Medicaid Expansion and Primary Care Utilization:

A Post-ACA Analysis of Trends in the U.S.

MPP Capstone Project

In Coordination with Amaze Health LLC, Broomfield, Colorado

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Abstract: Primary care relationships form the backbone of the United States' healthcare system. These relationships are crucial for the early detection of diseases that, if left untreated, can impose significant financial and logistical constraints on the US healthcare system. Using data from the Medical Expenditure Survey (MEPS) from 2005 to 2022, this study evaluates the causal effects of Medicaid Expansion under the Affordable Care Act on primary care utilization through a difference-in-differences design. Three proxy outcomes were analyzed: number of doctor visits (NDV), usual source of care (USOC), and appointments made for primary care (MAPC). Results indicate statistically significant increases in NDV and USOC among Medicaid recipients post-2014, but a slight decline in MAPC, suggesting that expansion increased coverage without fully translating into increased usage. Robustness checks with demographic and socioeconomic controls affirm these findings.

Acknowledgments

I would like to thank David Silverstein for his insights, flexibility, and willingness to approve and mentor this project. Our meetings and discussions were helpful in both formulating the research question of this analysis and in understanding the healthcare and primary care industries. I would also like to thank Dr. Evan Johnson for advising on this project. He provided priceless insights, feedback, and advice that helped make this project more technically robust and aesthetically polished. Lastly, I would like to thank my cohort members, Caitlin Flanagan, Megan Forrestal, Bhairavi Jayaraman, and Payal Shah, for their support and feedback. They challenged me to think more critically of the problem, refine my methodology, and improve my ability to communicate these technical results, all of which have led to a finished product that I am both proud of and confident in.

Disclaimer

This is an independent research product conducted under the mentorship of David Silverstein, CEO of Amaze Health, and undertaken to fulfill the capstone requirement for the Master of Public Policy degree at the University of North Carolina at Chapel Hill. The author was never offered nor received any compensation for this work, and it was conducted voluntarily by all parties involved solely for course credit and research experience. The use of the Amaze Health LLC logo reflects the cooperation between the author and the company, but does not imply any formal relationship beyond the scope of this analysis. The following work and any opinions, results, errors, omissions, or other defects belong solely to the author and do not necessarily reflect the views of Amaze Health LLC.

Executive Summary

This study investigates the impact of the Affordable Care Act (ACA), particularly Medicaid Expansion, on primary care utilization in the United States using Medical Expenditure Panel Survey (MEPS) data from 2005 to 2022. By applying difference-in-differences (DiD) estimation models, the analysis isolates the effect of Medicaid Expansion by comparing trends in primary care usage between Medicaid recipients (treatment group) and non-recipients (control group), before and after 2014.

Three proxies for primary care usage were examined: (1) number of doctor visits (NDV), (2) having a usual source of care (USOC), and (3) making an appointment for primary care (MAPC). While the first two measures showed statistically significant increases post-expansion, the third—MAPC—revealed a statistically significant decrease among Medicaid recipients after 2014.

This counterintuitive finding suggests that although coverage and access (as measured by USOC) improved, actual engagement with primary care services may have declined. This raises questions about provider availability, access barriers, or administrative constraints faced by newly insured Medicaid patients.

To address this gap, policies that incentivize more medical students to work as primary care providers, provide subsidies and relocation adjustments to encourage more healthcare providers to move to rural and underserved areas, and educate the general public on the benefits of primary care services are recommended.

The robustness of these findings was confirmed across both naive and robust models. These results suggest that while Medicaid Expansion improved formal indicators of access, it may not have translated into increased real-world usage of primary care services.

Introduction

Primary care relationships are a critical piece of the United States' healthcare system. For this project, a primary care provider (PCP) is defined as a healthcare specialist who serves as the first point of contact for an individual's needs. These could be doctors, nurse practitioners, or physician assistants, and they usually work in outpatient clinics or offices. These relationships are crucial for the early detection of diseases that, if left untreated, can impose significant financial and logistical constraints on the US healthcare system. A greater usage of primary care services can theoretically lead to decreased healthcare costs and help ease the burden on the US healthcare system. Because of this, having a clear understanding of both the current usage rates of primary care services in the United States and how they have changed in response to previous policy interventions is crucial for policymakers.

One such policy that completely reshaped the U.S. healthcare system was the Affordable Care Act (ACA). The ACA had three stated goals: make affordable health insurance available to more Americans, expand Medicaid, and encourage innovative healthcare delivery methods (US Department of Health and Human Services, 2022). The ACA has helped millions of Americans qualify for insurance coverage and has saved lives (Center for American Progress, 2020). It has made navigating the healthcare system easier and more efficient and positively impacted numerous sectors (Center for American Progress, 2020).

The ACA has been widely studied since its passage in 2010. However, one aspect of the ACA that has not been studied in detail is its effect on the primary care market. While the ACA has increased healthcare utilization writ large, it is unclear what its direct effect has been on primary care utilization. Most governmental publications lump primary care services in with other services such as specialist visits and preventative screenings (US Department of Health and

Human Services, 2025). While one major benefit of the ACA has been a general decrease in the cost of preventative healthcare measures such as counseling, vaccines, and screening services, these are not the same as primary care visits or primary care relationships. (US Department of Health and Human Services, 2025). Furthermore, these studies often do not differentiate between Medicaid and non-Medicaid patients, although historically these two groups have vastly different healthcare usage rates (Allen et al., 2021). Because of this, there may be a confounding effect that is driving the narrative more than the actual effect.

This is relevant to public policy because, as mentioned previously, increased usage of primary care services can have wide-ranging benefits for both individuals and the US healthcare system overall. Medicaid spending accounts for roughly 9% of the federal budget and is the third-largest mandatory spending item in the budget (Peterson Foundation, 2024). Because of the high cost of this program, it is crucial to have a clear understanding of its true effects. The ACA was well-intentioned and has been greatly effective at establishing its set goals. However, there may be a murky narrative regarding the ACA and Medicaid Expansion's effects on primary care utilization. This analysis aims to clear up some of the opaqueness on this topic so that policymakers and those in the primary care industry can allocate resources effectively and equitably to help the most Americans gain access to quality and affordable healthcare.

Policy Question

Specifically, this analysis aims to answer the following policy question: Did the ACA and associated Medicaid Expansion increase or decrease the usage of primary care services, and are the claims present in governmental and scholarly sources consistent with, or overestimating the trends present in the data itself? It has been hypothesized that government data on the number of people who have a primary care relationship is potentially overstated. The numbers may be dominated by Medicaid patients, or are deceptive because people are required to designate a primary care provider in most insurance company portals to gain coverage. Because of this, the true effect of the ACA on primary care usage rates could be different than the rates claimed by both governmental and scholarly sources.

To test this objectively, a two-factor approach was undertaken. First, an in-depth literature review was conducted to elucidate the narrative regarding the ACA from both official government sources and academic research. Second, difference-in-differences estimation models were fit on three proxy variables that represent primary care usage from MEPS to see if the trends claimed in articles were found in the data itself.

Report Layout

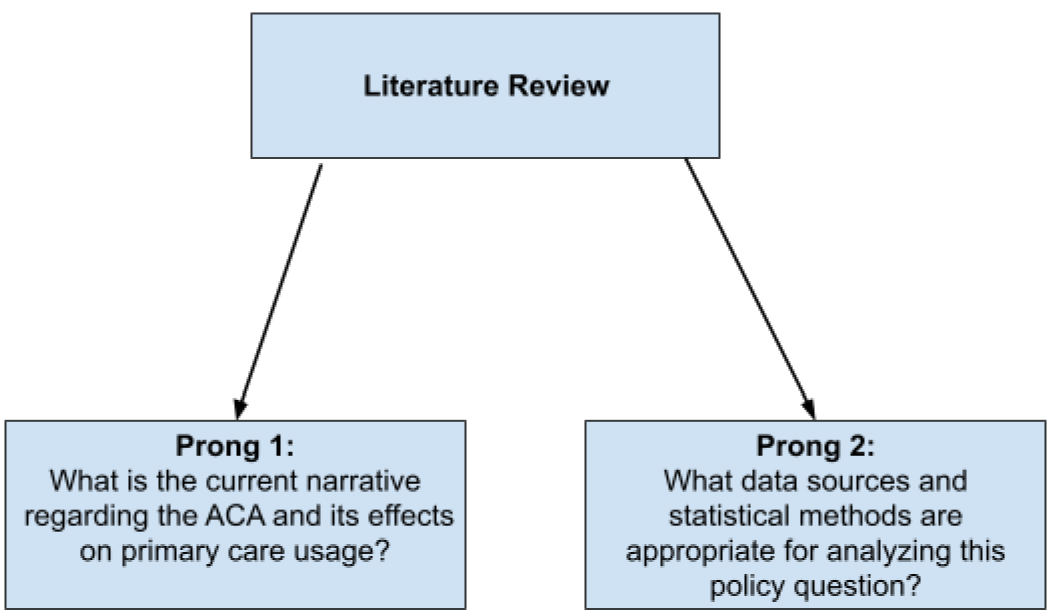
This report takes the form of a quantitative analysis of an existing policy. The goal of this project, at the request of Amaze Health LLC, was to answer a specific research question, not necessarily to introduce or compare policy alternatives or provide a recommendation. Because of this, the following report differs slightly from traditional policy analysis papers and is more empirical in nature. The paper includes the following sections: a **literature review** section that describes the background research conducted for this project, a **data** section that describes the data source used and its relevance, a **methodology** section that describes the statistical technique used in this analysis and its validity and appropriateness for this task, a **results** section that describes the key findings of this work, a **discussion** section that contextualizes the results, a **policy recommendations** section that provides three alternatives that could address the issues found in the analysis, a **limitations** section that addresses key issues with this work, and **future work** and **conclusion** sections that conclude the project and provide ideas for further analysis.

An **appendix** is also included that details the mathematics behind the chosen statistical approach and includes information that ensures the reproducibility of this work.

Literature Review

This literature review followed a two-pronged approach. The first prong focused on analyzing the current narrative from both governmental and scholarly sources regarding the effects the ACA and associated Medicaid Expansion had on primary care usage rates in the United States. The second prong focused on analyzing previous research to determine a suitable data source and statistical method to help answer the policy question.

Figure 1: Overview of Literature Review Approach



Prong one of the literature review focused on understanding the current narrative regarding the ACA and its effects on primary care usage in the US. Numerous academic articles and official governmental publications were analyzed. Overwhelmingly, the ACA was found to have had numerous positive effects, including increasing the number of Americans with insurance, decreasing the rates of preventable hospitalizations, and making the US healthcare system more accessible (Hall and Lord, 2014; Brown et al., 2017; and Shi, 2012).

When it comes to primary care usage rates, however, there appears to be an overall decline after Medicaid Expansion (Ganguli et al., 2019). This decline was attributed to numerous factors, including decreases in patients' ability, need, or desire to seek primary care; changes in primary care practice such as greater use of teams and non-face-to-face care; and replacement of in-person primary care visits with alternatives such as specialist, retail clinic, and commercial telemedicine visits (Ganguli et al., 2019 and Pathman 2019). This general decline also consistently impacted individuals from various demographic, socioeconomic, and geographic groups (Ganguli et al., 2019).

The narrative from official government sources tends to focus on the decrease in cost and increase in availability of preventative healthcare measures such as vaccines, counseling, and cancer screenings (US Department of Health and Human Services, 2025). While beneficial, these are not fully equivalent to primary care measures and do not factor in the wide range of available services across the country. The disconnect between governmental sources, which generally claimed an increase in healthcare metrics such as preventative health and overall doctor visits, and scholarly sources, which cite a decline in primary care usage, specifically provided a strong motivation to continue forward with this project.

The overall decline in primary care usage can be attributed to numerous complex and interlocking factors. First, there is an overall shortage of primary care physicians in the US (Weatherby Healthcare, 2024). Primary care is a far less attractive field for medical students to pursue because it pays less and is generally considered less prestigious (Handzel, 2023). Furthermore, rising medical student costs have led a greater percentage of students to seek more lucrative specialties (Handzel, 2023). Because of this, there is a supply gap, especially in rural areas of the country. This issue was compounded by one of the main benefits of the ACA: increasing access to the healthcare system for all US citizens. This injected a large demand into a market already struggling with supply (Handzel, 2023). The gap caused by increased demand and decreased supply has not been addressed in official government narratives regarding the benefits of the ACA, and may be a key explainer of the trends present in both the literature and the data. From a policy recommendation standpoint, policies that promote primary care as a career and increase compensation for PCPs could help close this gap.

After the current narrative regarding the ACA's effects on primary care utilization was researched, the literature review pivoted to the second prong: understanding what statistical methods and data sources could be used for this project. Numerous different data sources were used by scholars who research the effects of the ACA. One of the most common was MEPS, a robust and official U.S. government data source on healthcare utilization. Six papers, Romaire, Gotang et al., Wong et al., Jetty et al., and Olaisen et al. (twice) used this data for their analyses. Each of these six also specifically looked at either the association between ACA Medicaid Expansion and primary care usage or at the validity of using MEPS itself for healthcare research. All of them found that MEPS is a robust and appropriate data choice in this context.

Some other researchers used creative survey instruments to gather primary care-related data (Canaway et al., Ganguli et al., Gilchrist et al.). Collecting data was not feasible for this project due to time, logistical, and monetary constraints, however, this approach would be beneficial in future work to both cross-validate the findings of this analysis and to correct any blind spots.

One of the most common statistical techniques employed in the literature was a difference-in-differences (DiD) estimation model. Few cross-sectional techniques were used in the literature, although some interesting approaches incorporated logistic or negative binomial regression (Romaire and Wong et al.). Since this report seeks to analyze the change in outcomes over time given an intervention, it is natural that panel data methods were employed. This is overwhelmingly true in the data. Of the 17 methods papers reviewed, 9 used some form of panel method, such as DiD, or comparative interrupted time series. Of the remaining 8, 2 used a form of snowball sampling, 3 used mixed method approaches, 2 used generalized linear models, 2 used snowball sampling, and 1 conducted a meta-analysis. Overall, this prong of the literature review convinced the author of the appropriateness of using both the MEPS as their data source, and a DiD estimation model as their technique.

Data

This study uses data from MEPS from 2005 to 2022. MEPS is conducted by the Agency for Healthcare Research and Quality (AHRQ), a division of the U.S. Department of Health and Human Services (DHHS). It is a large-scale, annual survey that is widely considered the most complete source of data on the cost and use of health care and health insurance coverage in the United States. Numerous other studies on this topic used MEPS (see Olaisen et al., Romaire, Wong et al., and Jetty et al.). This data was collected by an official U.S. government agency and thus is an authoritative and credible source of information about the true relationship between the ACA and primary care usage rates. Because of this, and because of the thoroughness, consistency, and completeness of the data, MEPS is an appropriate source to use for this analysis.

To use a DiD approach to answer this policy question, large amounts of data from the years before and after Medicaid Expansion were needed. MEPS stores data in yearly consolidated data files. To collect this data, each file for every year of interest was downloaded and loaded into R. The yearly files from 2005-2022 were used. The individual annual files were then merged and cleaned using a function written by the author. The merged data had 587,446 observations and 13 features. Two additional features were engineered to conduct the DiD estimation. These variables were an indicator of whether the response was recorded before or after 2014, and the other was an interaction term between those on Medicaid after 2014. Two features, *Years of Education* and *Made Appointment for Routine Care,* had missing data, but each still had over 500,000 observations and thus were considered robust. **Table 1** features a complete list of all numeric features and their associated summary statistics, while **Table 2** features a complete list of all categorical features and their associated summary statistics.[1]

Table 1: Numeric Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Number_Doctor_Visits	587,446	2.8	5.5	0	265
Have_Usual_Source_of_Care	587,446	0.7	0.4	0	1
Medicaid	587,446	0.3	0.5	0	1
Made_Appointment_for_Routine_Care	506,749	0.4	0.5	0	1
Age	587,446	35.3	23.5	-1	85
Income	587,446	24,021.2	34,918.5	-333,392	731,653
Years_of_Education	550,506	8.4	6.6	-15	17
Employment_Status	587,446	1.3	2.1	-15	4
Year	587,446	2,013.1	5.0	2,005	2,022
Treatment_Group	587,446	0.3	0.5	0	1

[1] The negative values present in the minimum column for some variables correspond to a survey non-response code, they are not true values. They were adjusted for and removed during the actual analysis.

Table 2: Categorical Descriptive Statistics

Variable	Values	Frequency	Valid	Missing
	1. Asian	36,463 (6.2%)		
	2. Black	109,854 (18.7%)		
Race	3. Other	15,903 (2.7%)	587,446	0
	4. Unknown	8,261 (1.4%)		
	5. White	416,965 (71.0%)		
Sex	1. Female	306,965 (52.3%)	587,446	0
	2. Male	280,481 (47.7%)		
	1. Midwest	11,572 (19.0%)		
	2. Northeast	87,774 (14.9%)		
Region	3. South	216,881 (36.9%)	587,446	0
	4. Unknown	16,861 (2.9%)		
	5. West	154,358 (26.3%)		

Dependent Variables: Proxies that Represent Different Aspects of Primary Care Utilization

Three proxy variables that represent different facets of the research question were used as dependent variables in this analysis. The first, *Number of Doctor Visits in a Year* (NDV), is a continuous variable that tracks the number of times each respondent visited a doctor in the year of measurement. This variable does not distinguish between generalists (such as primary care providers) or specialists and thus is used as a general proxy for healthcare system usage. This variable is used as a baseline to see how healthcare utilization as a whole changed after the ACA and subsequent Medicaid Expansion.

The second dependent variable is *Has a Usual Source of Care* (USOC). This binary variable indicates whether or not each respondent had a primary care provider during the year surveyed. This variable represents the existence of a primary care relationship. Importantly, it does not track whether or not the relationship was used. This key distinction is the crux of this analysis. On the surface, greater rates of individuals claiming to have a PCP provide evidence of increased utilization. However, it does not factor in contextual information, such as the requirement for patients to put a PCP on insurance forms, which could be skewing this data.

The third and final dependent variable is *Made an Appointment to see a Primary Care Provider* (MAPC)**.** This binary variable tracks whether or not each respondent made an appointment to see a PCP in the surveyed year. This is considered the key variable of this analysis because it moves beyond simply representing the existence of a PCP but is a reasonable proxy for usage. All together, each of these three dependent variables represent some aspect of primary care relationships and thus is important to study both before and after the ACA's passage.

Methodology

The objective of this analysis was to answer the following question: Did the ACA and associated Medicaid Expansion increase or decrease the usage of primary care services, and are the claims present in governmental and scholarly sources consistent with, or overestimating the trends present in the data itself? Of particular interest were the effects Medicaid Expansion had on the USCOC and MAPC variables. If Medicaid Expansion increased the rates of the first but decreased the rates of the second, there is evidence that the ACA may have had an overestimated effect on increasing the actual usage of primary care services.

To analytically evaluate the trends present in MEPS, DiD estimation models were fit. Diff-in-diff is a statistical technique used to estimate the causal effect of a treatment or intervention by comparing the changes in outcomes over time between a treatment group (those who receive the intervention) and a control group (those who do not). This technique helps to isolate the effect of the treatment by accounting for any underlying trends that would have affected both groups in the absence of the treatment. This method is an especially powerful tool for analyzing how different groups were affected over time by a policy change.

Examining the ACA's effects on primary care usage provides a natural experiment with a pre- and post-time period, which makes a diff-in-diff suitable. The treatment group for this analysis were those on Medicaid, while the control group consisted of those not on Medicaid. The logic for this approach was as follows: if primary care usage trends are consistent in the pre-ACA period for both Medicaid and non-Medicaid patients but change only for the Medicaid group after the ACA, there is evidence that Medicaid expansion had a direct effect on primary care usage rates.

Due to the large and messy nature of MEPS, extensive data cleaning and feature engineering was undertaken. Each year's data file was loaded individually into R and then merged to create one large dataset for all years. The data was then pivoted to long form to allow for successful modeling. All variables were renamed for interpretability, and only features relevant to this analysis were kept.

After merging, cleaning, and simplifying the dataset, a decision had to be made regarding missing data. While some variables had no missing data, others had roughly 50,000 missing observations. Even with this, however, every variable had at least 500,000 observations across the fifteen sampled years. Because of this, all missing values were dropped to allow the models to be fit.

After the data was cleaned, three variables were engineered that were necessary to run the diff-in-diff models. The first was an indicator variable that equaled 1 if the respondent was on Medicaid and 0 if they were not. The second was a pre/post period indicator variable that equaled 1 if the response was after 2014 and 0 if it was before. Lastly, an interaction term between these two variables was created to serve as the main coefficient of interest in the diff-in-diff model. This variable equaled 1 if the response was on Medicaid and after 2014 (treatment group and after the intervention), and equaled 0 otherwise.

After all data merging, cleaning, simplifying, and preprocessing were completed, the pre- and post-trends for each of the three proxy dependent variables were plotted to assess whether the assumptions required for the validity of this technique were satisfied. Each plot and an associated explanation can be found in the **results** section.

After the pre- and post-trends were plotted and analyzed, six DiD estimation models were fit. The first three were naive models that had only the specific proxy variable as the response and the diff-in-diff features as predictors. The other three were robust models that controlled for age, race, income, education, and the geographic region of the respondent. For categorical variables, the most common factor was used as the reference level. This corresponded to the male sex, white race, and the southeast region. Both sets of models had similar results, although the scale was slightly different. After all modeling was completed, the findings from the literature review were compared with the findings from the statistical analysis to see if the trends claimed in official sources matched up with the trends found in the official data.

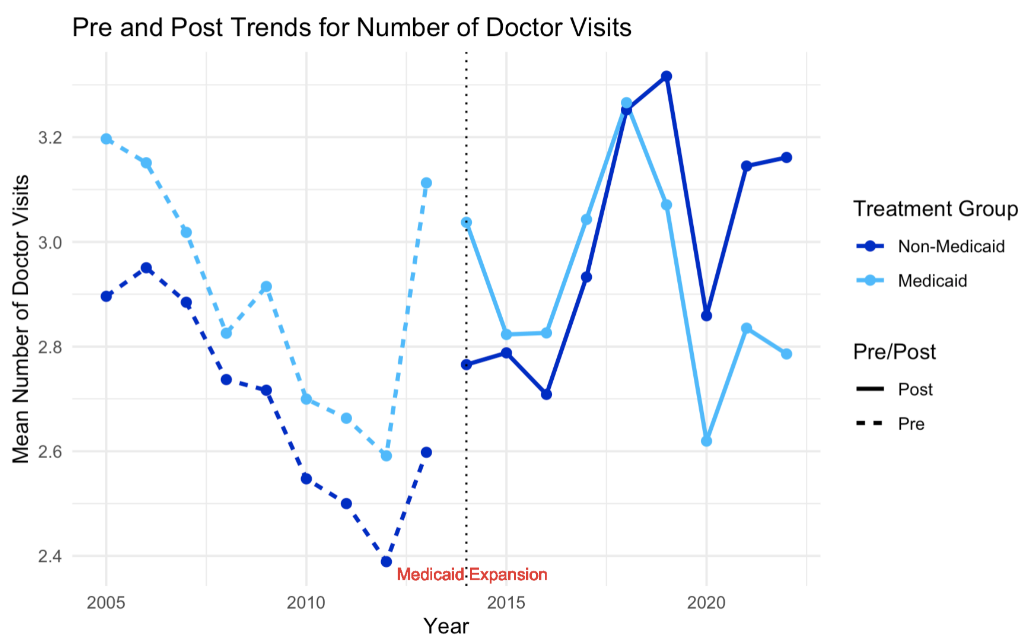
Results

The first step of the statistical analysis was to plot the pre- and post-trends for each proxy variable to ensure that the core assumption of a DiD estimation model was valid. The main assumption is called the parallel trends assumption. This condition requires that in the absence of the intervention, the difference between the treatment and control group is constant over time (Columbia University, 2023). For an in-depth mathematical breakdown of diff-in-diff, please see the **Mathematical Excursus** section of the **Appendix.**

For all three proxy variables, the parallel trend assumption appears to hold. The trends between the Medicaid and non-Medicaid groups appear consistent and parallel until after Medicaid Expansion.

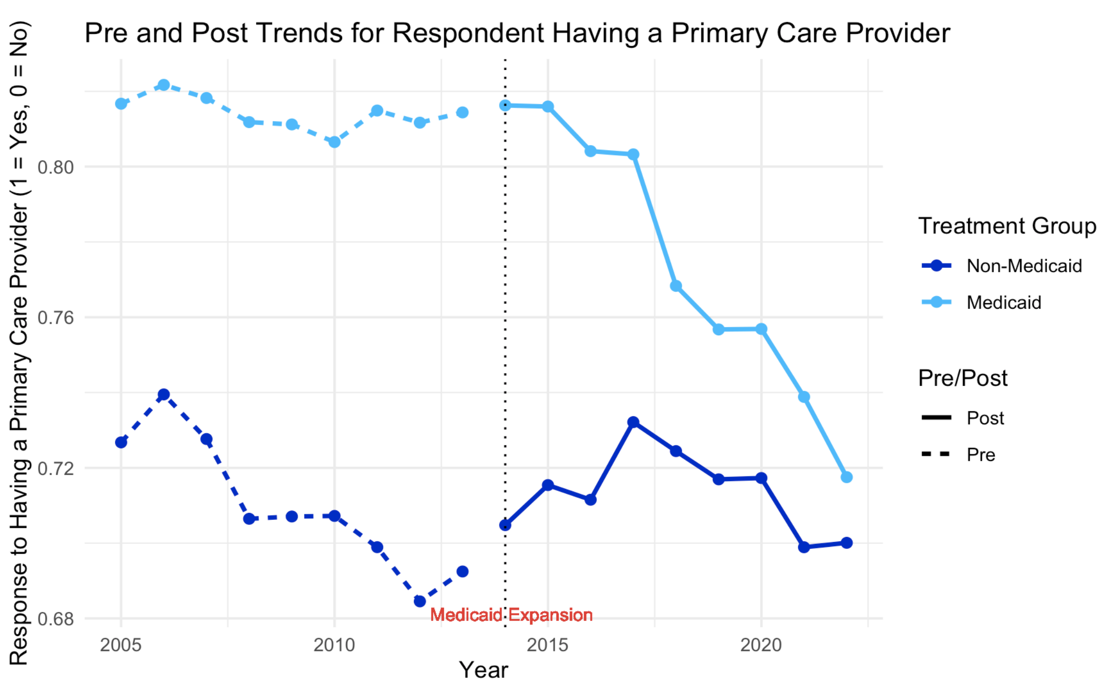
The first proxy variable, *number of doctor visits* (NDV), represented usage of the US healthcare system at large. It does not differentiate between what type of doctor was seen, so it serves mainly as a baseline metric for this analysis. As can be seen in **Figure 2**, before Medicaid Expansion, on average, Medicaid patients appeared to visit doctors more than non-Medicaid patients. After Medicaid Expansion was proposed and subsequently passed in the ensuing years, these trends flipped. There was a sharp decrease in the average yearly number of doctor visits for the Medicaid population in the sample. This could be due to numerous factors. One of them could be basic math. The ACA greatly increased the number of individuals covered by Medicaid. This increase in numbers may not have had an associated increase in actual visits, which could cause the drop present in the plot.

Figure 2: Pre and Post-Trends for Number of Doctor Visits Variable



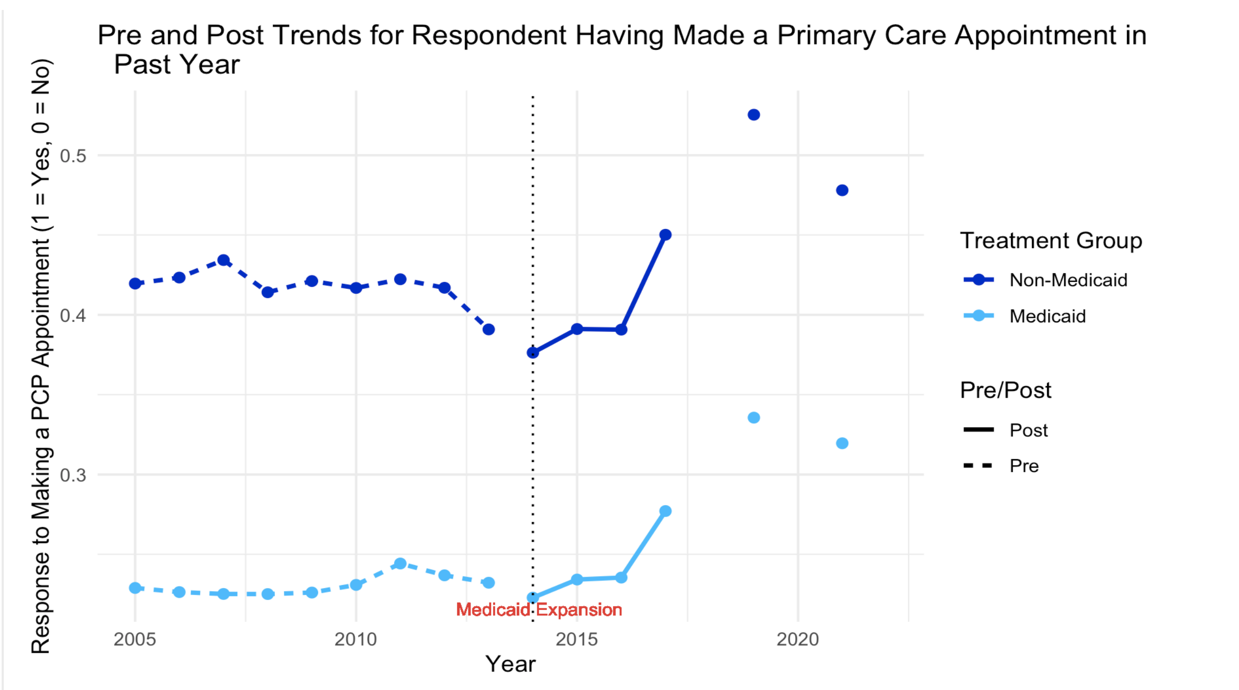
The second proxy variable, *has usual source of care* (USOC), represents the existence of a primary care relationship. It does not report if the respondent actually saw their PCP. This variable is a key driver in the official narrative regarding the effects of the ACA. Numerous publications point out the increased rates of primary care relationships, but do not go a step further to see if the relationships were actually utilized (US Department of Health and Human Services, 2025). As can be seen in **Figure 3**, before Medicaid Expansion, on average, Medicaid patients appeared to have a formal primary care relationship at far higher rates than their non-Medicaid counterparts. After Medicaid Expansion was proposed and subsequently passed in the ensuing years, there was a steep decline in the trends for both groups. Like the first proxy, this result could be due to numerous factors. Again, basic math may be at play. The drop in the rates for the Medicaid population could be due mainly to the sharp increase in the number of patients covered by Medicaid.

Figure 3: Pre and Post-Trends for Respondents Having a Primary Care Provider Variable



Lastly, the third proxy variable, *made appointment for primary care* (MAPC), represents the actual usage of a primary care service. This serves as a good counterfactual to the USOC variable as it digs deeper and measures actual usage. As can be seen in **Figure 4**, before Medicaid Expansion, on average, non-Medicaid patients appeared to use primary care services at a far higher rate than their non-Medicaid counterparts. After Medicaid Expansion was proposed and subsequently passed in the ensuing years, there was an increase in the trends for both groups. Interestingly, non-Medicaid patients appeared to increase their usage of primary care services after Medicaid Expansion at a far higher rate than Medicaid patients. This data does suffer from missing data because MEPS did not ask this question in the 2018, 2020, or 2022 versions of the survey.

Figure 4: Pre and Post-Trends for Having Made a Primary Care Appointment in the Past Year Variable



After the trends were analyzed and assumptions checked, six models were fit to statistically examine the actual trends present in the data. The first three models were naive; they only featured the necessary diff-in-diff variables and did not control for any other features. The first naive model fit had the feature NDV as the response variable. The main coefficient, *Treatment X Post,* was positive and statistically significant, which indicates that, on average, after Medicaid Expansion, Medicaid patients had a slight increase in the number of doctor visits in a given year.

The second naive model fit had the feature USCOC as the response variable. The main coefficient, *Treatment X Post* was positive and statistically significant, which indicates that on average, after Medicaid Expansion, Medicaid patients had a slight increase in the likelihood of having a usual source of care.

The third and final naive model fit had the feature MPAC as the response variable. This was the main variable for this analysis because it represented an actual attempt to use primary care services, not just the existence of a primary care relationship. The main coefficient, *Treatment X Post,* was negative and statistically significant, which indicates that, on average, after Medicaid expansion, Medicaid patients had a slight decrease in the likelihood of actually using primary care services, as measured by the proxy. The results of these naive regression models can be found in **Table 3.**

Table 3: Naive Regression Results

	Dependent variable:	
	Made_Appointment_for_Routine_Care	Have_Usual_Source_of_Care
	Made Appointment for Primary Care	Has Usual Source of Care
	(1)	(2)
Treatment Group	-0.168***	0.068***
	(0.002)	(0.002)
Post (Pre vs Post)	-0.015***	-0.004***
	(0.002)	(0.001)
Treatment × Post	-0.018***	0.036***
	(0.003)	(0.003)
Constant	0.432***	0.714***
	(0.001)	(0.001)
Observations	506,749	587,446
R^2	0.028	0.008
Adjusted R^2	0.028	0.008
Note:		*p<0.1; **p<0.05; ***p<0.01

After the naive models were fit, three additional robust models were fit, with each of the three proxy variables serving as the response variable for one of the models. Alongside the diff-in-diff specific predictors, various demographic, socioeconomic, and geographic variables were included to control for confounding effects that could otherwise bias the results. Included in these models were the following variables: *region, race, years of education, age, income,* and *employment status.*

The first robust model fit had the feature NDV as the response variable. The main coefficient, *Treatment X Post,* was positive and statistically significant, which indicates that, on average and holding all else equal, after Medicaid Expansion, Medicaid patients had a slight increase in the number of doctor visits in a given year.

The second robust model fit had the feature USOC as the response variable. The main coefficient, *Treatment X Post,* was positive and statistically significant which indicates that on average and holding all else equal, after Medicaid Expansion, Medicaid patients had a slight increase in the likelihood of having a usual source of care.

The third and final robust model fit had the feature MPAC as the response variable. This was the main variable for this analysis because it represented an actual attempt to use primary care services, not just the existence of a primary care relationship. The main coefficient, *Treatment X Post,* was negative and statistically significant, which indicates that on average and holding all else equal, after Medicaid Expansion, Medicaid patients had a slight *decrease* in the likelihood of actually using primary care services, as measured by the proxy. The results of these robust regression models can be found in **Table 4.** Overall, the metrics that measured the existence of a primary care relationship or the number of doctor visits increased after Medicaid Expansion, but the actual usage of primary care relationships decreased slightly.

Table 4: Robust Regression Results

	Dependent variable:	
	Made_Appointment_for_Routine_Care	Have_Usual_Source_of_Care
	Made Routine Appointment	Has Usual Source of Care
	(1)	(2)
Intercept	0.034***	0.085***
	(0.002)	(0.002)
Treatment Group	0.026***	0.016***
	(0.001)	(0.001)
Post (Pre vs Post)	0.037***	0.085***
	(0.002)	(0.002)
Midwest	0.017***	0.078***
	(0.002)	(0.002)
Northeast	0.015***	-0.340***
	(0.004)	(0.004)
Unknown Region	-0.016***	0.011***
	(0.002)	(0.002)
West	0.007***	0.002***
	(0.00004)	(0.00004)
Age	0.00000***	0.00000***
	(0.00000)	(0.00000)
Income	-0.038***	-0.029***
	(0.003)	(0.002)
Asian	-0.025***	-0.026***
	(0.002)	(0.002)
Black	0.002	0.017***
	(0.004)	(0.004)
Other Race	-0.019***	0.037***
	(0.005)	(0.005)

Unknown Race	0.102***	0.066***
	(0.001)	(0.001)
Female	0.008***	-0.006***
	(0.0001)	(0.0001)
Education	0.024***	-0.015***
	(0.0004)	(0.0004)
Employment Status	-0.013***	0.027***
	(0.003)	(0.003)
Treatment × Post	-0.093***	0.631***
	(0.002)	(0.002)
Observations	469,809	550,506
R^2	0.303	0.056
Adjusted R^2	0.303	0.056
Note:		*p<0.1; **p<0.05; ***p<0.01

Discussion

The results of this study offer a nuanced view of Medicaid Expansion and its impact on primary care utilization. While the ACA succeeded in broadening insurance coverage among low-income Americans through Medicaid, this analysis reveals that the expansion did not uniformly translate into increased usage of primary care services.

First, the statistically significant increases in both NDV and the likelihood of having a USOC among Medicaid recipients suggest that insurance coverage did indeed improve general healthcare access and the establishment of primary care relationships. These findings align with the ACA's core policy goal: to reduce barriers to care by extending coverage. Moreover, they mirror results found in previous literature, including studies by Olaisen et al. and Romaire, which also report increased access metrics post-expansion.

However, the decline in the likelihood of making a primary care appointment (MAPC) among Medicaid recipients post-2014 is particularly striking. Despite having coverage and identifying a usual source of care, Medicaid patients were statistically less likely to make appointments with primary care providers after the expansion. This counterintuitive finding points to an important limitation in the ACA's implementation: insurance coverage alone does not guarantee care access or usage. Systemic barriers — such as provider shortages, administrative burdens, stigma, and appointment availability — may disproportionately affect Medicaid enrollees and limit the translation of coverage into actual care-seeking behavior.

This divergence between access (USOC) and usage (MAPC) is especially relevant in policy discourse. Many governmental reports tout increased provider connections as evidence of success, but this analysis suggests that those relationships may be superficial or underutilized. In other words, having a primary care provider "on file" may not reflect a meaningful care relationship, particularly if the system is too overburdened or inaccessible for patients to schedule appointments.

Furthermore, the robustness of these findings, even after controlling for demographic, socioeconomic, and geographic variables, strengthens the credibility of the causal inference. The consistency of the direction and significance of key coefficients across both naive and controlled models increases confidence that Medicaid Expansion did not uniformly improve all aspects of primary care usage.

Finally, the implications of these results extend beyond the ACA. They underscore the need for holistic policy design that accounts not just for coverage, but for provider capacity, access logistics, and patient outreach. Efforts to bolster the primary care workforce, reduce administrative barriers for Medicaid patients, and address social determinants of health may be essential in translating insurance coverage into real-world healthcare utilization.

Policy Recommendations

Based on the results of this analysis, policymakers should work to increase primary care usage rates. One of the largest barriers to accessing primary care is geography. Rural communities have fewer healthcare professionals overall and thus fewer primary care providers (Pathman, 2019). This supply gap can be addressed through targeted policy initiatives that provide financial incentives to not only train more primary care providers, but also have them work in rural and underserved communities.

This can be accomplished through two targeted policy alternatives. The first, providing federal grants as subsidies or signing bonuses to encourage medical students to choose primary care as their career path, could directly address one of the key drivers behind the supply gap: compensation. This program would be effective, but financially costly and politically unpopular due to the increased spending this would require.

The second policy alternative is to provide relocation assistance and incentives to encourage current primary care providers to work in rural and underserved communities. While this does not address the supply gap in general, it does address the supply gap geographically. Connecting primary care providers with new communities could greatly increase the usage of primary care services and be highly effective in improving access to the healthcare system. However, this alternative is also costly and likely to be politically infeasible.

A third alternative that would likely be politically feasible and cost-efficient would be to craft a targeted educational campaign that highlights the benefits of primary care services and shows where these services could be found in each community. This would be an efficient way to share important information that simply may not be known. The effectiveness of this alternative is unclear, it could be highly or minimally effective depending on the quality of the materials developed and the level of engagement from the public.

These three alternatives are recommended as concrete and tangible policies that can be implemented to help address the decline in primary care usage rates after the ACA Medicaid Expansion. A tabular comparison of the three recommended policies can be found in **Table 5.**

Table 5: Policy Alternatives Matrix

Policy	Effectiveness	Efficiency	Political Feasibility
Signing Bonuses for Medical Students who choose Primary Care	High	Low	Low
Relocation Assistance for Current PCPs who move to Rural and Underserved Areas	High	Medium	Low
Educational Campaign to Highlight Benefits of Primary Care	Medium	High	High

Limitations

This work has some key limitations that affect both the generalizability of these findings as well as the direction future research on this subject should take. The first main limitation is a robustness issue. Medicaid Expansion was not uniform. The decision to expand coverage or not was left to each individual state, and thus, the adoption rate and levels vary significantly across geographic boundaries. These heterogeneous effects directly impact the external validity of these findings. While region fixed effects were included in each model, within-group variation between states, counties, and even zip codes caused by varying demographic, socioeconomic, and cultural factors likely introduced bias to the estimates found.

Ideally, state fixed effects could be used within the DiD models to control for these heterogeneous effects. However, due to the sensitive nature of the data collected in MEPS, the Agency for Healthcare Research and Quality restricts access to the geographic information of each respondent. To access this confidential data, a researcher would need to fill out the appropriate forms and get project approval from AHRQ. Even then, there is no guarantee that the actual state FIPS code would be made available; oftentimes, a set of dummy variables is sent in place of the actual state codes to further protect the respondents' privacy. The author attempted to control for this by incorporating regional fixed effects. While more robust than the naive models, it is still less than ideal. A thorough and more robust analysis should incorporate state fixed effects instead.

Another limitation of this work is the likely impact that confounding effects had on the statistical analysis. An almost infinite number of factors influence whether an individual chooses to see a primary care provider or not. Cultural, economic, and familial situations all factor into this decision. Furthermore, emergency room visits are far more common than primary care visits, even for routine matters that could be treated by a primary care provider (Wu & Woloski, 2024). This analysis does not control for individual choice between generalists and specialists. It simply seeks to compare the narrative regarding the effects of the ACA and associated Medicaid Expansion with the actual trends present in official data. None of the three proxies used controlled for an individual's preference between seeing, for example, a dermatologist or a primary care provider for a mole. A more robust analysis should control for more detailed and nuanced factors such as these.

Future Work

As mentioned above, future work on this subject should employ more robust controls to account for the nuances present within different geographic, demographic, and socioeconomic strata. Similarly, different statistical techniques could be tried to either examine the same question from a different angle or to approach a different side of the same problem.

One interesting idea is to incorporate the K-Nearest Neighbors machine learning algorithm to try to cluster MEPS respondents on some demographic, geographic, or socioeconomic variable. After clustering, within-group analyses could be conducted on the three proxy variables used in this analysis to further identify how different groups responded to Medicaid Expansion, specifically in the form of primary care usage rates.

Another approach that could be undertaken would be to formulate a survey and collect data directly from individuals regarding their usage of primary care services before and after the ACA was passed. This approach would allow for a direct comparison between official data and personally collected data, and as long as robust sampling methods were followed, could help further elucidate the true effects of the ACA on primary care usage rates.

This approach has several limitations, most notably time, administrative, and financial costs. Surveys are notoriously complex, especially with randomized and stratified samples. Additionally, the scope of this analysis would require a large amount of data from across the country. This would be an administrative burden for a solo researcher and would likely be untenable due to high financial costs. Furthermore, collecting healthcare data requires administrative work, such as Institutional Review Board (IRB) approval, which can take a long time. Lastly, due to the sensitive and potentially politically inflammatory nature of this survey, the results would likely be beset by voluntary response bias.

Conclusion

Studying the true effects of a public policy intervention is an important but tricky task. This is especially true for something as large, complex, impactful, and politically controversial as the ACA. Any future work on this subject should approach this topic with respect, objectivity, and creativity. At the end of the day, working to help more and more Americans at the peripheries of society gain access to quality healthcare is an important and noble task. If any conflicting claims are found between official sources and true outcomes, they should be discussed magnanimously, fairly, and truthfully so that adverse effects can be corrected and beneficial outcomes multiplied. It is only through this approach that future work on this subject can be both insightful and impactful. Disagreements drive the US political system forward by forcing all sides to consider topics more robustly. There is great potential to do a tremendous amount of good by making the primary care market more accessible. The author hopes that this work leads to respectful, thorough, and objective discussions as well as robust future work that can lead to more equitable healthcare outcomes for all Americans.

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Appendix

Code

All analysis for this project was done using R version 4.4.3 and the following packages: *readr, dplyr, skimr, foreign, ggplot2, GGally, naniar, kableExtra, summarytools, stargazer, gtsummary, tidyr, modelsummary, knitr,* and *broom*. The complete R Markdown file containing all code used in this analysis is available upon request.

Data

All data for this analysis was downloaded from the Medical Expenditure Panel Survey website and can be found here.

Mathematical Excursus:

This appendix section is meant as a more technical overview of how a difference-in-differences (DID) estimation model works. A DID model is typically used to estimate the causal treatment effect of an intervention, whether planned, such as a policy change, or unplanned/unexpected, such as a revolution or natural disaster (Columbia University, 2023).. These models are naturally suited for panel data because they require time series data to evaluate trends both before and after the intervention. In general, a difference-in-difference model tracks the changes of two groups: a control group not directly affected by the intervention and a treatment group that is directly affected by the intervention (Columbia University, 2023). The technique first looks at the trends of the two groups before the intervention occurred. These trends are then compared to the new trends that occur after the intervention. If the treatment group had similar trends to the control group before the intervention, and then vastly different trends after, **with the control group maintaining a similar trend as before,** there is causal evidence that the intervention had a direct impact on the treatment group.

Mathematically, this approach can be modeled in the following way:

$Y = \beta 0 + \beta 1*[Time] + \beta 2*[Intervention] + \beta 3*[Time*Intervention] + \beta 4*[Covariates]+\varepsilon$

The key covariate in this model is the Time*Intervention term. This corresponds to the treatment group after the intervention. If this coefficient is statistically significant, then there is evidence that the intervention had a causal effect on the treatment group (Columbia University, 2023). This model is flexible, interpretable, and computationally efficient.

Difference-in-differences estimation is a robust technique due to its unique ability to model natural experiments. Often, the control and treatment groups studied in these analyses are naturally formed. For example, if analyzing the effects of a tsunami on spending habits, those affected and not affected by the disaster can be considered (for simplicity) randomly assigned their fate and thus can be considered a robust sample.

This technique has a few key assumptions that are essential to avoid biased and invalid results. The first and main assumption is called the parallel trends assumption. It requires that in the absence of the intervention, the difference between the treatment and control group is constant over time (Columbia University, 2023). Although there is no statistical test for this assumption, visual inspection is often very useful (Columbia University, 2023). In general, the smaller the time period tested, the more likely the assumption is to hold (Columbia University, 2023). Violation of the parallel trend assumption will lead to biased estimation of the causal effect (Columbia University, 2023). The other main assumptions that are critical for the validity of this method are that the allocation of the treatment was not determined by the outcome, there were no contemporaneous shocks that could confound the treatment effect, and that the treatment and control groups are similar enough to ensure generalizability and internal validity (Columbia University, 2023).

Figure 5: Graphical Explanation of Difference-in-Differences Estimation Method (Source: Columbia University)