginal effects, while PPML accommodates potential non-linearities and heteroskedasticity. Results prove robust across both approaches.

The PPML estimator offers several advantages for this application. First, it handles zero outcomes without arbitrary transformations or sample restrictions. Second, it provides consistent estimates under weak distributional assumptions. Third, the exponential mean function naturally captures potential non-linear relationships between insurance expansion and establishment counts. Recent work by Correia et al. (2020) demonstrates the particular advantages of PPML for policy evaluation with count outcomes.[21]

5.3 Event Study Specification

While the DDD specification in Equation (1) enables identification of the average treatment effect of Medicaid expansion on ambulance service establishments, it does not reveal the dynamic evolution of these effects over time. To examine how the impact of Medicaid expansion unfolds relative to its implementation and test for parallel pre-trends, we extend the DDD framework to an event study design:

$$\begin{aligned}
Y_{dcst} = \alpha_0 &+ \sum_{k\neq -1} \alpha_{1k}(\text{Uninsured}_{cs} \times \mathbb{1}(\text{Rel}_t = k)) \\
&+ \sum_{k\neq -1} \alpha_{2k}(\mathbb{1}(\text{Medicaid Expansion State}) \times \mathbb{1}(\text{Rel}_t = k)) \\
&+ \sum_{k\neq -1} \alpha_{3k}(\mathbb{1}(\text{Medicaid Expansion State}) \times \text{Uninsured}_{cs} \times \mathbb{1}(\text{Rel}_t = k)) \\
&+ X'_{dcst}\beta + \gamma_c + \delta_s + \theta_t + \varepsilon_{dcst}
\end{aligned} \tag{3}$$

[21] Correia et al. (2020): "Fast Poisson Estimation with High-Dimensional Fixed Effects"

In this specification, $\mathbb{1}(\text{Rel}_t = k)$ is an indicator for time period t being k years from Medicaid expansion implementation (2014), with $k \in -3, -2, -1, 0, 1, 2$. We omit the indicator for $k = -1$ (2013), making the year immediately preceding ACA implementation the reference period against which all coefficients are interpreted. The coefficients of primary interest are α_{3k}, which capture the triple-difference effect of Medicaid expansion in each year relative to the reference period. These coefficients represent how the impact of Medicaid expansion on ambulance service establishments varies with local pre-ACA uninsurance rates across different time periods.

The event study approach offers several advantages over the static DDD specification. First, it provides a direct test of the parallel trends assumption. The coefficients α_{3k} for pre-treatment periods ($k < 0$) should not be statistically different from zero if the parallel trends assumption holds. As shown in Figure 5, the flat pre-treatment coefficients support this identifying assumption.

Second, it reveals the temporal dynamics of policy effects, showing whether impacts emerge immediately or gradually, persist, strengthen, or diminish over time. This temporal dimension is particularly important for healthcare infrastructure responses, which may involve significant adjustment costs and regulatory processes (Buchmueller et al., 2016; Goodman-Bacon, 2021).

For consistency with the DDD specification, we maintain the same control variables $Xdcst$ and include county fixed effects γ_c, state fixed effects δ_s, and year fixed effects θ_t to account for time-invariant local characteristics and common temporal shocks. Standard errors are clustered at the state level to account for serial correlation in the error term (Bertrand et al., 2004). The event study coefficients α_{3k} can be interpreted as the causal effect of Medicaid expansion on ambulance service establishment probability in year k relative to implementation, per percentage point of pre-ACA uninsured rate. To obtain the total effect at mean uninsurance levels, these coefficients can be multiplied by the average pre-expansion uninsured rate in the sample (Courtemanche et al., 2019).

5.4 Control Variables and Fixed Effects

The specification includes a comprehensive set of control variables and fixed effects to address potential confounding factors. County fixed effects (γ_c) control for time-invariant local characteristics that might affect both baseline uninsurance rates and ambulance service availability. State fixed effects (δ_s) absorb state-level factors, including regulatory environments and Medicaid policies unrelated to ACA expansion. Year fixed effects (θ_t) control for common temporal shocks affecting all counties.

Time-varying county characteristics (X_{dcst}) include economic conditions from the Regional Economic Information System: employment-to-population ratios, per capita earnings, and transfer payment receipts. Demographic controls from the Surveillance, Epidemiology, and End Results program capture population composition changes, including age distributions and demographic characteristics that may affect ambulance service demand.

We also include controls for local healthcare market structure, particularly hospital presence, to isolate the effects of insurance expansion on ambulance services from concurrent changes in broader healthcare infrastructure. This is crucial given documented relationships between hospital closures and EMS service patterns (Alexander and Richards, 2023).

Standard errors are clustered at the state level to account for potential serial correlation and common shocks within states. This approach provides conservative inference while acknowledging that treatment assignment occurs at the state level for Medicaid expansion decisions.

6 Results

6.1 Main Results: Triple-Difference Poisson Estimates

Table 2 presents the central findings from the Poisson pseudo-maximum likelihood estimation of the triple-difference specification. The results provide compelling evidence that Medicaid expansion substantially increased ambulance service availability, with effects concentrated in areas with higher baseline uninsured rates.

The coefficient of primary interest is the triple interaction term (Uninsured Rate × Medicaid Expansion × Post), which identifies how Medicaid expansion effects vary with local pre-ACA uninsurance rates. For the extensive margin, the estimated coefficient of 0.726 ($p < 0.01$) indicates that a one percentage point increase in pre-expansion uninsured rates amplifies the probability of having any ambulance establishment in Medicaid expansion states relative to non-expansion states. The intensive margin results are even more striking, with coefficients of 1.596 ($p < 0.01$) when examining the count of establishments conditional on market presence.

To interpret these magnitudes meaningfully, we calculate implied percentage effects relative to pre-treatment means. For the extensive margin, each percentage point increase in the pre-ACA uninsured rate corresponds to a 131 percent increase in the likelihood of having an ambulance establishment relative to the pre-treatment mean of 0.555. The intensive margin effects indicate a 52 percent increase in the number of establishments relative to the conditional pre-treatment mean of 3.097 for counties with existing services.

The distinction between extensive and intensive margins reveals important market dynamics. The extensive margin captures fundamental entry decisions where firms overcome fixed costs to establish service in previously unserved markets. The smaller observation count for intensive margin regressions (21,466 versus 30,849) confirms that this specification correctly conditions on counties with existing ambulance service, isolating capacity expansion decisions from entry decisions. This methodological refinement provides a cleaner identification of how insurance expansion affects different aspects of market structure.

These substantial effects reflect several unique features of ambulance service markets compared to other healthcare infrastructures. Duggan et al. (2022) find that Medicaid expansion increased hospital revenues by 6 to 18 percent, while Lindrooth et al. (2018) document 4 to 6 percentage point reductions in hospital closure probabilities. The larger percentage effects for ambulance services likely reflect lower barriers to entry, more direct relationships between insurance coverage and service utilization, and greater financial vulnerability to uncompensated care burdens.

The economic mechanisms operate through multiple reinforcing channels in high-uninsurance areas. First, Medicaid expansion directly reduces uncompensated care that historically strained ambulance service finances. Garthwaite et al. (2018) and Nikpay et al. (2020) document substantial reductions in uncompensated care following coverage expansion, which directly improves provider financial viability. Second, increased insurance coverage stimulates emergency service utilization as newly insured individuals face lower out-of-pocket costs for ambulance transportation (Taubman et al., 2014; Sommers et al., 2015).

Third, ambulance services benefit from broader healthcare system responses to Medicaid expansion. Miller et al. (2021) document increased hospital emergency department capacity following expansion, generating derived demand for ambulance transportation. The concentration of effects in high-uninsured areas creates a natural targeting mechanism where treatment intensity varies proportionally with baseline market conditions, as these areas experience the largest coverage gains from expansion (Courtemanche et al., 2017; Frean et al., 2017).

The robustness of results across specifications with and without controls demonstrates that concurrent economic or demographic changes do not drive the findings. The PPML approach properly handles the count nature of establishments and accommodates the substantial number of zeros in the data, yielding precise parameter estimates that support confident conclusions about insurance expansion effects on emergency medical infrastructure.

6.2 Decomposing ACA Effects: Medicaid Expansion versus Private Marketplace Components

The triple-difference framework enables a nuanced decomposition of ACA effects, revealing fundamentally different impacts of public versus private insurance expansion mechanisms. Table 3 presents this decomposition, calculated at the sample mean pre-treatment uninsured rate of 18.59 percent following Courtemanche et al. (2017). The results demonstrate that Medicaid expansion and private marketplace components operated through distinctly different channels with opposing effects on ambulance service availability.

Panel A reports the coefficient estimates from the PPML specification. The triple interaction term (Medicaid Expansion × Uninsured Rate × Post) provides strong evidence of positive Medicaid expansion effects: 0.726 ($p < 0.01$) for the extensive margin and 1.596 ($p < 0.01$) for the intensive margin conditional on market presence. In contrast, the coefficient on Uninsured Rate × Post reveals negative effects of private marketplace components: -0.395 ($p < 0.01$) for the extensive margin and -0.644 ($p < 0.05$) for the intensive margin.

Panel B translates these coefficients into economically interpretable implied effects at the mean uninsured rate. Private marketplace components reduced ambulance service presence by 7.35 percentage points ($p < 0.01$) on the extensive margin and 11.96 percentage points ($p < 0.05$) on the intensive margin. These negative effects likely reflect several mechanisms. Private insurance products introduce varying reimbursement rates, complex prior authorization requirements, and network restrictions that increase administrative costs and create revenue uncertainty (Dafny et al., 2012; Ho and Lee, 2017). Additionally, increased competition for newly insured patients may pressure less efficient providers to exit or consolidate.

Medicaid expansion generated offsetting positive effects: increasing ambulance service presence by 13.49 percentage points ($p < 0.01$) on the extensive margin and 25.95 percentage points ($p < 0.01$) on the intensive margin. These effects substantially exceed those documented for other healthcare providers, reflecting the particular vulnerability of ambulance services to uncompensated care and their direct benefit from predictable Medicaid reimbursement rates.

The net ACA effect combines these opposing forces. The full ACA increased ambulance service availability by 6.14 percentage points ($p < 0.01$) on the extensive margin and 13.99 percentage points on the intensive margin, though the latter estimate lacks statistical precision. This decomposition reveals that examining only aggregate ACA effects would mask substantial policy-relevant heterogeneity in how different insurance mechanisms affect healthcare infrastructure.

The opposing effects of public versus private expansion reflect fundamental differences in how these programs interface with healthcare markets. Medicaid provides standardized billing procedures, predictable reimbursement, and immediate revenue improvements through reduced uncompensated care (Garthwaite et al., 2018; Nikpay et al., 2020). Private marketplace expansion introduces market complexity that may initially disrupt provider operations, particularly for smaller ambulance services lacking administrative scale.

These findings contribute important evidence to debates about optimal coverage expansion approaches. The substantially larger positive effects of Medicaid expansion suggest that public insurance programs may be particularly effective for improving emergency medical infrastructure. This pattern aligns with evidence that Medicaid provides more stable revenue streams for safety-net providers compared to private insurance markets (Currie and Gruber, 1996; Wherry and Miller, 2016).

The geographic concentration of effects in high-uninsurance areas indicates that both positive Medicaid effects and negative private marketplace effects intensify where baseline coverage gaps are largest. This creates a natural experiment where treatment intensity varies with local market conditions, strengthening causal identification while revealing how the insurance market structure fundamentally shapes healthcare infrastructure development.

6.3 Dynamic Effects and Temporal Patterns

The static triple-difference estimates provide evidence of Medicaid expansion effects on ambulance services, but understanding the temporal evolution of these effects offers crucial insights into the underlying mechanisms and validates the identifying assumptions. This section examines how insurance expansion effects unfold over time, using both visual evidence and formal event study analysis, to demonstrate that the impacts emerged immediately following policy implementation and strengthened over the subsequent years.

Figure 4 provides visual evidence of the geographic expansion of ambulance services following ACA implementation. The 2013 baseline map reveals substantial gaps in ambulance coverage, particularly across the central United States and rural areas. The transformation became apparent in 2014 when counties highlighted in yellow represented areas that gained ambulance services after previously having none. This pattern of service expansion accelerates markedly by 2015 and 2016, with the number of transitioning counties increasing substantially over time.

The geographic concentration of these gains in Medicaid expansion states provides compelling visual evidence in support of the causal interpretation of the regression results. The spatial pattern suggests that policy-induced changes in insurance coverage and reimbursement, rather than secular trends or unobserved factors, drove the observed expansion in ambulance service availability. The progressive nature of these changes over the 2014-2016 period indicates that infrastructure responses to insurance expansion require time to materialize as providers adjust capacity and enter new markets fully.

The formal event study analysis in Table 4 provides rigorous statistical validation of these visual patterns while testing the parallel trends assumption that is crucial for causal identification. The lead coefficients for years t-3 through t-1 provide strong support for the parallel trends assumption underlying the triple-difference design. The coefficients for t-3 and t-2 are small and statistically insignificant (0.3384 and 0.3523, respectively), indicating no systematic differences in pre-treatment trends between high and low uninsured areas across expansion and non-expansion states.

The marginally significant coefficient for t-1 (0.4111, $p < 0.10$) merits careful interpretation. This result likely reflects anticipatory responses as ambulance service providers prepared for the policy changes they knew would take effect in 2014. Such anticipatory effects are common in healthcare markets where providers make forward-looking investment decisions based on expected changes in demand and reimbursement (Dranove and White, 1994; Garthwaite et al., 2017; Cutler and Morton, 2013). The modest magnitude suggests that while some preparation occurred, the primary effects emerged after actual policy implementation rather than from anticipatory behavior.

The post-implementation coefficients reveal a clear and economically significant pattern of growing effects over time. The immediate impact in the implementation year (t=0) shows a coefficient of 0.4637 ($p < 0.05$), indicating that the impact of Medicaid expansion was evident quickly following the policy changes. The effects strengthen in subsequent years, with coefficients of 0.4776 ($p < 0.05$) for t+1 and 0.4421 ($p < 0.10$) for t+2, indicating persistent and potentially growing impacts rather than temporary adjustments.

This temporal pattern aligns with economic theory regarding healthcare infrastructure investment and capacity adjustment. Dranove and White (1994); Cutler and Morton (2013) document that healthcare providers face significant adjustment costs when responding to policy changes, including time required for business planning, financing arrangements, regulatory approvals, and staff recruitment. The strengthening effects over time suggest that initial responses involved relatively quick adjustments, such as billing changes and service area expansions, while longer-term responses included more substantial capacity investments and market entry decisions.

Figure 5 translates these dynamic patterns into confidence interval plots that provide clear visual evidence of both the parallel trends assumption and the evolution of treatment effects. Panel (a) for the extensive margin and Panel (b) for the intensive margin both demonstrate flat pre-treatment coefficients that lie within confidence intervals centered around zero, supporting the validity of the identification strategy. The post-treatment coefficients show clear positive effects that grow over time, with confidence intervals that exclude zero for the implementation year and subsequent periods.

The consistency of patterns across both extensive and intensive margins provides additional confidence in the results. The extensive margin effects indicate that Medicaid expansion increased the probability that counties gained their first ambulance establishment. In contrast, the intensive margin effects show that areas with existing services experienced an expansion in the number of providers. This dual response suggests that insurance expansion operated through multiple channels, supporting both market entry in underserved areas and capacity expansion in areas with established services.

Figure A3 provides an alternative visualization that plots the complete time series of triple-difference coefficients with confidence intervals. The stable pre-treatment coefficients followed by an immediate increase at implementation and sustained positive effects thereafter offer compelling visual confirmation of the causal impact. The absence of pre-treatment trends and the immediate emergence of effects at policy implementation provide strong evidence against alternative explanations based on unobserved confounding factors.

The dynamic pattern observed in these results has important implications for understanding the mechanisms through which insurance expansion affects healthcare infrastructure. The immediate positive effects likely reflect rapid responses to improved revenue streams and reduced uncompensated care burdens. The strengthening effects over time suggest more substantial structural adjustments as providers made longer-term investment decisions based on the improved financial environment created by Medicaid expansion.

The persistence of effects through 2016 suggests that insurance expansion led to lasting changes in emergency medical service availability rather than temporary adjustments. This persistence is particularly important for policy evaluation, as it indicates that the infrastructure benefits of Medicaid expansion extend beyond the immediate coverage effects to create durable improvements in healthcare access. The growing magnitude of impact over time also implies that longer-term evaluations of insurance expansion policies may reveal larger benefits than studies focusing solely on immediate impacts.

6.4 Robustness Checks

The PPML estimates provide compelling evidence of the effects of Medicaid expansion on ambulance services. To validate these findings, we conduct comprehensive robustness checks examining alternative estimation methods, sample specifications, and control variable combinations. The results demonstrate stability across specifications, strengthening the causal interpretation.

Alternative Estimation Methods. Tables 5 and 6 present OLS estimates using the identical triple-difference specification employed in the PPML analysis. The OLS results confirm the sign and statistical significance of the main findings while demonstrating the superior precision achieved through the use of appropriate count data methods. For the extensive margin, the OLS triple interaction coefficient of 0.367 ($p < 0.10$) aligns with the PPML estimate's direction but exhibits larger standard errors. The intensive margin OLS coefficient of 1.959 ($p < 0.10$) similarly confirms the positive Medicaid expansion effects identified in the PPML specification.

The implied effects decomposition in Table 6 using OLS methods validates the key finding that Medicaid expansion and private marketplace components had opposing effects. The private marketplace components exhibit negative effects of 3.25 percentage points (extensive margin) and 5.31 percentage points (intensive margin), whereas Medicaid expansion yields positive effects of 6.82 and 36.41 percentage points, respectively. These patterns align with the PPML findings, confirming that the fundamental policy insights are not dependent on the specific estimation approach.

Alternative Intensive Margin Specifications. Table 7 addresses a critical econometric issue in modeling intensive margin effects. The main specification models the count of establishments conditional on having at least one, properly separating entry from expansion decisions. As an alternative, we model additional establishments beyond the first by using count minus one as the dependent variable for counties with existing services. This specification isolates pure capacity expansion, abstracting from the initial entry decision.

The results demonstrate remarkable consistency across these approaches. The main specification yields a coefficient of 1.396 ($p < 0.01$) without controls and 1.794 ($p < 0.01$) with controls. The alternative specification, which models additional establishments, produces coefficients of 2.006 ($p < 0.01$) and 2.667 ($p < 0.01$), respectively. The larger magnitudes in the alternative specification make economic sense, as they capture the intensive margin effect conditional on having already overcome entry barriers. Both approaches confirm that Medicaid expansion not only induced market entry but also encouraged capacity expansion among existing providers.

Specification Robustness. Table 8 demonstrates the stability of extensive margin results across alternative specifications. The triple interaction coefficient ranges narrowly from 0.353 to 0.428 across models that exclude various control sets, employ different time trend specifications, and modify sample weights. The estimates remain stable when replacing state-specific time trends with state-by-year fixed effects, addressing concerns about differential pre-treatment trends that might confound the results (Goodman-Bacon, 2021).

Table 9 provides parallel evidence for intensive margin outcomes. The coefficient estimates range from 1.729 to 2.062 across specifications, maintaining statistical significance in most models. The consistency across control variable combinations indicates that neither omitted variable bias nor specific modeling choices drive the results.

Key Validation Tests. Two robustness checks merit special emphasis. First, the stability of estimates when including state-by-year fixed effects provides strong evidence against confounding from unobserved state-level shocks that might correlate with both Medicaid expansion decisions and trends in ambulance service. This specification absorbs any time-varying state characteristics that could generate spurious correlations. Second, the proper conditioning of intensive margin estimates on positive establishment counts validates that we are measuring genuine expansion effects rather than conflating entry and growth decisions.

The convergence of evidence across PPML and OLS methods, combined with stability across diverse specifications and careful treatment of margin definitions, provides strong validation of the central findings. The systematic nature of these robustness patterns, particularly the consistency between different intensive margin approaches, strengthens confidence that Medicaid expansion causally increased ambulance service availability in areas with higher baseline uninsured rates.

7 Discussion & Conclusion

This paper demonstrates that Medicaid expansion substantially increased ambulance service availability in areas with higher baseline uninsured rates, while private marketplace components of the ACA produced opposing effects. Using Poisson pseudo-maximum likelihood estimation of a triple-difference design, we find that for each percentage point increase in pre-ACA uninsured rates, Medicaid expansion increased the likelihood of having any ambulance establishment by 131 percent and the number of establishments by 52 percent relative to pre-treatment means.

At the sample mean uninsured rate of 18.59 percent, Medicaid expansion increased ambulance service presence by 13.5 percentage points on the extensive margin and 29.7 percentage points on the intensive margin conditional on existing service. In contrast, private marketplace components reduced availability by 7.4 and 12.0 percentage points, respectively. This divergence reflects fundamental differences in how public versus private insurance expansion affects provider incentives: Medicaid provides predictable reimbursement and reduces uncompensated care burdens, while private mechanisms introduce administrative complexity and competitive pressures.

The methodological contribution of properly separating extensive and intensive margins strengthens these conclusions. By conditioning intensive margin analysis on counties with existing establishments, the estimates cleanly identify capacity expansion decisions distinct from entry decisions. The event study analysis validates the causal interpretation, showing flat pre-treatment trends and immediate post-implementation effects that strengthen over time.

These findings extend the literature on insurance expansion effects (Courtemanche et al., 2017; Garthwaite et al., 2018) by documenting heterogeneous impacts on emergency medical infrastructure. The results contribute to understanding healthcare market structure (Dafny et al., 2012) by revealing how different insurance mechanisms generate opposing provider responses. The concentration of benefits in high-uninsurance areas indicates that Medicaid expansion functions as a geographically targeted intervention.

The policy implications are clear: public insurance expansion appears more effective than private marketplace mechanisms for improving emergency medical infrastructure, particularly in underserved areas.

The separate identification of entry versus expansion effects suggests that Medicaid expansion operates through multiple channels, both bringing services to previously unserved areas and increasing capacity where services already exist.

Several limitations suggest future research directions. Data constraints prevent analysis of service quality, response times, or health outcomes. Examining heterogeneous effects across provider types and geographic characteristics could reveal additional policy-relevant variation. Despite these limitations, the findings demonstrate that insurance expansion can effectively address geographic disparities in emergency medical access, but the structure of coverage expansion fundamentally determines policy success.

References

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

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.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, "How much should we trust differences-in-differences estimates?," *The Quarterly journal of economics*, 2004, *119* (1), 249–275.

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.

Card, David, Carlos Dobkin, and Nicole Maestas, "The impact of nearly universal insurance coverage on health care utilization: evidence from Medicare," *American Economic Review*, 2008, *98* (5), 2242–2258.

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.

Correia, Sergio, Paulo Guimarães, and Tom Zylkin, "Fast Poisson estimation with high-dimensional fixed effects," *The Stata Journal*, 2020, *20* (1), 95–115.

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.

— , — , — , — , — , and Ishtiaque Fazlul, "The three-year impact of the Affordable Care Act on disparities in insurance coverage," *Health services research*, 2019, *54*, 307–316.

Currie, Janet and Jonathan Gruber, "Health insurance eligibility, utilization of medical care, and child health," *The Quarterly Journal of Economics*, 1996, *111* (2), 431–466.

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.

Dranove, David and William D White, "Recent theory and evidence on competition in hospital markets," *Journal of Economics & Management Strategy*, 1994, *3* (1), 169–209.

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.

Einav, Liran and Amy Finkelstein, "Moral hazard in health insurance: what we know and how we know it," *Journal of the European Economic Association*, 2018, *16* (4), 957–982.

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.

Fulton, Brent D, "Health care market concentration trends in the United States: evidence and policy responses," *Health Affairs*, 2017, *36* (9), 1530–1538.

Garthwaite, Craig, Tal Gross, and Matthew J. Notowidigdo, "Hospitals as Insurers of Last Resort," *American Economic Journal: Applied Economics*, January 2018, *10* (1), 1–39.

— , — , 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.

Goodman-Bacon, Andrew, "Difference-in-differences with variation in treatment timing," *Journal of Econometrics*, 2021, *225* (2), 254–277. Themed Issue: Treatment Effect 1.

Hackmann, Martin B, Jonathan T Kolstad, and Amanda E Kowalski, "Adverse selection and an individual mandate: When theory meets practice," *American Economic Review*, 2015, *105* (3), 1030–1066.

Ho, Kate and Robin S Lee, "Insurer competition in health care markets," *Econometrica*, 2017, *85* (2), 379–417.

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

Kolstad, Jonathan T and Amanda E Kowalski, "Mandate-based health reform and the labor market: Evidence from the Massachusetts reform," *Journal of health economics*, 2016, *47*, 81–106.

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.

Miller, Katherine EM, Hailey J James, George Mark Holmes, and Courtney H Van Houtven, "The effect of rural hospital closures on emergency medical service response and transport times," *Health services research*, 2020, *55* (2), 288–300.

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.

— , Luojia Hu, Robert Kaestner, Bhashkar Mazumder, and Ashley Wong, "The ACA Medicaid Expansion in Michigan and Financial Health," *Journal of Policy Analysis and Management*, 2021, *40* (2), 348–375.

Nikpay, Sayeh, India Pungarcher, and Austin Frakt, "An Economic Perspective on the Affordable Care Act: Expectations and Reality," *Journal of Health Politics, Policy and Law*, 10 2020, *45* (5), 889–904.

Silva, JMC Santos and Silvana Tenreyro, "The log of gravity," *The Review of Economics and statistics*, 2006, pp. 641–658.

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.

Sommers, Benjamin D, Munira Z Gunja, Kenneth Finegold, and Thomas Musco, "Changes in self-reported insurance coverage, access to care, and health under the Affordable Care Act," *Jama*, 2015, *314* (4), 366–374.

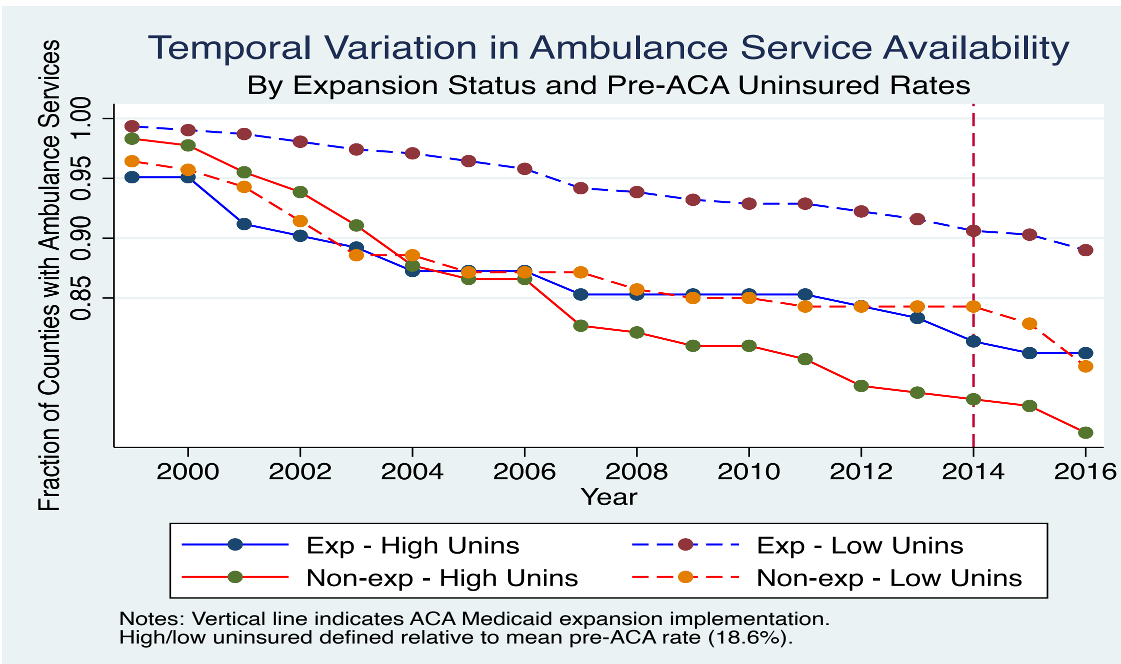
Taubman, Sarah L, Heidi L Allen, Bill J Wright, Katherine Baicker, and Amy N Finkelstein, "Medicaid increases emergency-department use: evidence from Oregon's Health Insurance Experiment," *Science*, 2014, *343* (6168), 263–268.

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.

Williams, Janet M, Peter F Ehrlich, and John E Prescott, "Emergency medical care in rural America," *Annals of emergency medicine*, 2001, *38* (3), 323–327.

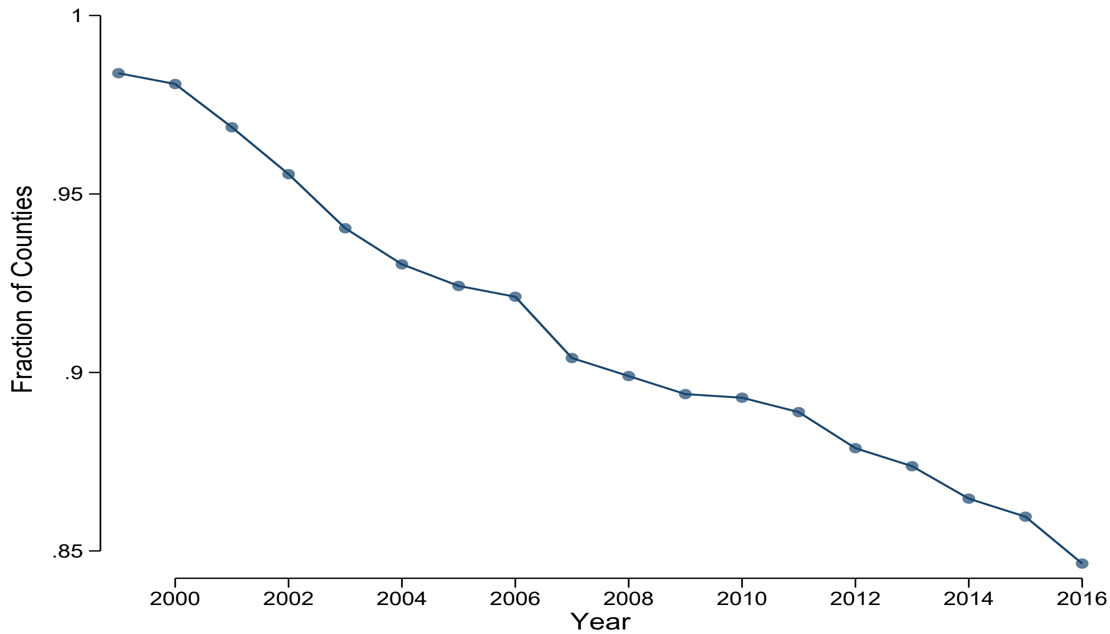
Figures

Figure 1: Trends in Ambulance Service Availability by Medicaid Expansion Status and Pre-ACA Insurance Coverage

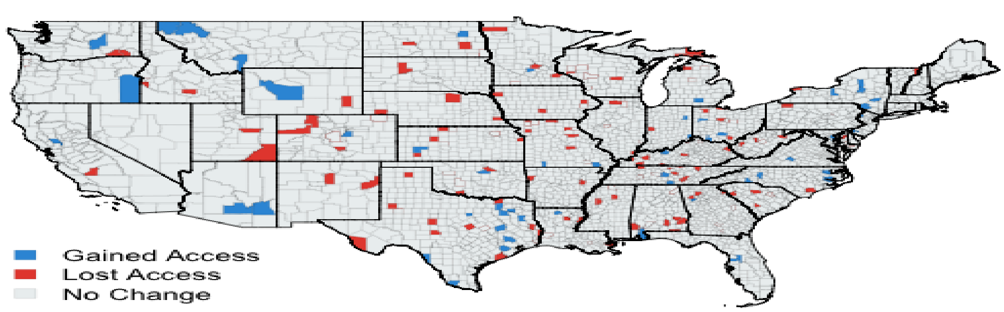


Notes: Data from County Business Patterns, 1999-2016. The figure illustrates the temporal patterns in ambulance service availability across different county groups. Counties are categorized by whether they are in Medicaid expansion states and by their pre-ACA uninsured rates relative to the national mean (18.6%). The vertical line indicates ACA Medicaid expansion implementation in 2014. The divergent trends across these categories—particularly in the post-2014 period—inform the triple-difference analytical approach used in this study. A county is designated as having ambulance service if it has at least one establishment providing these services in a given year.

Figure 2: Temporal and Spatial Variation in Access to Ambulance Services



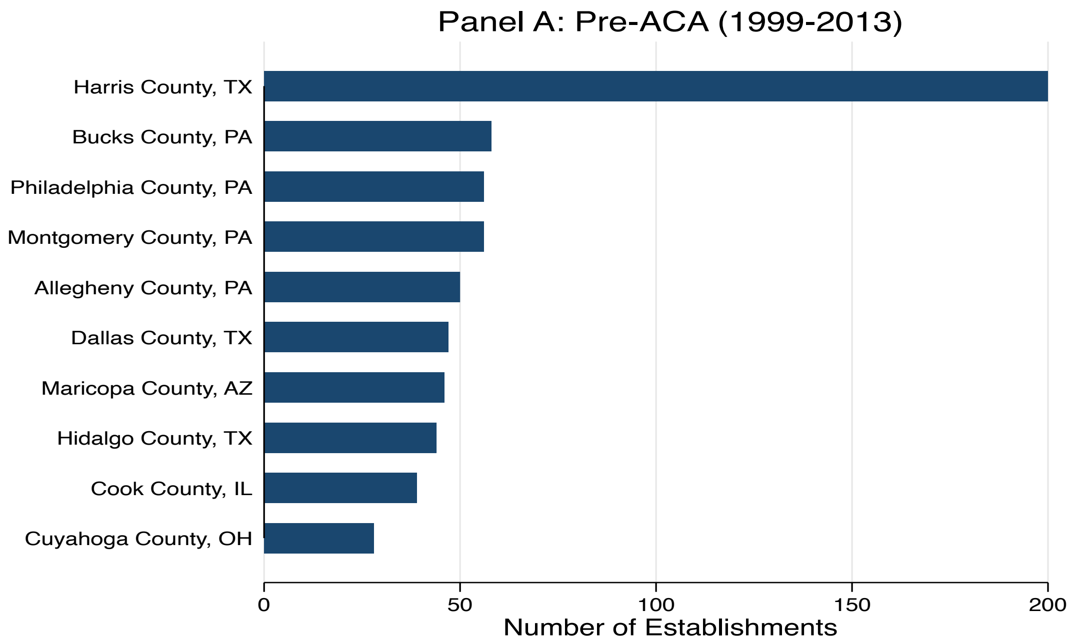
(a) Trend in Access to Ambulance Services



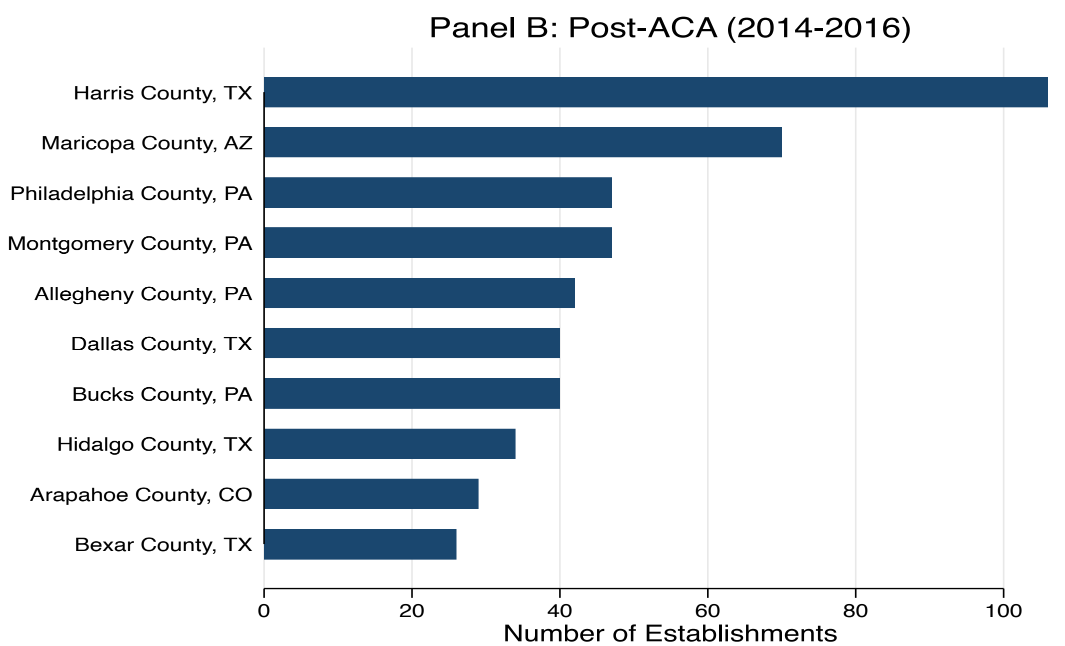
(b) Ambulance Services Access Loss and Gain

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 3: Distribution of Ambulance Establishments Across Counties



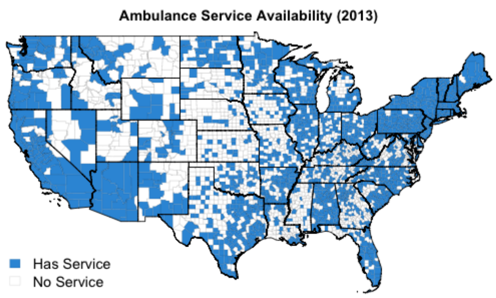
(a) Pre-ACA Period (1999-2013)



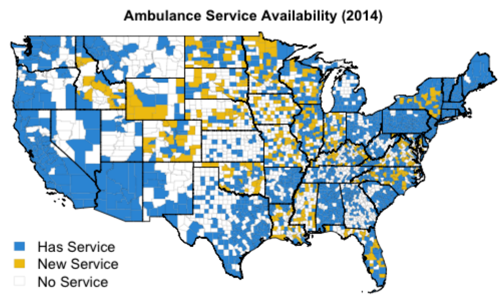
(b) Post-ACA Period (2014-2016)

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

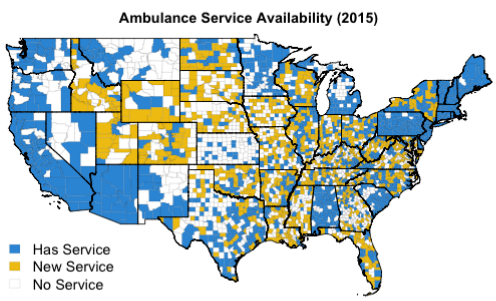
Figure 4: Evolution of Ambulance Service Availability (2013-2016)



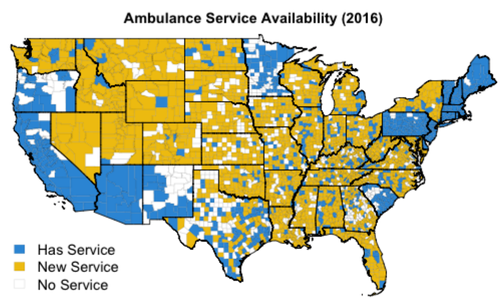
(a) Pre-ACA (2013)



(b) ACA Implementation (2014)



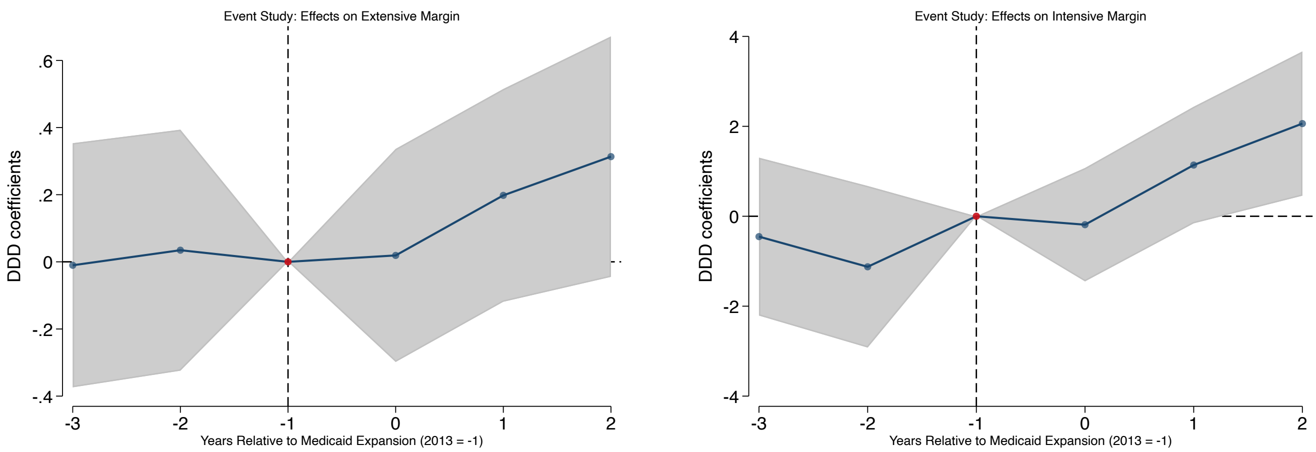
(c) Post-ACA Year 1 (2015)



(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: Event Study: Effect of ACA Medicaid Expansion on Ambulance Services



(a) Extensive Margin (Any Establishment)

(b) Intensive Margin (Number of Establishments)

Notes: These event studies show the evolution of triple difference coefficients (Medicaid Expansion × Uninsured Rate × Year) over time, normalized with year -1 (2013) as the reference period. The vertical line indicates ACA implementation (between years -1 and 0). Panel (a) shows effects on the extensive margin (probability of any establishment), while panel (b) shows effects on the intensive margin (number of establishments). The flat pre-treatment coefficients support the parallel trends assumption, while the post-treatment coefficients demonstrate the causal effect of Medicaid expansion on ambulance services. Shaded areas represent 95% confidence intervals. Standard errors clustered at the state level.

Tables

Table 1: Summary Statistics for Pre-Treatment Period

	Non-Expansion States			**Expansion States**		
	Mean	Min	Max	Mean	Min	Max
Extensive Margin						
Ambulance Service Presence (0/1)	0.384	0.000	1.000	0.555	0.000	1.000
Intensive Margin						
Number of Establishments	0.890	0.000	200.000	1.718	0.000	58.000
Number of Counties		1,714			900	

Notes: Pre-treatment means reported for counties in Medicaid expansion and non-expansion states. All states that expanded Medicaid in either 2014 or 2015 are classified in the treatment group. Data derived from 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. Sample period: 1999-2016.

Table 2: Triple-Difference Poisson Estimates: Effect of Medicaid Expansion on EMS Establishments

	Extensive Margin Pr(Any EMS Establishment)		Intensive Margin Count | Any Establishment	
	(1)	(2)	(3)	(4)
Uninsured Rate × Medicaid Expansion × Post	0.7258**	0.5253	1.3963**	1.7943***
	(0.3697)	(0.4116)	(0.6625)	(0.6812)
Pre-Treatment Mean	0.555	0.555	3.097	3.097
Observations	30,849	30,108	21,466	20,969
County Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
State-Specific Time Trends	Yes	Yes	Yes	Yes
Economic Controls	No	Yes	No	Yes
Demographic Controls	No	Yes	No	Yes

Notes: This table presents triple-difference Poisson pseudo-maximum likelihood (PPML) estimates. The extensive margin (columns 1-2) uses the full sample and models the probability of any EMS establishment (0 vs 1+). The intensive margin (columns 3-4) uses only county-years with at least one establishment and models the count conditional on entry. The key coefficient is the triple interaction of uninsured rate, Medicaid expansion status, and post-2014 indicator. Note that columns (3) and (4) have fewer observations as they condition on counties having entered the EMS market. All specifications include county fixed effects, state fixed effects, and state-specific linear time trends. Economic controls include employment-to-population ratio. Demographic controls include population age shares. Pre-treatment means are calculated for the appropriate sample in each case. Standard errors clustered at the state level in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 3: PPML Triple-Difference Results: Implied Effects

	Extensive Margin Pr(Any EMS Establishment)		Intensive Margin Count | Any Establishment	
	(1)	(2)	(3)	(4)
Panel A: Triple Difference-in-Differences Estimates				
Uninsured Rate × Post	-0.3954***	-0.4042***	-0.6436**	-0.5710***
	(0.0883)	(0.0921)	(0.2751)	(0.1396)
Medicaid Expansion × Uninsured Rate × Post	0.7258**	0.5253	1.3963**	1.7943***
	(0.3697)	(0.3789)	(0.6625)	(0.6812)
N	30849	30108	21466	20969
Panel B: Implied Effects at Mean Pre-Treatment Uninsured Rate				
Sample Mean Pre-Treatment Uninsured Rate		0.1859		
Private (Non-Medicaid Expansion)	-0.0735***	-0.0751***	-0.1196**	-0.1061***
	(0.0164)	(0.0171)	(0.0511)	(0.0259)
Medicaid Expansion	0.1349**	0.0976	0.2595**	0.3335***
	(0.0687)	(0.0704)	(0.1231)	(0.1266)
Full ACA (Private + Medicaid Expansion)	0.0614**	0.0225	0.1399**	0.2274***
	(0.0707)	(0.0725)	(0.1333)	(0.1293)
County Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
State-Specific Time Trends	Yes	Yes	Yes	Yes
Economic Controls	No	Yes	No	Yes
Demographic Controls	No	Yes	No	Yes
Observations	30,849	30,108	21,466	20,969

Notes: This table presents Poisson pseudo-maximum likelihood (PPML) triple-difference estimates and implied effects. Panel A shows the triple-difference coefficients from equation (1), excluding the Medicaid Expansion × Post coefficient Panel B shows implied effects calculated at the mean pre-treatment uninsured rate. The extensive margin (columns 1-2) uses the full sample and models the probability of any EMS establishment. The intensive margin (columns 3-4) conditions on counties with at least one establishment and models the count. Note the different observation counts between margins, reflecting the conditional nature of the intensive margin. All specifications include county fixed effects, state fixed effects, and state-specific linear time trends. Columns (1) and (3) include only the triple-difference terms and fixed effects. Columns (2) and (4) add economic controls (employment-to-population ratio) and demographic controls (share of population under 19, ages 20-34, 35-49, 50-64, and 65+). Standard errors clustered at the state level in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 4: 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) $\times$ Uninsured$_{cs}$ $\times$ $\mathbb{1}$ (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.

Table 5: Robustness Check: Triple-Difference OLS Estimates

	Extensive Margin Any Ambulance Establishment		Intensive Margin Number of Establishments	
	(1)	(2)	(3)	(4)
Uninsured Rate $\times$ Medicaid Expansion $\times$ Post	0.3336	0.3670*	1.2254	1.9588*
	(0.2023)	(0.2069)	(1.0170)	(0.9965)
Effect Relative to Pre-Treatment Mean (%)	60.14	66.16	71.33	114.02
Observations	45,252	45,252	45,252	45,252
Adjusted R^2	0.697	0.697	0.845	0.849
County Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
State-Specific Time Trends	Yes	Yes	Yes	Yes
Economic Controls	No	Yes	No	Yes
Demographic Controls	No	Yes	No	Yes

Notes: This table presents triple-difference estimates of the effect of Medicaid expansion on ambulance services. The dependent variable in columns (1) and (2) is an indicator for any ambulance establishment in the county-year. The dependent variable in columns (3) and (4) is the count of ambulance establishments. All specifications include county fixed effects, state fixed effects, and state-specific linear time trends. Columns (1) and (3) include only the triple-difference terms and fixed effects. Columns (2) and (4) add economic controls (employment-to-population ratio) and demographic controls (share of population under 19, ages 20-34, 35-49, 50-64, and 65+). The coefficient shown is the triple interaction of uninsured rate, Medicaid expansion status, and post-2014 indicator. Effect Relative to Pre-Treatment Mean shows the percentage impact per 1 percentage point change in the uninsurance rate, calculated as (coefficient/pre-treatment mean)$\times$100, where pre-treatment means are 0.555 for the extensive margin and 1.718 for the intensive margin. All regressions are weighted by county population. Standard errors clustered at the state level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 6: Robustness Check: OLS Implied Effects Decomposition

	(1) Extensive	(2) Intensive
Panel A: Triple Difference-in-Differences Estimates		
Uninsured_$cs \times \mathbb{1}(\text{Post}_t)$	-0.1750***	-0.2858
	(0.0557)	(0.1713)
$\mathbb{1}$(Medicaid Expansion State) $\times \mathbb{1}(\text{Post}\_t)$	-0.0485	-0.3455*
	(0.0333)	(0.1854)
$\mathbb{1}$(Medicaid Expansion State) $\times$ Uninsured_$cs \times \mathbb{1}(\text{Post}_t)$	0.3670*	1.9588*
	(0.2069)	(0.9965)
N	45252	45252
Panel B: Implied Effects at Mean Pre-Treatment Uninsured Rate		
Sample Mean Pre-Treatment Uninsured Rate	0.1859	
Private (Non-Medicaid Expansion)	-0.0325***	-0.0531*
	(0.0104)	(0.0318)
Medicaid Expansion	0.0682*	0.3641**
	(0.0385)	(0.1853)
Full ACA (Private + Medicaid Expansion)	0.0357*	0.3110**
	(0.0398)	(0.1880)
Economic Controls	Yes	Yes
Demographic Controls	Yes	Yes
County Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
State-Specific Time Trends	Yes	Yes
Sample Weights	Yes	Yes
Observations	45252	45252
Adjusted R^2	0.697	0.849

Notes: Heteroskedasticity robust standard errors clustered by state are in parentheses. (* p<0.10 ** p<0.05 *** p<0.01). Column (1) shows results for the extensive margin (any ambulance establishment), while column (2) shows results for the intensive margin (number of ambulance establishments). Both models include economic controls (employment-to-population ratio) and demographic controls (age composition variables). Both specifications also include county fixed effects, state fixed effects, and state-specific time trends. The models are weighted using population weights. Data on ambulance establishments 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 7: Robustness Check: Alternative Intensive Margin Specifications

	Main Specification		Additional Establishments	
	Count | Any Establishment		(Count - 1) | Any Establishment	
	(1)	(2)	(3)	(4)
Uninsured Rate × Medicaid Expansion × Post	1.3963**	1.7943***	2.0087**	2.6667***
	(0.6625)	(0.6812)	(0.9773)	(0.9914)
Observations	21,466	20,969	16,154	15,810
Controls	No	Yes	No	Yes

Notes: This table shows robustness of intensive margin results to alternative specifications. Columns (1-2) model the count of establishments conditional on having at least one. Columns (3-4) model additional establishments beyond the first (count - 1) conditional on having at least one. All models condition on Establishments > 0 to focus on the intensive margin of expansion.

Table 8: Robustness Checks: Triple-Difference Estimates for Any Ambulance Establishment (Extensive Margin)

	(1) Full Model	(2) No Econ. Controls	(3) No Demo. Controls	(4) No State Trends	(5) State× Year FE	(6) No Sample Weights
Sample Mean Pre-Treatment Uninsured Rate			0.1859			
Unins. Rate × Medicaid Exp. × Post	0.3670*	0.3853*	0.3200	0.5654**	0.8436	0.2834
	(0.2069)	(0.2040)	(0.2046)	(0.2761)	(0.5147)	(0.1759)
Implied Effect at Mean Unins. Rate	0.0682*	0.0716*	0.0595	0.1051**	0.1568	0.0527
	(0.0385)	(0.0379)	(0.0380)	(0.0513)	(0.0957)	(0.0327)
Effect Relative to Pre-Treatment Mean (%)	66.13	69.42	57.65	101.87	152.00	51.07
Economic Controls	Yes	No	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	No	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	No	Yes
State-Specific Time Trends	Yes	Yes	Yes	No	No	Yes
State × Year Fixed Effects	No	No	No	No	Yes	No
Sample Weights	Yes	Yes	Yes	Yes	Yes	No
Observations	45,252	45,252	45,252	45,252	45,252	45,372
Adjusted R^2	0.697	0.697	0.697	0.693	0.698	0.715

Notes: This table presents robustness checks for the triple-difference estimates of the effect of Medicaid expansion on the presence of any ambulance establishment in a county (extensive margin). Column (1) presents the full model with all controls. Column (2) excludes economic controls. Column (3) excludes demographic controls. Column (4) excludes state-specific time trends. Column (5) includes state-by-year fixed effects instead of state-specific time trends. Column (6) excludes sample weights. The Effect Relative to Pre-Treatment Mean row shows the percentage impact per 1 percentage point change in uninsurance rate, calculated as (coefficient/pre-treatment mean of expansion states)*100. Pre-treatment mean of 0.555 for the extensive margin is used, as reported in Table 1. Standard errors clustered at the state level in parentheses. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

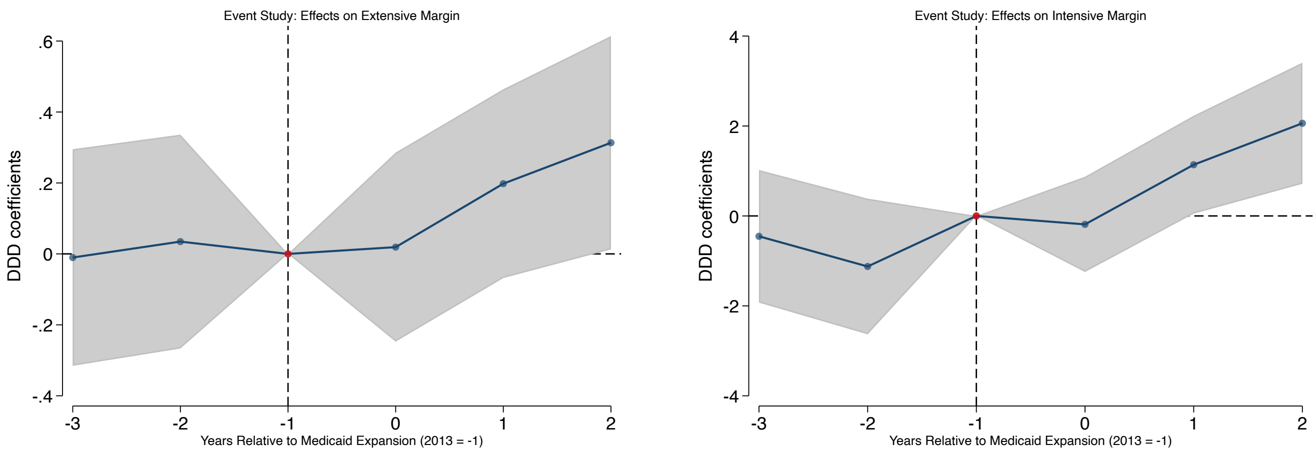
Table 9: Robustness Checks: Triple-Difference Estimates for Number of Ambulance Establishments (Intensive Margin)

	(1) Full Model	(2) No Econ. Controls	(3) No Demo. Controls	(4) No State Trends	(5) State× Year FE	(6) No Sample Weights
Sample Mean Pre-Treatment Uninsured Rate			0.1859			
Unins. Rate × Medicaid Exp. × Post	1.9588*	1.9925*	1.1848	0.3067	0.4636	3.7266
	(0.9965)	(0.9990)	(1.0147)	(0.9331)	(1.6671)	(2.2569)
Implied Effect at Mean Unins. Rate	0.3641*	0.3704*	0.2203	0.0570	0.0862	0.6928
	(0.1853)	(0.1857)	(0.1886)	(0.1735)	(0.3099)	(0.4196)
Effect Relative to Pre-Treatment Mean (%)	114.01	115.98	68.97	17.85	26.98	216.91
Economic Controls	Yes	No	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	No	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	No	Yes
State-Specific Time Trends	Yes	Yes	Yes	No	No	Yes
State × Year Fixed Effects	No	No	No	No	Yes	No
Sample Weights	Yes	Yes	Yes	Yes	Yes	No
Observations	45,252	45,252	45,252	45,252	45,252	45,372
Adjusted R^2	0.849	0.849	0.845	0.847	0.851	0.891

Notes: This table presents robustness checks for the triple-difference estimates of the effect of Medicaid expansion on the number of ambulance establishments in a county (intensive margin). Column (1) presents the full model with all controls. Column (2) excludes economic controls. Column (3) excludes demographic controls. Column (4) excludes state-specific time trends. Column (5) includes state-by-year fixed effects instead of state-specific time trends. Column (6) excludes sample weights. The Effect Relative to Pre-Treatment Mean row shows the percentage impact per 1 percentage point change in uninsurance rate, calculated as (coefficient/pre-treatment mean of expansion states)*100. Pre-treatment mean of 1.718 for the intensive margin is used, as reported in Table 1. Standard errors clustered at the state level in parentheses. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

Appendix Figures

Figure A1: Event Study: Effect of ACA Medicaid Expansion on Ambulance Services (90% Confidence Intervals)

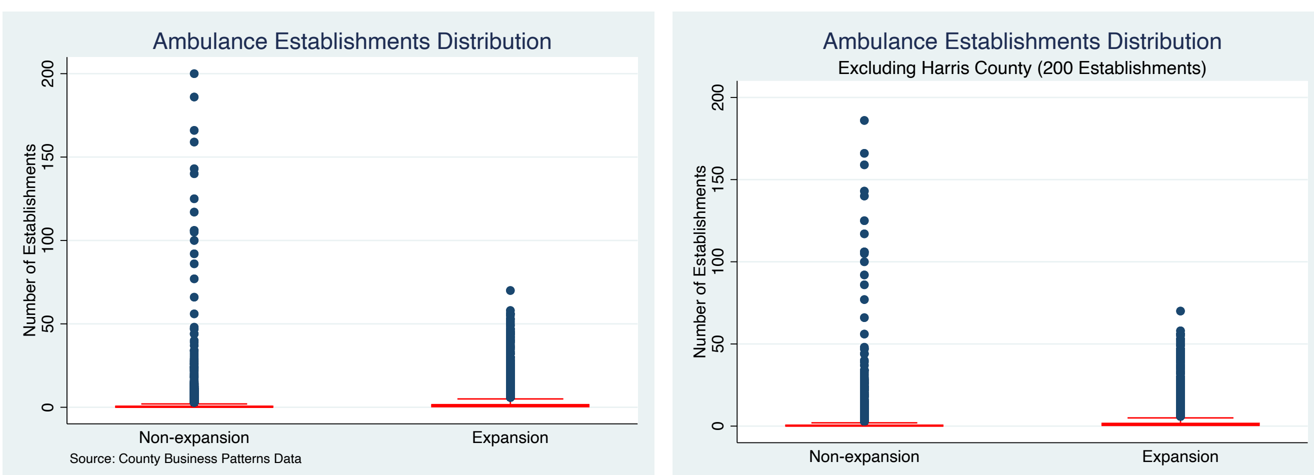


(a) Extensive Margin (Any Establishment)

(b) Intensive Margin (Number of Establishments)

Notes: These event studies replicate Figure 5 from the main text but display 90% confidence intervals instead of 95% confidence intervals. Panel (a) shows effects on the extensive margin (probability of any establishment), while panel (b) shows effects on the intensive margin (number of establishments). The narrower confidence bands help visualize the pattern of effects. All other specifications remain identical to the main analysis.

Figure A2: Box Plots of Establishments by Medicaid Expansion Status

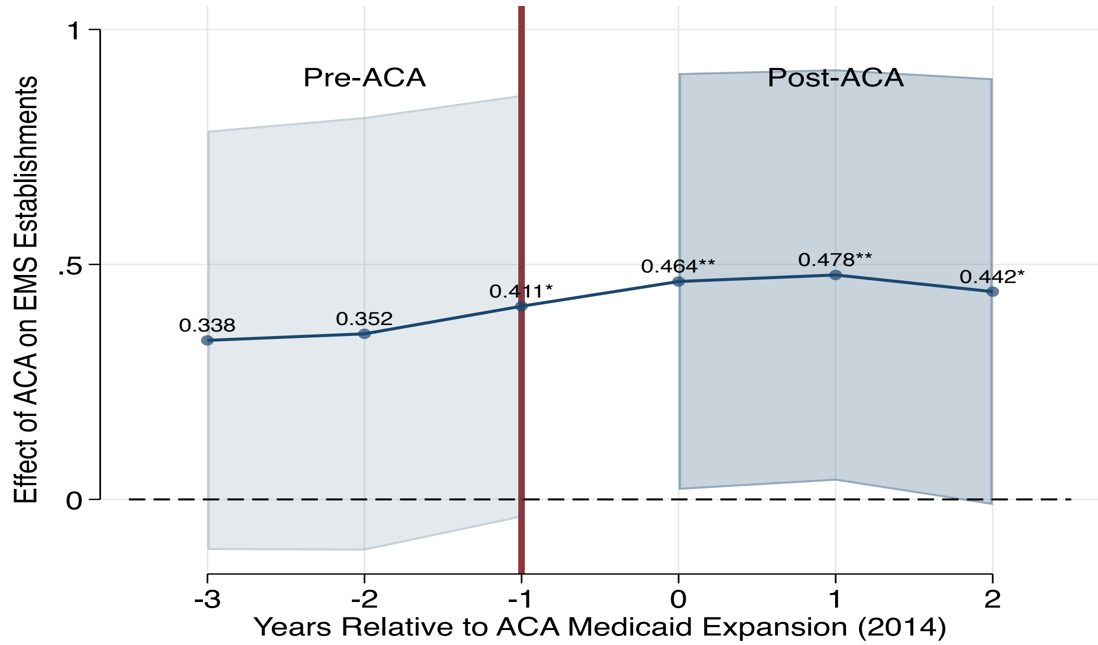


(a) Including All Counties

(b) Excluding Harris County, TX

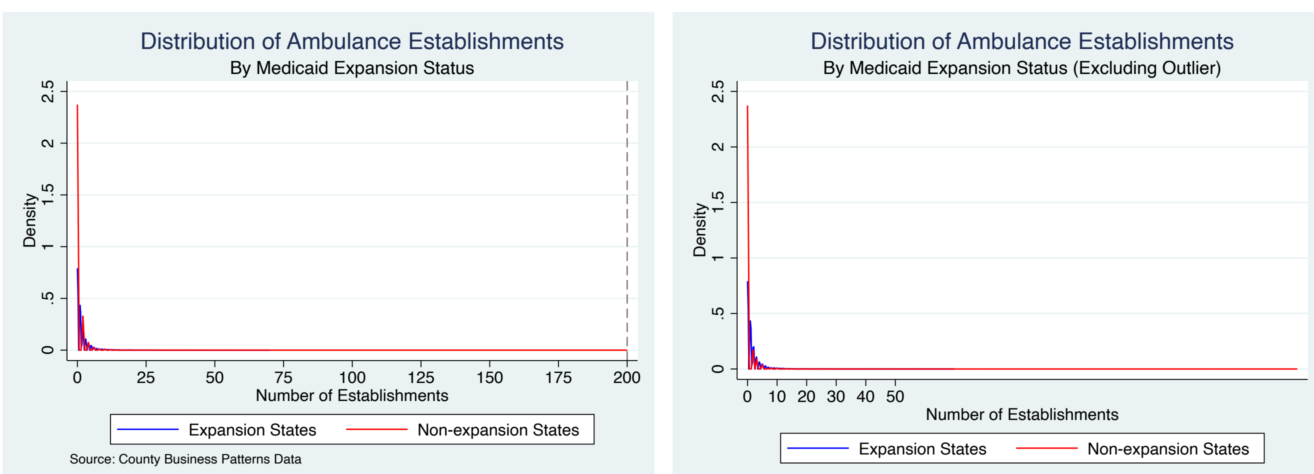
Notes: The box plots show the distribution of ambulance establishments across counties, grouped by whether the state expanded Medicaid under the Affordable Care Act. The middle line represents the median, the box shows the interquartile range (IQR), and the whiskers extend to 1.5 times the IQR from the 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 A3: Effect of ACA Medicaid Expansion on Ambulance Services Establishments



Notes: Graph shows triple difference coefficients (Medicaid Expansion × Uninsured Rate × Post) and 95% confidence intervals. Year -1 is the last pre-treatment year. Vertical line indicates ACA implementation in 2014. The stable pre-treatment coefficients support the parallel trends assumption, while the increasing and statistically significant post-treatment coefficients demonstrate the causal effect. *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by county.

Figure A4: 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).