ECON H195B

# The Effect of ACA Medicaid Expansion on Ambulance Demand

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## 1.1 Abstract

This paper examines ambulance demand trends as a result of changes in healthcare law, comparing Medicaid expansion states versus states that chose not to expand Medicaid. The analysis was made possible by the creation of a dataset containing ambulance company patient care reports compiled by the EMS national data repository NEMSIS. Using different groupings of states, we found significant differences in ambulance demand trends between expansion and non-expansion states, with the direction of those trends inconsistent and region-specific. When controlling for differences between healthcare markets, we found that Medicaid expansion had little impact on the demand for ambulance care.

## 1.2 Introduction

On March 21, 2010, despite bipartisan opposition in the U.S. Senate and House, Congress passed by reconciliation the Patient Protection and Affordable Care Act by reconciliation. President Obama would sign the bill on March 23, setting up the most significant overhaul of the American healthcare system since Medicare and Medicaid were enacted in 1965. Since its passage, the ACA has remained a highly contentious bill in American political debate, both in terms of its mixed economic effect on the healthcare market, and its moral insinuations on the right of all citizens to affordable healthcare. The purpose of this paper will be to examine ambulance demand as an economic effect of the law's passing.

One of the primary market-expansion elements of the ACA was Medicaid, where the Federal government expanded Medicaid to uninsured adults and children whose incomes were below 138% of the federal poverty level (FPL). Many states with GOP governors and legislatures chose to limit expansion of Medicaid in their states. Accurately studying the impacts of increasing healthcare coverage has only been made possible now due to the natural control formed by the markets in states that chose not to expand Medicaid. The national percentage[1] of Americans covered by Medicaid increased from 17.5% to 19.5% upon the 2014 expansion due to the ACA. Since then, that percentage has remained steady: 19.6% in 2015 and 19.5% in 2016.

With that well-defined and time-specific treatment in place, researchers have been able to study the 2014 ACA Medicaid expansion as a quasi-natural experiment as much like the Oregon Medicaid lottery study (Finkelstein, 2012). Additionally, studying the emergency medicine effects of Medicaid expansion offer a market free from many of the consumer choice bias that plague the study of other healthcare sectors. In emergency care, providers are almost always randomly assigned, both for emergent cases, and for the Medicaid/Medicare dialysis, etc. non-emergent transports where patients rarely have market power to choose their provider. Therefore, comparison studies of populations with and without Medicare become empirically powerful when examining emergency medicine, with patients having, in theory, relatively inelastic demand and little choice in provider. Healthcare is not a traditionally efficient economic marketplace and so studies of demand can be tainted my bias, such as the quality of healthcare in a state leading to greater or lesser demand. Thus, it is empirically important to find areas where natural experiments can occur, such that demand will not be as impacted by the socioeconomic status of the patient or the quality of the provision, and where differences in patient markets can be controlled. This can be addressed by looking at emergency healthcare provision as a result of changes in Medicaid enrollment across states that have opted in or out of Medicaid expansion.

While studies have already been conducted on emergency department use, increased consistency in reporting by local EMS companies now provides the ability to conduct this

[1] U.S. Census Bureau, Current Population Survey, 2014 to 2017 Annual Social and Economic Supplements.

analysis on ambulance demand. Ambulances have a prominent role in our healthcare markets whose financial/economic costs certainly demand investigation. In 2011, the United States spent about $14 billion on ambulance services, $5.3 billion of which Medicare paid for[2]. Furthermore, they represent an ideal type of care for studying demand changes. We expect ambulance demand to be a particularly demand elastic healthcare service, as recent studies have estimated nearly 30% of ambulance trips are unnecessary. There is also evidence to suggest defensive care can reduce the demand for emergency care provision including ambulance use, which will be outlined in the next section. For empirical purposes, ambulances provide a relatively constant and now measurable healthcare provision to study emergency care demand. They are randomly assigned, preventing issues of bias due to patients preferring higher-quality care. Finally, ambulance cost is not as variable as many other healthcare services, partly due to the standardized and limited scope of treatment, as the cost of a transport stays relatively constant depending on the condition being treated.

In this paper, we will study ambulance transport demand to hypothesize a model for the demand-side elasticity of ambulance transport when Medicaid expansion lowers the price of transport for many low-income consumers but also increases their access to defensive care. To measure the effectiveness of the ACA in reducing expensive ambulance demand, we will use ambulance data from the University of Utah School of Medicine, collected via the voluntary participation of states across the U.S. This data comes from the patient care reports of Ambulance providers, both public and private. These reports are legally-binding documents, filled out for the purposes of billing and quality control in EMS, and thus theoretically have

[2] Frakt, Austin. "Uber, Lyft and the Urgency of Saving Money on Ambulances." New York Times [New York] October 1, 2018. Print.

strong empirical validity. From counts of these reports, weighted by population, we will use a differences in differences analysis to measure the relative demand increases for ambulance transport in Medicaid-expansion states versus states that rejected expansion. From this analysis, we will relate our results to existing models of emergency care demand, and draw conclusions about the demand characteristics of U.S. ambulance transport, and thus establish a review of one of the primary policy goals of the ACA: reducing expensive emergency care provision by making preemptive care more available to high-risk populations.

### 1.3 Literature Review

While passed in 2010, the major provisions of the ACA did not come into force until 2014. These major provisions included Guaranteed Issue, otherwise known as prohibiting the denial of insurance based on pre-existing conditions, the Individual Mandate, which allowed taxation for members of the population without health insurance, and finally the subsidies, which were payments to families between 100% and 400% of the poverty level to assist them in acquiring health insurance.

In addition to these subsidies, a key component of increasing access to healthcare was the expansion of Medicaid. Here, the Federal government would increase the maximum income eligibility for access to Medicaid from 100% of the poverty level to 133% of the poverty level. However, in the 2012 case *NFIB v. Sebelius,* the Supreme Court ruled this provision of the ACA to be “coercive,” and mandated the federal government to “allow states to continue at pre-ACA levels of funding and eligibility if they chose.”[3]

[3] "National Federation of Independent Business v. Sebelius: The Patient Protection and Affordable Care Act." Harvard Law Review 126, no. 1 (2012): 72-82. http://www.jstor.org/stable/23415891.

The individual impact of expanding Medicaid is clear and has been well-documented by the National Center for Health Statistics (Martinez et al., 2017), "States that chose to expand Medicaid coverage to people with low incomes had the ranks of their uninsured cut in half, to 9.2 percent in 2016 from 18.4 in 2013. In states that did not expand Medicaid, the rate moved down slightly, to 17.9 percent in 2016 from 22.7 percent in 2013. States that chose to expand Medicaid coverage to people with low incomes had the ranks of their uninsured cut in half, to 9.2 percent in 2016 from 18.4 in 2013. In states that did not expand Medicaid, the rate moved down slightly, to 17.9 percent in 2016 from 22.7 percent in 2013."

With it being well-established in the non-partisan literature that the expansion of Medicaid has led to increased participation in the health insurance pool, we now focus on the next extension of the logic: that increased coverage has led to greater utilization of healthcare. In a previous analysis of the expansion of Medicaid, researchers took advantage of a unique Medicaid lottery that randomly assigned Medicaid to "low-income" individuals in Oregon. The results of the NBER working paper showed overwhelmingly that newly covered individuals had "substantively and statistically significantly higher health care utilization" compared to their uninsured peers (Finkelstein et al., 2012).

Having established that the expansion of Medicaid led to greater insurance utilization rates in the states that expanded it, and further establishing that covered low-income individuals have higher healthcare utilization rates than their uninsured peers, the resulting syllogism would state that the expansion of Medicaid increases healthcare utilization rates. Where these utilization rates occur is important to the analysis of the law's economic impact.

This paper seeks to analyze/quantify a specific segment of potential healthcare savings as a result of Medicaid expansion, namely the healthcare costs saved as a result of newly insured patients in Medicaid expansion states electing to receive defensive primary care, rather than utilize the emergency room, where the government ends up footing the entirety of the expensive emergency care bill, including transport and procedure.

The negative economic effect of utilization of expensive emergency care by the uninsured is often cited as a reason for universal healthcare. In 1986, the Emergency Medical Treatment and Active Labor Act (EMTALA) was passed, which prohibits hospitals from denying emergency care to patients based on their ability to pay for it, potentially leading to the uninsured utilizing the emergency room for conditions that could be treated or prevented in a physician's office. This potential economic impact became a major selling point[4] for the ACA around the time of its genesis.

These arguments are not without empirical origin. As evidenced above, Policy-makers argue that providing public health insurance lowers long-run costs by reducing the need for emergency department visits later in life. Some of the best evidence of this effect come from analysis of the 2006 Massachusetts healthcare law, legislations that the ACA was largely modeled on. These studies have found that the Massachusetts bill increased the use of primary care and preventative services, such as office visits, check-ups and flu shots (Miller 2012; Long, Stockley, and Dahlen 2012; Kolstad and Kowlaski 2012). More recently, when researchers have looked at the health impacts of Medicaid expansion on children (Wherry, Miller, Kaestner & Meyer, 2018). They found that having more years of Medicaid eligibility in childhood "is associated with fewer hospitalizations and emergency department visits in adulthood for blacks."

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[4] On Tuesday, April 29th, 2008 in South Bend, Ind., Hillary Clinton remarked that "Every family health insurance policy has "a $900 hidden tax" to subsidize health care costs of the uninsured," implying this tax was the result of "emergency room visits." In an interview on This Week with George Stephanopoulos on September 20th, 2009, Barack Obama claimed that "Families are paying $900, on average, "in higher premiums because of uncompensated care."

Those effects are particularly evident for conditions related to chronic illnesses and for patients living in low-income neighborhoods. Much of ambulance transport affects these health communities specifically, and so decreasing rates of ambulance utilization in states affected by Medicaid expansion could be a reasonable expectation.

Many opponents of a public option insist this argument to be null and void on the basis that emergency care represents a small portion of total health expenditure, that portion in fact remains large. Some studies cite the Medical Expenditure Panel Survey, which counts 49 million ER visits accounting for roughly 2% of national healthcare spending. A 2008 survey[5] endorsed by the American College of Emergency Physicians (an ER doctor advocacy group) discovered that the total expenditure on emergency care – "including physician and other emergency-room services" -- was $47.3 billion (2% of the multi-trillion annual U.S. healthcare spend). More recently, a study by researchers from the Alpert School of Medicine at Brown and Harvard Medical School showed that emergency medical spend may be as high as 10% of total healthcare spending (Lee, Levin, Schuur, 2013).

Another critique of the preventative services argument is that while preventative health service utilization does not necessarily lead to lower rates of hospitalization. The Oregon Medicaid Lottery showed this effect (Finkelstein et al., 2012).

When it comes to emergency room visits, there exists a great deal of recent data that indicates emergency room visits actually increased with greater proliferation of health insurance coverage. Two recent studies, (Eili et al., 2017; Nikpay et al., 2017), used differences in

[5] Agency for Healthcare Research and Quality. Emergency Room Services-Mean and Median Expenses per Person With Expense and Distribution of Expenses by Source of Payment: United States, 2008. Medical Expenditure Panel Survey Household Component Data. Generated interactively. (September 10, 2018)

differences analysis to confirm visits are actually on the up since the enacting of the healthcare law. In particular, the Nickpay 2017 study used Medicaid expansion states vs non-expansion states as study groups, a process used by this paper as well. This increase may seem counterintuitive, but a variety of explanations exist for this behavior.

Demographics may play a role in these increases, as older Americans, as a total percent of the population are on the rise, and thus may contribute to the rising incidence of emergency care naturally since they use emergency care at higher rates than the rest of the population. Indeed, age would seem to be a lurking variable, perhaps making older states appear more reliant on emergency care, when in fact this greater prevalence of emergency care usage. A 2015 study done by the FAIR Health Survey[6] offered evidence to contradict this explanation, finding that older folks were actually less likely to use the emergency room for non-emergent medical issues than their younger counterparts, thus giving credence to the notion these increases were not due to more visits for frivolous medical issues among older populations. Either way, this paper seeks to negate the effects of age by running a differences in differences approach which will eliminate any confounding effects due to average age of the state, assuming the relative population distributions stay similar. This may not always be the case, and that is why this paper's analysis will also include the control variable for % population above 65.

[6] "FAIR Health Survey: Viewpoints about ER Use for Non-Emergency Care Vary Significantly by Race, Age, Education and Income." PR Newswire: News Distribution, Targeting and Monitoring. May 6, 2015. Accessed September 17, 2018.

| Question: In the event that you require treatment for a non-emergency or non-life-threatening situation, where would you most likely go for care? | | | | |
|---|---|---|---|---|
| **Age** | **Emergency Room** | **Primary Care** | **Urgent Care** | **Walk-in Clinic at a Pharmacy or Retail Center** |
| 18-34 | 25% | 43% | 21% | 7% |
| 35-44 | 21% | 54% | 19% | 3% |
| 45-54 | 19% | 64% | 8% | 5% |
| 55-64 | 16% | 62% | 13% | 7% |
| 65+ | 22% | 59% | 9% | 4% |
| Total Population | 21% | 55% | 15% | 5% |

Another possibility for the increases could be due to difficulties among Medicaid patients in finding primary care providers. A 2017 paper by researchers at the Urban Institute found Medicaid rates in 2014 (Zuckerman, Skopec & Epstein, 2017), the year Obamacare was put into practice, were just two-thirds the amount of equivalent Medicare payments, meaning doctors lack the financial incentive to find primary care homes for these patients. That leads to more emergency care visits, especially since "two-thirds of emergency visits occur on weekends and when doctors' offices are closed," per Laura Gore, a spokeswoman for the American College of Emergency Physicians.

Perhaps the most significant reason why these visits do not decrease is that visits to all forms of care providers increase when a population lacking healthcare suddenly is provided it.

The Oregon Medicaid Lottery cited earlier presents the best evidence for this phenomenon as holding all else constant, those with newly acquired health insurance had higher utilization rates "across many settings, including the doctor's office, the pharmacy, the hospital, and the emergency room," per Katherine Baiker, a professor of health economics at Harvard University's T.H. Chan School of Public Health and co-author of the Oregon study. She notes that "This is what one might expect from the basic economics: Medicaid took health care that was expensive and made it free, so people used more of it."

This study seeks to expand on the existing literature as while evidence exists to suggest that emergency room usage has increased after 2014 in part thanks to Medicaid expansion (Hernandez, Burns, Wang, Baker & Goldstein 2014), there is little to no corresponding research for ambulance use. While hard to measure due to the fragmentation of the system, ambulance use contributes significantly to the overall emergency healthcare bill. While impossible to find the entire number across the EMS web, Medicare tallies represent a way we can estimate these costs. In 2002[7], Medicare reimbursed ambulance transport to the amount of $3 billion. In 2002, another research study[8] found that only 55% of the money made by ambulance companies came from Medicare reimbursements, meaning the amount American consumers spend on ambulance transport may be double that number. Now in the most recent data[9] published by the Center for Medicare and Medicaid (CMS), that reimbursement total now stands at $5.8 billion for 2013.

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[7] Office of Inspector General and Department of Health and Human Services. Medicare payments for ambulance transports. OEI-05-02-00590. Washington, DC. 2006.

[8] Overton J. Reimbursement in emergency medical services: How to adapt in a changing environment. Prehosp Emerg Care. 2002;6(1):137-140.

[9] Centers for Medicare & Medicaid Services (CMS), 2003 and 2012 Part B National Summary Data Files.

The economic impact of ambulance transport on taxpayers and the government in Medicare alone remains significant and is growing.

Despite being unable to accurately track the full economic impact of ambulance transport outside of Medicare reimbursement, transport remains a significant cost in even the leaner Obamacare plans. For Silver plans, a lower-tier plan within the Affordable Care Act's exchange-purchased insurance provision, an initial copay of nearly $250 for the emergency room is matched and exceeded on average by a $250 or more minimum copay for the ambulance transport to the ER. Beyond Medicare, ambulance transport remains a significant cost for U.S. consumers.

Thus, this paper seeks to measure the economic impact of increases/decreases in ambulance transport and pre-hospital care, specifically as caused by Medicaid expansions, an effect that can be measured by differences in differences due to the fact that there exist similar patient populations between states that expanded Medicaid and those that chose not to expand.

Despite the evidence listed above that points to emergency room visits increasing after Medicaid expansion among affected populations, there is reason to believe the picture may be more complicated in terms of ambulance transport. A study looking at ambulance data across several types of patient populations between 2004 and 2006 found "visits by patients with Medicaid and the uninsured were more likely to arrive by ambulance than visits by patients with private insurance. Ambulance use among the uninsured was most pronounced in metropolitan areas" (Meisel et al., 2011).

Utilizing an approach modeled after a differences in differences study estimating the effect of a practice becoming PCMH-certified on ED visits employing either practice or patient fixed effects, this paper will present a similar estimation of the effect of Medicaid expansion on the utilization of ambulance transport and pre-hospital care (David, 2014). We will be using control variables related to the possible changes in the patient pool over time for each state examined that could confound the effect we wish to measure. The data comes from the NEMSIS repository, an exhaustive database comprising the millions of patient care reports filled out by EMS services on every patient they see.

### 1.4 Model, Methods, Data

Before we empirically compare ambulance utilization rates in Medicaid expansion states vs non-Medicaid expansion states, we will build a model for ambulance demand. Some of the first microeconomic analysis done on this type of demand was done on the subscription model for ambulance service in Australia (Butler, 1981). Demand for ambulance was seen as a function of the randomness of the event, where true emergencies represented inelastic demand and where consumers could offset this uncertainty by first learning how to mitigate the risk of their own activities, and second, paying someone else to bear the risks of the uncertainty of that injury. Butler found a demand slope of -.0529 for emergent trips for the uninsured (fairly inelastic), while the demand curve for non-emergent trips among the uninsured was -5.3296 (fairly elastic). Overall, the demand curve for both insured and non-insured populations combined was -.0183 for emergent and -.3331 for non-emergent.

Therefore, if we were to model demand for ambulances, we would begin with the following:

**P(ambulance utilization per time period) = f(emergent status of the condition)**

This variable also partially takes into account the impact of finances on demand for ambulance care. It has been shown that individuals gaining Medicaid when before they had no coverage significantly lowered their unpaid medical bills as well as the likelihood that a third-party collection agency would come after them (Hu, Kaestner, Mazumber, Miller & Wong, 2018). If we were to fully take this variable into account we would add an insured element to our demand model: those who are insured are more likely to use ambulance service. Our model is now:

**P(ambulance utilization per time period) = f(emergent status of the condition, insured status, socioeconomic status)**

Finally, with respect to demographics, there exist differences in demand across certain groups, diverging whether the condition is emergent or non-emergent. In the 65+ age bracket, we see higher demand for non-emergent ambulance transport (Butler, 1981; Street et al., 1996). Furthermore, we see higher demand for both non-emergent and emergent transport among males (Butler, 1981). Therefore, with demographics included, our final hypothetical model for ambulance demand resembles:

**P(ambulance utilization per time period) = f[emergent status of the condition, insured status, socioeconomic status, amount of preventative care previously obtained, sex, age (65+)]**

With our demand function modeled, we will strive to incorporate as many facets influencing that demand as possible into our differences in differences model below. In the model we used with data, we were unable to obtain emergent status of the condition, but we will assume that these rates stayed constant over time (perhaps not the same between the states but the differences between the states stayed relatively constant).

The data used for this project is courtesy of the National Emergency Medical Services Information System (NEMSIS), which is the national database that is used to store EMS data from the U.S. States and Territories. Dr. N. Clay Mann, PhD, MS, approved the use of the confidential elements of the data set, including information protected by physician privilege laws in the state of Utah, where this database operates.

Another key a confidentiality issue regarding the NEMSIS dataset is the states' individual wishes for anonymity of its EMS organizations, and so the effects measured in this study must be made in comparisons of no less than three states for any given comparison such that the individual data for each state could be hidden from identification. In this paper, we wish to establish if an effect exists, not to identify the geographical identity of that effect.

The NEMSIS data sets for 2010-2016, are cross-sectional and contain, with exceptions[10], all reported EMS calls performed in the years 2010-2016. It contains about 29 million data elements (EMS calls), each with a unique call ID. Calls occasionally have multiple patients and multiple units responding to the scene, such as in the event of a Mass Casualty Incident. These calls are unique in treatments administered and stress-related to the care providers, and also represent an infinitesimal fraction of the total EMS calls made. Nevertheless, this paper seeks to analyze the cost effects of every patient, given that each requires a separate transport and billing, and so these MCIs have been left in the dataset.

[10] Key exceptions include the state of Texas, which released limited data to NEMSIS, as well as scattered ambulance companies who did not report or are delinquent in their reporting. The IRB at the University of Utah Medical School has assured the author of this study that it did its best to report as complete figures within the states provided, and noted where data did not comprise a good estimation of the number of calls, so that those states could be omitted from the differences in differences comparisons.

Because of the confidentiality concerns from the states, we were given a single variable equal to one if a Medicaid expansion state, and equal to zero if not a Medicaid expansion state. We were given a list of states in each group for the first comparison, in which we compared all states with good reportable data. We excluded states without good data and left in states who adopted slightly late. We provided the list[11] of Medicaid expansion states to NEMSIS.

From the NEMSIS overall data, we consolidated the 7 discs of data for each year onto one Stata dataset, where we ran counts of the total number of calls in each treatment group in each year. To standardize the counts, we used Census data[12] to produce population counts for the states in each group. The count of EMS calls became the numerator, and the population of the states in the group were used as a denominator. The resulting number we will call the "EMS frequency", that is the number of EMS activations per population.

**$\hat{Y}_{j,t}$ = Count(EMS Calls for year t, treatment group j)/(Total Population of States in Treatment group j)**

Below represents an organization of the relevant variables in the differences in differences regression. J refers to treatment group where 1 represents the treatment group that

[11] The Henry J. Kaiser Family Foundation. (2018). *State Decisions on Health Insurance Marketplaces and the Medicaid Expansion*. [online] Available at: https://www.kff.org/health-reform/state-indicator/state-decisions-for-creating-health-insurance-exchanges-and-expanding-medicaid/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D#note-1 [Accessed 18 Sep. 2018].
[12] U.S. Census Bureau; American Community Survey, 2010-2017 American Community Survey 1-Year Estimates, Table GCT0101; generated by Sam Melville; using American FactFinder; <http://factfinder.census.gov>; (1 September 2018).

comprises the EMS counts from states that expanded Medicaid, and 0 represents the treatment group that comprises the EMS counts from states that did not expand Medicaid.

We will first perform a broad analysis across all reporting Medicaid expansion states against reporting non-Medicaid expansion states. Later, we will drill down on smaller comparisons to search for more statistically-significant effects.

For the first comparison, the states are organized as follows:

**Treatment group 1**: CA, OR, WA, MT, ND, MN, IA, IL, IN, OH, KY, WV, PA, MD, DE, RI, NJ, NY, VT, NH, MA, CT, ME, AR, LA, CO, NM, AZ, AK, HI, NV, MI

**Treatment group 0**: ID, WY, UT, SD, NE, KS, OK, MO, WI, TN, VA, NC, SC, GA, AL, MS, FL

The time variable, $D_t$, equals to 0 for counts in the years 2010-2013, and equals to 1 for counts in the years 2014-2016.

Below represents a table of the differences in differences approach with j referring to the treatment groups (Medicaid, no Medicaid), and t referring to the time groups (2010-2013, 2014-2016).

| $Y_{j,t}$ | $j = 1$ | $j = 0$ | Difference |
|---|---|---|---|
| $t = 1$ | $Y_{1,1}$ | $Y_{0,1}$ | $Y_{0,1} - Y_{1,1}$ |
| $t = 0$ | $Y_{1,0}$ | $Y_{0,0}$ | $Y_{0,0} - Y_{1,0}$ |
| Change | $Y_{1,0} - Y_{1,1}$ | $Y_{0,0} - Y_{0,1}$ | $(Y_{0,0} - Y_{1,0}) - (Y_{0,1} - Y_{1,1})$ |

**The highlighted box represents the effect we seek to estimate, approximated in the regression as $\hat{\beta}_3$ of $\hat{\beta}_3(D_t)(D_j)$, where $D_t$ is the time variable and $D_j$ is the treatment group variable.

The overall differences in differences regression stands as below:

$$\boldsymbol{\hat{Y}_{j,t} = \hat{\beta}_0 + \hat{\beta}_1 (D_j) + \hat{\beta}_2 (D_t) + \hat{\beta}_3 (D_t)(D_j) + \hat{\beta}_n (Xn) + \varepsilon}$$

Xn refers to set of controlling variables, which are used to negate the effects of confounding variables. The differences in differences approach already controls for confounding variables that stay constant in each population over the time of the experiment. Using U.S. Census data[13], we included control variables that might account for population changes in these states overtime. From our discussion of ambulance demand at the start of this section, we included controls deemed relevant to the ceteris paribus assumption of our demand model: sex ratio (#females/#males), median age, % above age 65, % not covered, and median house income. Each of these variables were identified and used in a similar empirical format as the papers mentioned in the beginning of this section.

Because of the anonymity concerns of the states, it remained impossible to use individual state data to construct a differences in differences analysis without using averages across states as the response variable. Unfortunately, this naturally produces a level of autocorrelation within our data as a states' average one year will be autocorrelated with those same states' average the next year. To alleviate this bias, which will could inflate or deflate our standard errors depending on the autocorrelation, we could use bootstrapped standard errors[14] (Efron, Bradley & Tibshirani,

[13] U.S. Census Bureau; American Community Survey, 2010-2017 American Community Survey 1-Year Estimates, Table GCT0101; generated by Sam Melville; using American FactFinder; <http://factfinder.census.gov>; (5 September 2018).
[14] Efron, Bradley, and Robert Tibshirani, An Introduction to the Bootstrap, Monograph in Applied Statistics and Probability, No. 57 (New York, NY: Chapman and Hall, 1994).

1994). This technique would draw random samples from our panel data (state groups, years) with replacement, and produce bootstrapped standard errors from that sample. However, to simplify the analysis and make the output more coherent, we decided to use a means table to directly compare the ambulance demand rate per population between the non-Medicaid expansion states and the Medicaid expansion states, separating each comparison between before and after.

Included with this means table will be a t statistic calculated from a test for the differences in means. It will be used to estimate the effects of Medicaid expansion on the increase in ambulance demand. By collapsing the means and finding a t stat for the difference between the ambulance demand increase in Medicaid expansion states vs. the ambulance demand increase in non-Medicaid expansion states, we avoid correlated standard errors as might be an issue in the differences in differences regression.

Finally, we will include a Wald Estimator for each comparison (G1-G4), which will measure the following relationship among the Medicaid expansion states:

**Wald** = X% increase in ambulance transport per 1% increase in Medicaid coverage

Or written in formal notation:

$$\widehat{\beta}_{\text{Wald}} = \frac{(\bar{y}_1 - \bar{y}_0)}{(\bar{x}_1 - \bar{x}_0)}$$

where in the above y1 is the average ambulance demand per population of the Medicaid expansion states AFTER the expansion of Medicaid, y0 is the average ambulance demand per population of the Medicaid expansion states BEFORE the expansion of Medicaid, x1 is the average Medicaid coverage increase per population of the Medicaid expansion states AFTER the expansion of Medicaid, and finally x0 is the average Medicaid coverage increase per population of the Medicaid expansion states BEFORE the expansion of Medicaid. This Wald estimator, effectively an IV estimate, is the difference in average demand per population before and after expansion divided by the difference in average coverage rate between the two groups. This measure is merely an estimation of the effect of Medicaid coverage increases on ambulance demand. This measure is only a reasonable measurement for regressions that showed a significant differences in differences estimator.

To help explain why possible differences in difference estimators may be weak, we will also be calculating several Wald estimators to show how significant Medicaid expansion was in the overall coverage expansion brought by the ACA in the states we will compare. To give a better sense of just how much Medicaid expansion actually expanded in Medicaid states over non-Medicaid expansion states, we will use a Wald estimator of the following form:

**Coverage Gains Comparison Wald** = (% of population that are Medicaid recipients in Medicaid expansion states after 2014 – % of population Medicaid recipients in Medicaid expansion states before 2014)/ (% of population that are Medicaid recipients in non-Medicaid expansion states after 2014 – % of population Medicaid recipients in non-Medicaid expansion states before 2014)

In summation, the Coverage Gains Comparison Wald measures the gain in the % of the population covered by Medicaid per 1% gain in Medicaid-covered population in the non-Medicaid states.

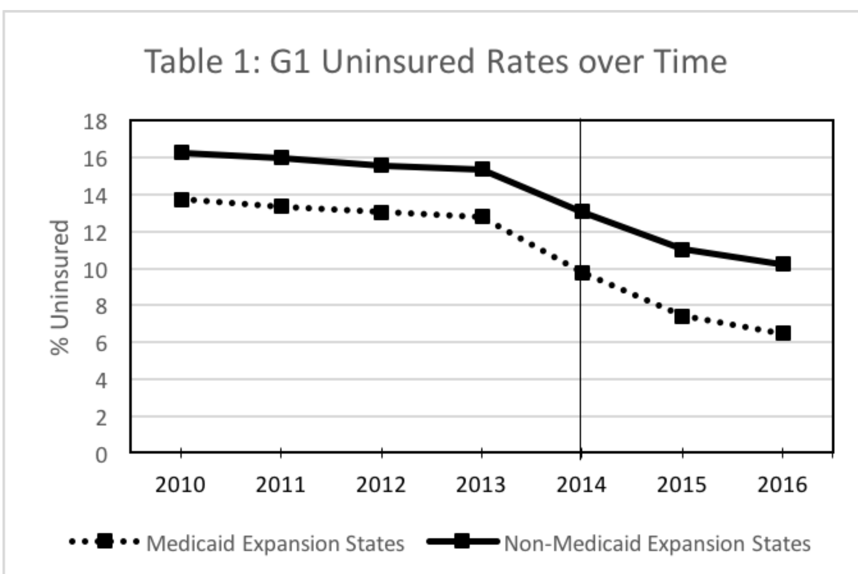
To give a sense for the total Medicaid expansion compared to the overall expansion in coverage across all areas of the population (due to the ACA's exchanges).

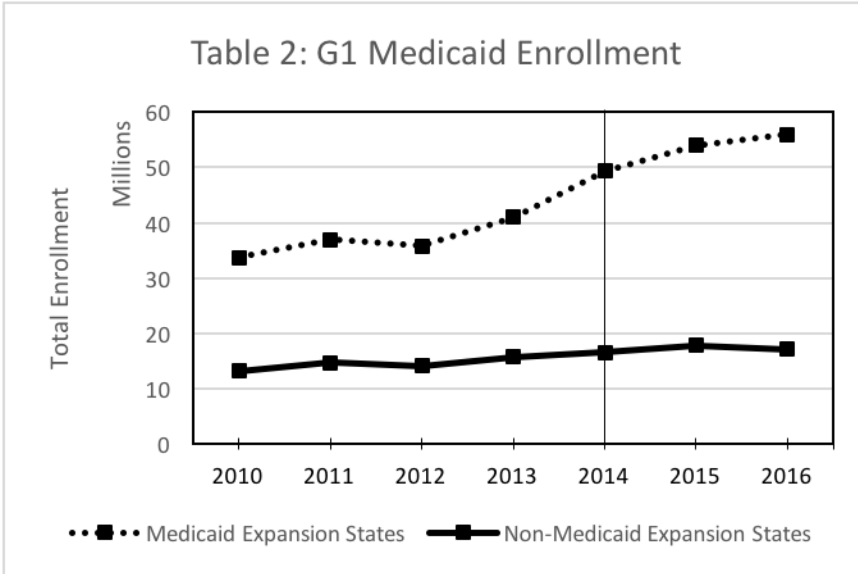
**Relative Medicaid Gains % Wald** = (average % of total covered population on Medicaid in the sampled Medicaid expansion states after 2014 – average % of total covered population on Medicaid in the sampled Medicaid expansion states before 2014)/(% of total population with health insurance after2 2014 in sampled Medicaid expansion states – % of total population with health insurance before 2014 in sampled Medicaid expansion states)

In summary, this Wald measures the amount of Medicaid expansion with respect to the total expansion within that state group (only done for Medicaid Expansion states). This will help us determine how much Medicaid expansion was a determinant in the total amount of coverage expansion, all of which would impact ambulance demand.

### 1.5 Results and Discussion

We begin our analysis with the first comparison, which we called G1, where we took all of the states we received data from.





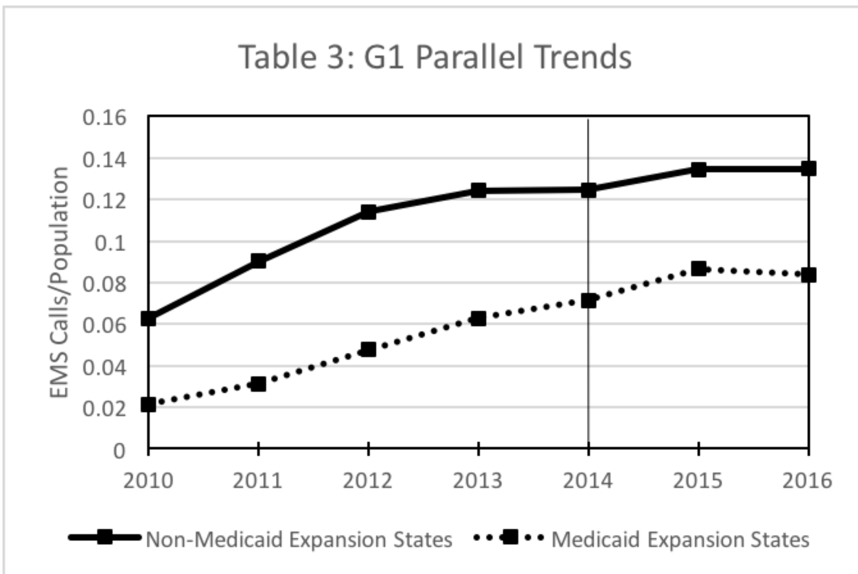

**Coverage Gains Comparison Wald** = 3.2758

This statistic shows the number of additional Medicaid recipients in the Medicaid expansion states per one additional Medicaid recipient in the non-expansion states. Here, we can verify the effects of Medicaid expansion on the actual population before proceeding with our analysis. This Wald will be larger in state groups where the Medicaid expansion states more-effectively on-boarded the uninsured and where non-expansion states kept more eligible recipients from enrolling.

**Relative Medicaid Gains % Wald** = 1.1750

This statistic represents the average number of new Medicaid recipients per one new health insurance recipient. It may seem odd that the number of new Medicaid recipients is greater than the overall number of additional new healthcare recipients, making the Wald greater than one. This may be due to a greater rate of turnover among the overall insured population (which includes those individuals later in life on Medicare for instance). Either way, the coverage gains comparison Wald represents a relative measure used to compare the strength of

Medicaid recipient growth across each state group comparison (G#), and so does not need to represent an actual numerical finding. Rather it simply needs to demonstrate the relative strength of the Medicaid onboarding effect, which will be used to see how a larger relative increase in the Medicaid population affects the T test for ambulance demand. Either way, the differences in differences regression will ensure the controlling of this effect (Medicaid population and total coverage is a variable in the regression).




The Achilles' heel of DID is when something other than the treatment changes in one group but not the other at the same time as the treatment, implying a violation of the parallel trend assumption. All the assumptions of the OLS model apply equally to DID. In addition, DID requires a parallel trend assumption. The parallel trend assumption says that the time estimators are the same in both j=0 and j=1. From a parallel trends plot, we can approximate the validity of this assumption.

As seen above in Table 3, in the years 2010-2013 before the treatment was applied, there exists a relatively parallel trend between non-Medicaid expansion states and Medicaid expansion states.

We also included tables of the total % uninsured in each treatment group within G1, as well as the total number of Medicaid enrollees per state. We felt it pertinent to include the total number of Medicaid enrollees and not a % as to give a better sense for the absolute differences between the state groups.

Below is the means table discussed earlier for the comparison G1, comprising of all the states where data could be reasonably obtained. We have the following null and alternative hypothesis for the variables where x1 is the estimation of the difference between the ambulance demands per population for the Medicaid states before and after expansion, while x2 is the estimation for the difference between the ambulance demands per population for the non-Medicaid states, their corresponding μ's (population mean differences) form the following null and alternative hypothesis:

**$H_0$: $\mu_1$ - $\mu_2$ = 0** against **$H_a$: $\mu_1$ - $\mu_2$ $\neq$ 0**

$H_0$ is the null hypothesis while $H_a$ is the alternative hypothesis that the difference in ambulance demand over time between the Medicaid and the non-Medicaid state groups is non-zero. Below is the calculation for the test statistic. The standard deviations below are sample and estimated from the standard deviations of the before and after groups.

$$= \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$$

| G1 Means | Non-Medicaid Exp. States | Medicaid Exp. States |
|---|---|---|
| Before Expansion | 0.098 | 0.041 |

| | | |
|---|---|---|
| After Expansion | 0.131 | 0.081 |

| G1 Stdddev's | Non-Medicaid Exp. States | Medicaid Exp. States |
|---|---|---|
| Before Expansion | 0.0274 | 0.0181 |
| After Expansion | 0.0058 | 0.0080 |

| | |
|---|---|
| G1 T stat | 1.025000452 |
| P value | 0.16279114 |

| | |
|---|---|
| G1 Wald | 0.5082% |
| G1 Dif in Dif Estimator | 0.0187 |
| P value | 0.0752 |

We lack the evidence to reject the null hypothesis and thus cannot conclude that the expansion of Medicaid increased or decreased ambulance demand greater than that of the non-Medicaid expansion states from this analysis alone. The Wald estimator shows a .5% increase in ambulance demand per population increase per 1% increase in Medicaid expansion in the Medicaid-expansion states of comparison G1.

Next, we performed the differences in differences regression to eliminate extraneous factors and efficiently analyze this natural Medicaid experiment with a complete framework for comparing the treatment groups while setting other factors that may affect ambulance demand constant.

The first comparison's (G1) regression output appears below.

| All States (G1) | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | frequencyems | frequencyems | frequencyems | frequencyems | frequencyems | frequencyems |
| Year | 0.0482** | 0.0407*** | 0.0476** | 0.0356*** | 0.0510** | 0.0385 |
| | (3.29) | (4.78) | (3.48) | (4.94) | (3.36) | (1.97) |
| Dpost | -0.0131* | -0.0132* | -0.00804 | -0.0143 | -0.0180** | -0.00686 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (-2.48) | (-2.36) | (-1.04) | (-1.91) | (-2.97) | (-0.55) |
| DTr | 0.998 | 0.0548* | 1.602 | 0.839 | 1.336 | 2.066 |
| | (1.21) | (2.11) | (1.72) | (0.89) | (1.33) | (1.49) |
| Pop | -9.38e-09 | | -1.56e-08 | -7.94e-09 | -1.27e-08 | -2.08e-08 |
| | (-1.16) | | (-1.72) | (-0.85) | (-1.28) | (-1.53) |
| sexratio | -0.0471 | -0.0648* | | -0.0315 | -0.0213 | -0.00663 |
| | (-1.92) | (-2.25) | | (-0.83) | (-0.73) | (-0.11) |
| medianage | -0.0656 | -0.0610 | -0.0480 | | -0.0708 | -0.0176 |
| | (-1.09) | (-1.26) | (-0.98) | | (-1.15) | (-0.20) |
| %notcovered | 0.00296** | 0.00321** | 0.00227** | 0.00308** | | 0.00467 |
| | (4.27) | (3.38) | (2.90) | (3.49) | | (1.53) |
| medhouseinc | -0.0000101*** | -0.0000109*** | -0.00000922*** | -0.00000917*** | -0.0000116*** | |
| | (-6.47) | (-5.29) | (-5.38) | (-5.38) | (-4.39) | |
| difvar | 0.0187* | 0.0161* | 0.0169 | 0.0243** | 0.0196 | 0.0164 |
| | (2.24) | (2.30) | (1.85) | (3.22) | (1.88) | (0.91) |
| Constant | -88.48** | -72.68*** | -91.98** | -67.37*** | -96.12** | -74.26* |
| | (-3.34) | (-5.07) | (-3.63) | (-4.45) | (-3.50) | (-2.10) |
| Observations | 14 | 14 | 14 | 14 | 14 | 14 |

*t* statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < .01$
* $p < 0.1$, ** $p < 0.05$, *** $p < .01$

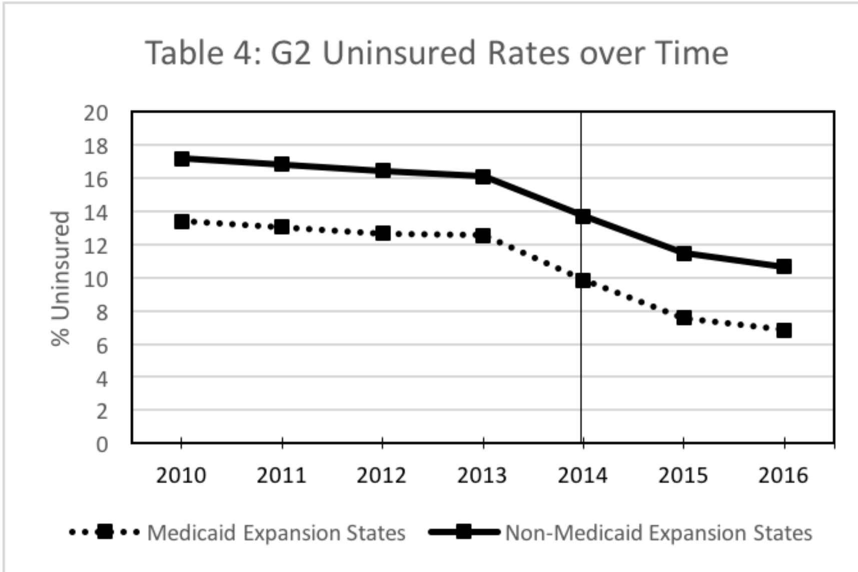
The main analysis to look at in the table above are the differences in differences coefficients. It appears from the table that since the Medicaid expansion went into effect, both groups have experienced a change in ambulance response by -.0131 calls per person, ceteris paribus (holding all else equal). “Call”, again, references a transport/treatment where a provider recognized a patient and submitted a patient care report. Meanwhile, the treatment group (Medicaid expansion states) experienced on average 1 more call per person than the non-treatment group (non-Medicaid expansion states. Most importantly, it appears that there was an increase in ambulance demand by .0187 calls per person in Medicaid expansion states compared to no-expansion states after the expansion occurred in 2014. This was a significant result only at the p = .1 significance level.

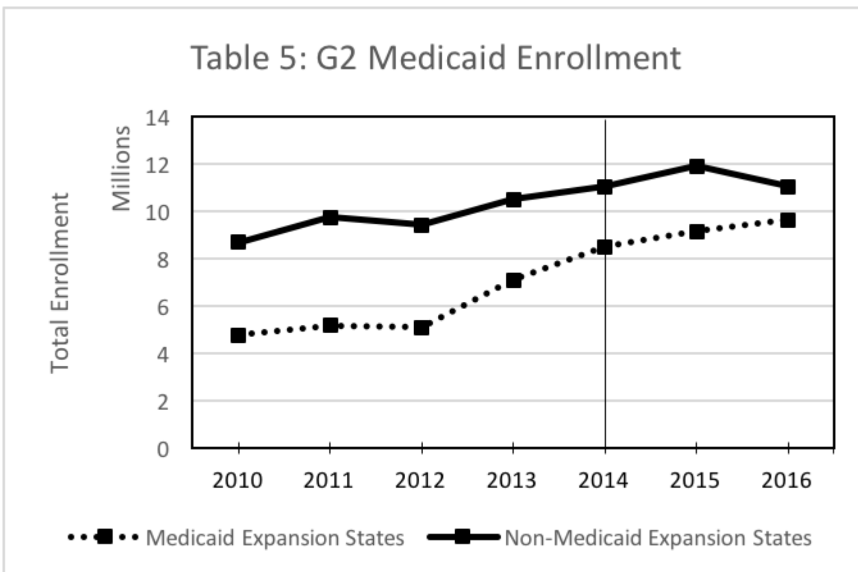
Using the first regression as an example, with every increase in the sexratio by 1, the number of calls per person in the state groups went down by .0471 ceteris paribus. This lines up with previous studies that saw higher demand for ambulances among men. It was only significant in the first regression, however and did not drastically change the difvar. With every increase in median age by 1 year, that state group's average EMS call volume per population decreased by -.0656 calls per person ceteris paribus. All of the control variables were important in reducing bias as the difvar (differences in differences variable) changed as a result of selective dropping from the model. This means that the error term and the difvar were highly correlated without the addition of the control variables and that each control variable controlled for a great deal of omitted variable bias. These control variables are essential in not under or overestimating our differences between treatment groups, as if one group's growth in gender ratio or household income was significant enough to change the ambulance call demand by itself, per population.

One of the issues with this first regression is that it included some states with limited data. A few EMS companies within each state can fail to report to NEMSIS, just like some states have not reported at all (Texas). Since the NEMSIS database is protected by confidentiality agreements, we asked the Internal Review Board at the Utah School of Medicine to choose states in which all EMS companies did in fact report their call volume to NEMSIS. We were left with new treatment groups below:

Treatment Group (Medicaid Expansion States): AK, CO, HI, ME, MI, NJ, NM, ND, WV
Control Group (no-Medicaid Expansion States): AL, FL, ID, KS, MS, MO, NE, NC, OK, SC, SD, UT

We decided to call this comparison G2. Below is the same analysis performed on G1, performed on state comparison group G2.

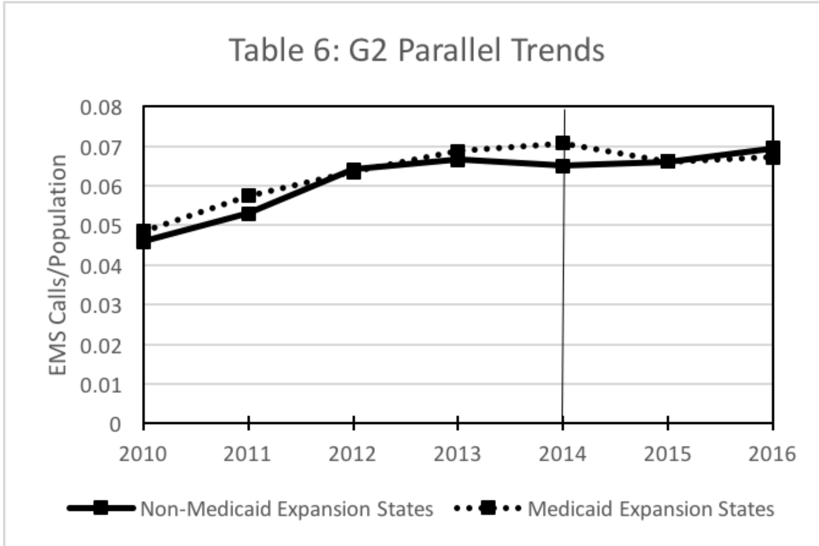



**Coverage Gains Comparison Wald** = 4.7590

This statistic shows that there were 4.7590 additional Medicaid recipients in the Medicaid expansion states per one additional Medicaid recipient in the non-expansion states (taken from averages before and after expansion in G2). We can thus verify the effects of Medicaid expansion on the actual population by pointing to the real increase in Medicaid coverage comparatively.

**Relative Medicaid Gains % Wald** = 1.7605




As seen above in Table 6, in the years 2010-2013 before the treatment was applied, there exists a relatively parallel trend between non-Medicaid expansion states and Medicaid expansion states, although perhaps slightly weaker than in G1. As before, we also included tables of the total % uninsured in each treatment group within G1, as well as the total number of Medicaid enrollees per state.

We performed the same mean differences test as well, below is the means table and resulting t statistic and p value for the test.

| G2 Means | Non-Medicaid Exp. States | Medicaid Exp. States |
|---|---|---|
| Before Expansion | 0.057 | 0.060 |
| After Expansion | 0.067 | 0.068 |

| G2 Stddev's | Non-Medicaid Exp. States | Medicaid Exp. States |
|---|---|---|
| Before Expansion | 0.0097 | 0.0087 |

| | | |
|---|---|---|
| After Expansion | 0.0023 | 0.0024 |

| | |
|---|---|
| G2 T stat | -0.440794248 |
| P value | 0.33359912 |

| | |
|---|---|
| G2 Wald | 0.0792% |
| G2 Dif in Dif Estimator | 0.000491 |
| P value | 0.9393 |

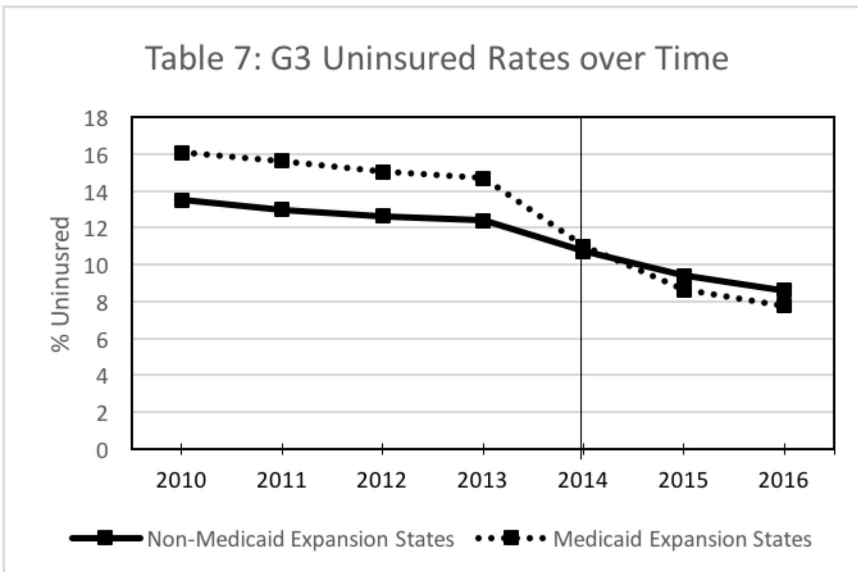
We lack the evidence to reject the null hypothesis and thus cannot conclude that the expansion of Medicaid increased or decreased ambulance demand greater than that of the non-Medicaid expansion states from this analysis of G2. The Wald estimator shows a .0792% increase in ambulance demand per population per 1% increase in Medicaid expansion coverage rate in the Medicaid-expansion states of comparison G1.

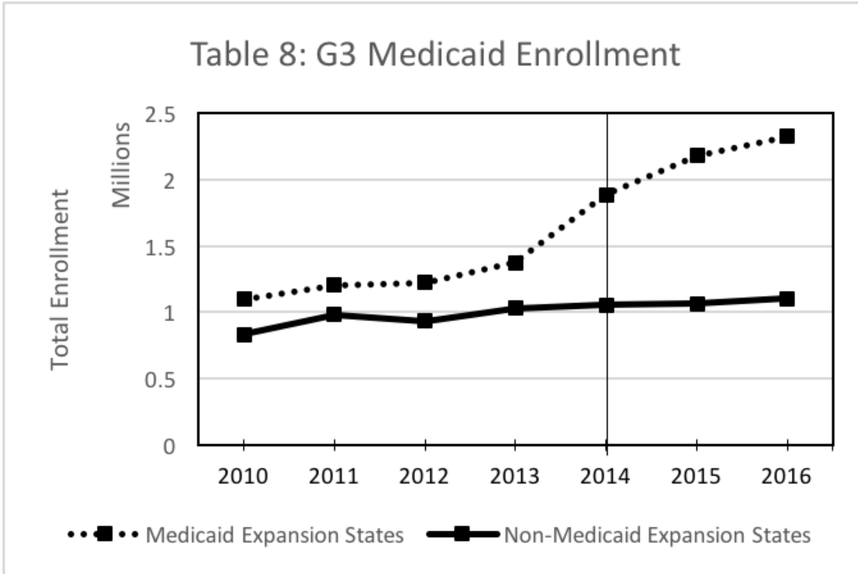
| G2 (Best Data States) | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | FrequncyEMS | FrequncyEMS | FrequncyEMS | FrequncyEMS | FrequncyEMS | FrequncyEMS |
| Year | 0.0183** | 0.0192*** | 0.0117** | 0.0112** | 0.0189 | 0.0116 |
| | (3.39) | (4.87) | (3.99) | (3.53) | (1.90) | (1.47) |
| Dpost | -0.000292 | -0.000148 | -0.000501 | -0.00105 | -0.00771** | 0.00178 |
| | (-0.08) | (-0.05) | (-0.11) | (-0.22) | (-2.83) | (0.54) |
| DTr | 0.145 | 0.107*** | 0.210 | 0.0898 | 0.111 | 0.153 |
| | (1.17) | (4.04) | (1.69) | (0.74) | (0.79) | (1.04) |
| Pop | 1.48e-09 | | 5.27e-09 | 1.17e-09 | 6.45e-11 | 3.42e-09 |
| | (0.31) | | (1.34) | (0.25) | (0.01) | (0.58) |
| sexratio | -0.0203 | -0.0237** | | -0.00744 | -0.0128 | -0.0128 |
| | (-1.37) | (-2.59) | | (-0.66) | (-0.46) | (-0.56) |
| medianage | -0.0347 | -0.0343 | -0.0163 | | -0.0275 | -0.0201 |
| | (-1.79) | (-1.81) | (-0.88) | | (-0.78) | (-0.64) |
| %notcovered | 0.00432*** | 0.00428*** | 0.00407** | 0.00416** | | 0.00587*** |
| | (4.73) | (4.61) | (3.81) | (3.99) | | (5.27) |
| medhouseinc | -0.00000355* | -0.00000368* | -0.00000295* | -0.00000273 | -0.00000740** | |
| | (-2.35) | (-2.44) | (-2.21) | (-1.95) | (-3.14) | |
| difvar | 0.000491 | -0.000331 | 0.00464 | 0.00657 | 0.000668 | 0.00294 |
| | (0.08) | (-0.08) | (0.96) | (1.23) | (0.06) | (0.37) |
| Constant | -33.40** | -34.80*** | -23.08*** | -21.87*** | -35.27* | -21.66 |
| | (-3.80) | (-5.29) | (-4.28) | (-4.13) | (-2.20) | (-1.73) |
| Observations | 14 | 14 | 14 | 14 | 14 | 14 |

*t* statistics in parentheses
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < .01$

In the differences in differences regression for G2, the control variables are mainly consistent with the results of G1, however the difvar was not significant this time, and thus ceteris paribus, Medicaid expansion had a negligible effect on the rate of ambulance demand. To verify this finding, we grouped geographically and location-similar states in smaller comparison groups and ran the same analysis. Below is our central/mountain state comparison G3:

Treatment Group (Medicaid Expansion States): CO, NM, ND
Control Group (no-Medicaid Expansion States): NE, UT, SD, KS

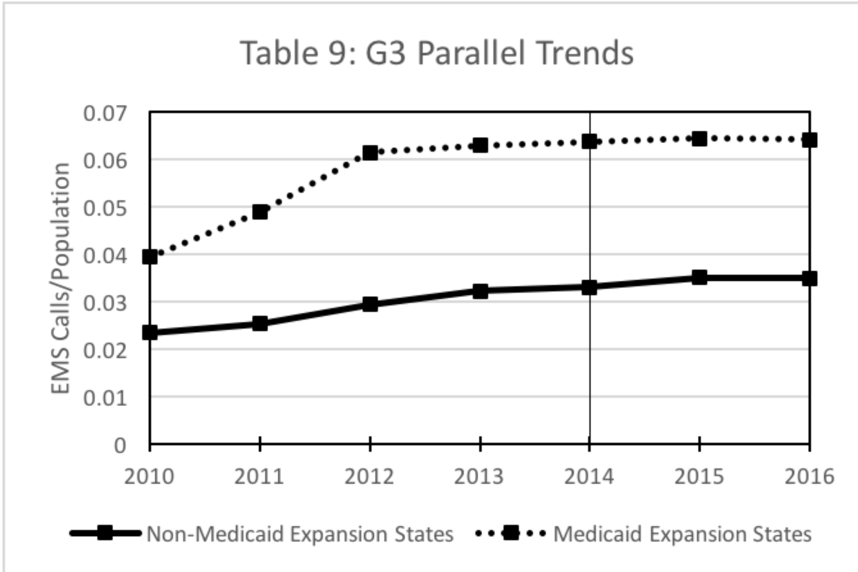





**Coverage Gains Comparison Wald** = 9.1081

This statistic shows that there were 9.1081 additional Medicaid recipients in the Medicaid expansion states per one additional Medicaid recipient in the non-expansion states (taken from averages before and after expansion in G3). We can thus verify the effects of Medicaid expansion on the actual population by pointing to the real increase in Medicaid coverage comparatively, and note that the G3 Medicaid expansion states were particularly effective at onboarding the newly Medicaid-eligible.

**Relative Medicaid Gains % Wald** = 1.1213




As seen above in Table 9, in the years 2010-2013 before the treatment was applied, there exists a relatively parallel trend between non-Medicaid expansion states and Medicaid expansion states, although this parallel trend is probably the weakest of all of our comparisons. Still however, the lines stay separate and there is enough parallel trend before the treatment occurs to perform the analysis. As before, we also included tables of the total % uninsured in each treatment group within G3, as well as the total number of Medicaid enrollees per state.

As before, we performed the mean differences test, below is the means table and resulting t statistic and p value for the test.

| G3 Means | Non-Medicaid Exp. States | Medicaid Exp. States |
|---|---|---|
| Before Expansion | 0.028 | 0.053 |
| After Expansion | 0.034 | 0.064 |

| G3 Stddev's | Non-Medicaid Exp. States | Medicaid Exp. States |
|---|---|---|

| | | |
|---|---|---|
| Before Expansion | 0.0039 | 0.0111 |
| After Expansion | 0.0011 | 0.0003 |

| | |
|---|---|
| G3 T stat | 1.84272626 |
| P value | 0.045099594 |

| | |
|---|---|
| G3 Wald | 0.1057% |
| G3 Dif in Dif Estimator | -0.00685 |
| P value | 0.5038 |

In comparison G3, we actually have enough evidence to reject the null hypothesis at the p=.05 probability that this difference in means is due to random chance, and thus can conclude that the expansion of Medicaid increased or decreased ambulance demand greater than that of the non-Medicaid expansion states from this analysis alone (increase in this case). Remember that as long as long as the population health/demographics stay constant relative to each other, that is they can change but must change in a relatively similar fashion. The Wald estimator shows a .1057% increase in ambulance demand per population increase per 1% increase in Medicaid expansion in the Medicaid-expansion states of comparison G3.

| G3 (Central U.S. States) | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | FrequncyEMS | FrequncyEMS | FrequncyEMS | FrequncyEMS | FrequncyEMS | FrequncyEMS |
| Year | -0.00732 | 0.00903 | -0.00696 | -0.00460 | -0.00357 | -0.00898 |
| | (-1.08) | (1.13) | (-1.24) | (-0.62) | (-0.50) | (-1.86) |
| Dpost | 0.00532 | -0.00609 | 0.00542 | 0.00505 | 0.00202 | 0.00580 |
| | (0.90) | (-1.00) | (1.06) | (0.64) | (0.47) | (1.29) |
| DTr | 0.190** | 0.0820* | 0.186** | 0.108* | 0.198** | 0.192** |
| | (3.27) | (2.32) | (3.53) | (2.57) | (3.34) | (3.32) |
| Pop | 0.000000211** | | 0.000000206** | 0.000000195* | 0.000000190* | 0.000000212** |
| | (2.82) | | (3.28) | (2.14) | (2.36) | (3.09) |
| sexratio | -0.00232 | 0.00205 | | -0.00236 | -0.00250 | -0.00275 |
| | (-0.31) | (0.17) | | (-0.39) | (-0.31) | (-0.46) |
| medianage | -0.0312 | -0.0260 | -0.0312* | | -0.0357* | -0.0327* |
| | (-2.04) | (-1.65) | (-2.27) | | (-2.23) | (-2.05) |
| %notcovered | 0.00280 | 0.000842 | 0.00282 | 0.00412 | | 0.00340 |
| | (0.91) | (0.27) | (1.06) | (1.41) | | (1.77) |
| medhouseinc | -0.00000147 | -0.00000187 | -0.00000166 | -0.00000327 | -0.00000389 | |
| | (-0.31) | (-0.30) | (-0.41) | (-0.62) | (-1.19) | |
| difvar | -0.00685 | 0.00731 | -0.00616 | 0.00252 | -0.0104 | -0.00711 |

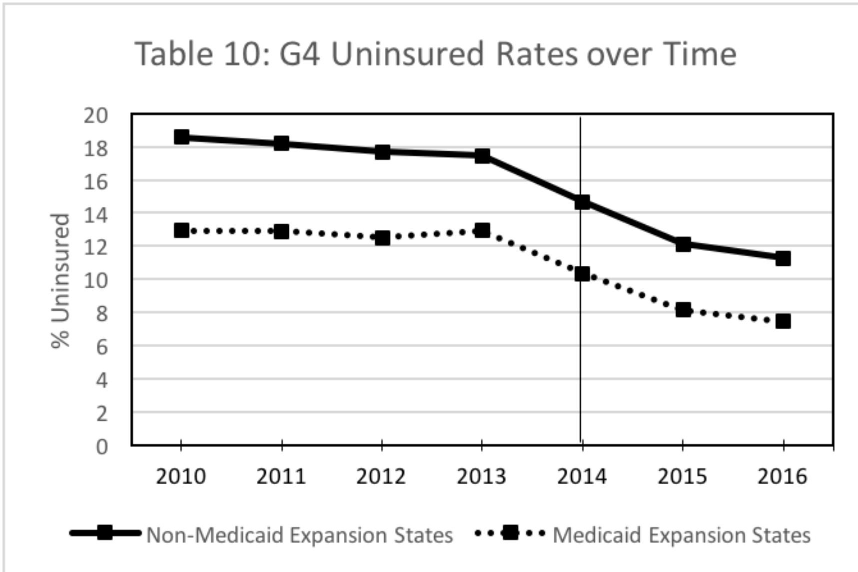
| | | | | | | |
|---|---|---|---|---|---|---|
| | (-0.72) | (0.95) | (-0.73) | (0.30) | (-1.19) | (-0.80) |
| Constant | 14.31 | -17.36 | 13.41 | 7.998 | 7.271 | 17.65 |
| | (1.09) | (-1.10) | (1.24) | (0.56) | (0.51) | (1.89) |
| Observations | 14 | 14 | 14 | 14 | 14 | 14 |

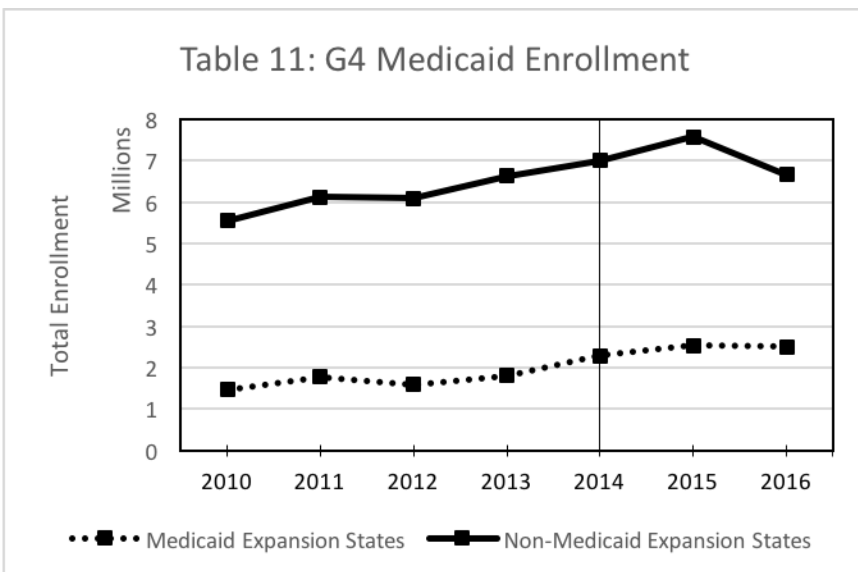
*t* statistics in parentheses
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < .01$

When we run the differences in differences approach however, we can see that the difvar fluctuates and a statistically insignificant difference is found between the two state groups' ambulance demand after Medicaid expansion. Unfortunately, this different result is probably a result of changing state patient demographics, as our means test had shown a significant increase in ambulance demand following Medicaid expansion. As seen in table 8, these states saw a massive increase in Medicaid utilization, and the population of uninsured decreased greatly through other means as well. Clearly, a control variable picked up enough of the variability in ambulance demand that we had assumed in the means test to be due to the change in Medicaid population. This change in outcome shows how crucial it was to model ambulance demand and control for population changes besides Medicaid expansion that could affect demand. Even with similar geography, shrinking the number of states in each group creates issues where demographic changes are less averaged-out. Median age has increased in these states considerably. Furthermore, many in these states received new care from the ACA exchanges and not just from Medicaid, so even though a considerable percentage of Medicaid users have a higher ambulance utilization rate, the overall number of new people who obtained insurance and now use the ambulance more or less is not solely represented by those with newly-acquired Medicaid coverage.

We thought it prudent to try another state comparison of the ambulance data to see if we could replicate some of our earlier results. All of the states east of the Mississippi that we had complete data for were chosen as comparison group G4.

Treatment Group (Medicaid Expansion States): WV, NJ, ME
Control Group (no-Medicaid Expansion States): NC, FL, AL, MS

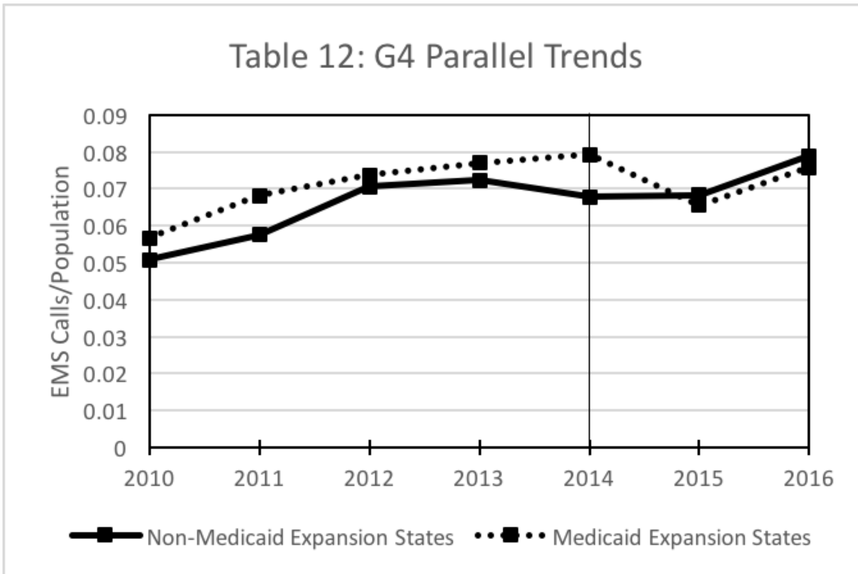



**Coverage Gains Comparison Wald** = 3.2419

This statistic shows that there were 3.2419 additional Medicaid recipients in the Medicaid expansion states per one additional Medicaid recipient in the non-expansion states (taken from averages before and after expansion in G4). We can thus verify the effects of Medicaid expansion on the actual population by pointing to the real increase in Medicaid coverage comparatively.

**Relative Medicaid Gains % Wald** = 1.3555




As seen above in Table 12, in the years 2010-2013 before the treatment was applied, there exists a really consistent parallel trend between non-Medicaid expansion states and Medicaid expansion states, among the best of our comparisons. As before, we also included tables of the total % uninsured in each treatment group within G3, as well as the total number of Medicaid enrollees per state. Table 10 shows a steep decline in the number of uninsured in the state, a signal that we might find the same issues among the output as we did in G3. If the number of uninsured is not significantly a result of Medicaid expansion, it will have a confounding impact on ambulance demand decreases or increases.

As before, we performed the mean differences test, below is the means table and resulting t statistic and p value for the test.

| G4 Means | Non-Medicaid Exp. States | Medicaid Exp. States |
|---|---|---|
| Before Expansion | 0.063 | 0.069 |
| After Expansion | 0.072 | 0.074 |

| G4 Stddev's | Non-Medicaid Exp. States | Medicaid Exp. States |
|---|---|---|
| Before Expansion | 0.0104 | 0.0089 |
| After Expansion | 0.0062 | 0.0072 |

| | |
|---|---|
| G4 T stat | -1.631889942 |
| G4 P | 0.064324812 |

| | |
|---|---|
| G4 Wald | 0.0731% |
| Dif in Dif Estimator | 0.00615 |
| P value | 0.5037 |

Interestingly, in this comparison we found ambulance demand to have decreased on average among Medicaid-expansion states vs. non-Medicaid expansion states. While an interesting result, we have to acknowledge that much of this variation is probably due to other factors such as many more non-Medicaid eligible individuals having insurance in these states that could drive ambulance demand. The differences in differences approach is essential here to confirm that intuition. With this approach, we can find the separate covariances between ambulance demand/Medicaid expansion, and ambulance demand/uninsured rates. We can see from table 10 and 11 that the changes in Medicaid enrollment were negligible compared to the huge decrease in the number of uninsured.

| G4 (Eastern U.S. States) | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | FrequncyEMS | FrequncyEMS | FrequncyEMS | FrequncyEMS | FrequncyEMS | FrequncyEMS |
| Year | 0.00887 | 0.0111 | 0.00509 | 0.00614 | 0.00871 | $0.0108^{**}$ |
| | (1.39) | (1.49) | (0.93) | (1.53) | (1.14) | (3.67) |
| Dpost | 0.000472 | 0.00492 | -0.00201 | 0.000772 | $-0.0161^{**}$ | 0.0000693 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (0.06) | (0.53) | (-0.26) | (0.11) | (-2.62) | (0.01) |
| DTr | 0.349 | 0.0508 | 0.432 | 0.294 | 0.374 | 0.354 |
| | (1.42) | (0.73) | (1.80) | (1.67) | (0.96) | (1.60) |
| Pop | 1.26e-08 | | 1.71e-08 | 1.13e-08 | 1.29e-08 | 1.20e-08 |
| | (1.31) | | (1.97) | (1.43) | (0.83) | (1.37) |
| sexratio | -0.0153 | -0.0292 | | -0.0136 | 0.00560 | -0.0176 |
| | (-0.97) | (-1.85) | | (-0.90) | (0.31) | (-1.24) |
| medianage | -0.0114 | -0.00200 | -0.00740 | | -0.0190 | -0.0159 |
| | (-0.51) | (-0.08) | (-0.32) | | (-0.55) | (-1.02) |
| %notcovered | 0.00713** | 0.00717* | 0.00635** | 0.00725** | | 0.00686** |
| | (3.38) | (2.44) | (3.22) | (3.62) | | (3.63) |
| medhouseinc | 0.000000955 | 0.000000208 | 0.00000193 | 0.00000179 | -0.00000221 | |
| | (0.34) | (0.06) | (0.71) | (0.86) | (-0.85) | |
| difvar | 0.00615 | -0.00155 | 0.00807 | 0.00732 | 0.00511 | 0.00541 |
| | (0.72) | (-0.17) | (0.95) | (0.94) | (0.29) | (0.68) |
| Constant | -16.51 | -19.62 | -10.72 | -11.61 | -17.61 | -19.92*** |
| | (-1.48) | (-1.47) | (-1.04) | (-1.68) | (-1.34) | (-4.17) |
| Observations | 14 | 14 | 14 | 14 | 14 | 14 |

*t* statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < .01$

Above is our differences in differences regression output for comparison G4. They largely confirm our earlier intuitions. While the effects of %notcovered had a statistically significant impact on ambulance demand, such that each additional 1 percent of covered individuals increased the ambulance demand rate by .00713, or .713%, our difvar coefficient was found to not be statistically significant. This would imply that the variance of the effect was too great to confirm that Medicaid expansion's effect on ambulance demand was due to chance. However, even if we found the difvar coefficient to be significant, it would still imply that Medicaid expansion had a positive effect on ambulance demand.

| State Comparison Group | G1 | G2 | G3 | G4 |
|---|---|---|---|---|
| T stat | 1.02500 | -0.44079 | 1.84273** | -1.63189* |
| Ambulance Demand Wald | 0.00508 | 0.00079 | 0.00106 | 0.00073 |
| Coverage Gains Comparison Wald | 3.27579 | 4.75901 | 9.10807 | 3.24186 |
| Relative Medicaid Gains Wald | 1.17504 | 1.76050 | 1.12128 | 1.35553 |
| Dif in Dif | 0.0187* | 0.00049 | -0.00685 | 0.00615 |

*=significant at .1 level, **=significant at .05 level

## 1.6 Conclusion

In our study of ambulance demand, we attempted to find differences between Medicaid expansion states and non-Medicaid expansion states using a variety of empirical strategies. A summary of all the statistics computed in the study is shown below:

We found that in almost every single comparison group (G#), when %notcovered was removed as a variable, the significance of the Differences in Differences coefficient rose significantly. This indicates that a great deal of the variation in ambulance demand came from the newly insured, not necessarily tied to Medicaid itself. There may be some overlapping effect on ambulance demand between the exchanges and Medicaid expansion.

Overall, we found the impact of Medicaid expansion on ambulance demand small, with mostly statistically insignificant relationships between the two in our study when controlling for all the factors that impacted ambulance demand. However, we did confirm some previous research on the demographic and socioeconomic effects on ambulance demand, as evidenced by the parameters for the control variables within the differences in differences regressions.

Through our calculated t statistics, we did find that in some areas Medicaid expansion led to more demand and in other areas we found the opposite effect, both statistically significant. In future studies, adding a variable for the amount of defensive care (primary care visits, immunizations, etc.) would help trace the root of these demand shifts. In summary, it seems that ambulance demand did experience region-specific statistically-significant shifts after the enacting of the ACA. In the literature review, we looked at some of the reasons why emergency care usage may increase (utilization rates increasing across all types of care, rapid increases in coverage lacking a corresponding increase in primary care availability). However, when controlling for other variables related to demand via the differences in differences model, we see that these changes cannot be specifically traced to Medicaid expansion. To confirm the roots of these demand changes, a more region-specific analysis of demand, perhaps involving ambulance company policies, private vs. public EMS market share, defensive care prevalence, etc., would be warranted. Another potential area of improvement for the analysis in this paper is time frame. Many non-emergent ambulance transports are due to health conditions stemming from long-term lifestyle/healthcare choices, such as dialysis visits. If the time period of this study was expanded, perhaps the level of demand for these types of ambulance transports would decrease as patients received more consistent kidney care.

The impact of ride-sharing companies on ambulance demand in the post-ACA environment represents another area of related additional study worth performing. A recent study (Moskatel and Slusky, 2017) found that Uber's entry into a city had decreased ambulance demand by 7%, ceteris paribus. This effect may have played a role in ambulance demand that should be controlled for in future studies on the ACA's effect on ambulance demand.

# Appendix

Stata Code for Data Organization:

```
clear all
set more off
cd "/Users/Administrator/Desktop/Honors Thesis 2018"
capture log close
log using "./test.log", replace

 program define main

			*ensure_no_duplicates
			*combine_stategroups
			*simplify_geotype
			*add_years
			*add_stategroups
			*renumber_dummy
			*count_calls
			paralleltrends_DiD
			DiD_regressions
			gen_tables_for_pub

end

program ensure_no_duplicates

			forvalues t = 2010/2016 {
				use "/Users/Administrator/Desktop/Honors Thesis 2018/`t'geocodes.dta", clear
				append using "/Users/Administrator/Desktop/Honors Thesis 2018/2016geocodes.dta"
				duplicates tag eventid, generate(dup)
				tab dup
				}
end

program combine_stategroups

				forvalues t = 11(1)16 {
				use "/Users/Administrator/Desktop/Honors Thesis 2018/stategroup10.dta", clear
					append using "/Users/Administrator/Desktop/Honors Thesis
2018/stategroup`t'.dta"
					save "../Honors Thesis 2018/stategroup10.dta", replace
					}

end

program simplify_geotype

			use "/Users/Administrator/Desktop/Honors Thesis 2018/2018_Thesis_data.dta", clear
				gen geotype = 0
				replace geotype = 1 if urbanicity == "Wilderness"
				replace geotype = 2 if urbanicity == "Rural"
				replace geotype = 3 if urbanicity == "Suburban"
				replace geotype = 4 if urbanicity == "Urban"
					drop urbanicity
```

```
				save "/Users/Administrator/Desktop/Honors Thesis 
2018/2018_Thesis_data.dta", replace

end

program add_years

		forvalues t = 12/16 {
		use "/Users/Administrator/Desktop/Honors Thesis 2018/stategroup`t'.dta", clear
			gen year = 20`t'
			save "/Users/Administrator/Desktop/Honors Thesis 2018/stategroup`t'.dta", replace
			}

end

program add_stategroups

			use "/Users/Administrator/Desktop/Honors Thesis 2018/2018_Thesis_data.dta", clear
			merge m:m eventid using "../Honors Thesis 2018/stategroup10.dta"
			drop _merge
			save "/Users/Administrator/Desktop/Honors Thesis 2018/2018_Thesis_data.dta", replace

end


program renumber_dummy

		use "/Users/Administrator/Desktop/Honors Thesis 2018/2018_Thesis_data.dta", clear
		gen group1 = .
		replace group1 = 1 if g1=="A"
		replace group1 = 0 if g1=="B"
		drop g1

		gen group2 = .
		replace group2 = 0 if g2=="A"
		replace group2 = 1 if g2=="B"
		drop g2

		gen group3 = .
		replace group3 = 1 if g3=="A"
		replace group3 = 0 if g3=="B"
		drop g3

		save "/Users/Administrator/Desktop/Honors Thesis 2018/2018_Thesis_data.dta", replace

end

program count_calls

		use "/Users/Administrator/Desktop/Honors Thesis 2018/2018_Thesis_data.dta", clear
			forvalues t = 10(1)16 {
			count if group1 ==0 & year == 20`t'
			count if group1 ==1 & year == 20`t'
			count if group2 ==0 & year == 20`t'
			count if group2 ==1 & year == 20`t'
			count if group3 ==0 & year == 20`t'
```

```
                    count if group3 ==1 & year == 20`t'
                    }

end

program paralleltrends_DiD

            use "/Users/Administrator/Desktop/Honors Thesis 2018/g3 data v1.dta", clear

            duplicates drop year, force
            graph twoway line frequencyems_residual year, xline(2014)
            *graph export "../Honors Thesis 2018/g3_parallel_trend.png"

            use "/Users/Administrator/Desktop/Honors Thesis 2018/g3 data v1.dta", clear
            xtset frequencyems year
            xtreg frequencyems dpost dtr pop sexratio over65 medianage notcovered medhouseinc
            *outreg2 using "../output/DiD_g3.txt", append

end

program DiD_regressions

            use "/Users/Administrator/Desktop/Honors Thesis 2018/g3 data v1.dta", clear

            gen difvar = dtr * dpost
            reg frequencyems year dpost dtr pop sexratio medianage notcovered medhouseinc difvar, r

            **http://www.princeton.edu/~otorres/DID101.pdf**
end

program gen_tables_for_pub

            use "/Users/Administrator/Desktop/Honors Thesis 2018/g3 data v1.dta", clear

            eststo: quietly regress frequencyems year dpost dtr pop sexratio medianage notcovered
medhouseinc difvar, r
            esttab, star(* 0.1 ** 0.05 *** .01)

            esttab using g3data_v1.rtf, replace label nogap onecell star(* 0.1 ** 0.05 *** .01)


            eststo clear
end

main
```

## References

Amy Finkelstein & Sarah Taubman & Bill Wright & Mira Bernstein & Jonathan Gruber & Joseph P. Newhouse & Heidi Allen & Katherine Baicker, 2012. "The Oregon Health Insurance Experiment: Evidence from the First Year," The Quarterly Journal of Economics, Oxford University Press, vol. 127(3), pages 1057-1106.

Butler, J.R.G. “Factors Affecting the Demand for Ambulance Services.” *International Journal of Transport Economics / Rivista Internazionale Di Economia Dei Trasporti*, vol. 8, no. 2, 1981, pp. 225–238. JSTOR, JSTOR, www.jstor.org/stable/42748098.

David, Guy & Gunnarsson, Candace & A. Saynisch, Philip & Chawla, Ravi & Nigam, Somesh. (2014). Do Patient-Centered Medical Homes Reduce Emergency Department Visits?. Health Services Research. 50. 10.1111/1475-6773.12218.

Eili Y. Klein, Scott Levin, Matthew F. Toerper, Michael D. Makowsky, Tim Xu, Gai Cole, Gabor D. Kelen, The Effect of Medicaid Expansion on Utilization in Maryland Emergency Departments, Annals of Emergency Medicine, Volume 70, Issue 5, 2017.

E. Martinez, Michael & P. Zammitti, Emily & Cohen, Robin. (2017). Health Insurance Coverage: Early Release of Estimates From the National Health Interview Survey, January-September 2016.

Frakt, Austin. "Uber, Lyft and the Urgency of Saving Money on Ambulances." New York Times [New York] October 1, 2018. Print.

Hernandez-Boussard T, Burns CS, Wang NE, Baker LC, Goldstein BA. The Affordable Care Act Reduces Emergency Department Use By Young Adults: Evidence From Three States. Health affairs (Project Hope). 2014;33(9):1648-1654. doi:10.1377/hlthaff.2014.0103.

Kolstad, J. T., and A. E. Kowalski. 2012. The Impact of an Individual Health Insurance Mandate on Hospital and Preventive Care: Evidence From Massachusetts. Journal of Public Economics 96( 11 -12):909 929.

Laura R. Wherry & Sarah Miller & Robert Kaestner & Bruce D. Meyer, 2018. "Childhood Medicaid Coverage and Later-Life Health Care Utilization," The Review of Economics and Statistics, vol 100(2), pages 287-302.

Leon S. Moskatel & David J.G. Slusky, 2017. "Did UberX Reduce Ambulance Volume?," Working Papers Series in Theoretical and Applied Economics 201708, University of Kansas, Department of Economics, revised Oct 2017.

Long, S., and K. Stockley. 2011. The Impacts of State Health Reform Initiatives on Adults in New York and Massachusetts. Health Services Research 46(l):365-387.

Long, S., K. Stockley, and H. Dahlen. 2012. Health Reform in Massachusetts as of Fall 2010: Getting Ready for the Affordable Care Act and Addressing Affordability. Urban Institute Research Report. Washington, D.C.: The Urban Institute.

Luojia Hu, Robert Kaestner, Bhashkar Mazumder, Sarah Miller, and Ashley Wong. The Effect of the Patient Protection and Affordable Care Act Medicaid Expansions on Financial Wellbeing. NBER Working Paper No. 22170 April 2016, Revised February 2018 JEL No. H20,I13,I38

Lee M.H., Schuur J.D., Zink B.J. Owning the cost of emergency medicine: Beyond 2%. Annals of Emergency Medicine, 62(5) , pp. 498-50.e3, 2013.

Meisel ZF, Pines JM, Polsky DE, Metlay JP, Neuman MD, Branas CC. Variations in Ambulance Use in the United States: the Role of Health Insurance. Academic emergency medicine : official journal of the Society for Academic Emergency Medicine. 2011;18(10):1036-1044. doi:10.1111/j.1553-2712.2011.01163.x

Miller, S. 2012a. The Effect of Insurance on Emergency Room Visits: An Analysis of the 2006 Massachusetts Health Reform. Journal of Public Economics 96(11-12):893-908.

"National Federation of Independent Business v. Sebelius: The Patient Protection and Affordable Care Act." Harvard Law Review 126, no. 1 (2012): 72-82. http://www.jstor.org/stable/23415891.

Nikpay, Sayeh et al. Effect of the Affordable Care Act Medicaid Expansion on Emergency Department Visits: Evidence From State-Level Emergency Department Databases. Annals of Emergency Medicine, Volume 70, Issue 2 , 215 - 225.e6, 2017.

Street P, McKay S, Allpleby N, et al. Emergency department use by the elderly: a study of older people's use of the emergency departments of three Melbourne hospitals. Melbourne: Bundoora Centre for Applied Gerontology, 1996.

Zuckerman S, Skopec L, Epstein M. Medicaid Physician Fees after the ACA Primary Care Fee Bump. Washington: Urban Institute; 2017. http://www.urban.org/research/ publication/medicaid-physician-fees-after-aca-primary-care-fee-bump. Published March 5, 2017.