REStat Fellowship Application – NBER Summer Institute 2025

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Current Research Summary

My research lies at the intersection of labor economics, public policy, and crime. My dissertation investigates the causal relationship between reservation wages and labor market conditions—an underexplored but vital dimension of labor supply. While much of the existing literature focuses on real wages, my work addresses a critical gap by examining the minimum wage a worker requires to accept employment, particularly within the framework of unemployment insurance (UI).

Using data from the Benefit Accuracy Measurement Program, I study how unemployment rates, employment-to-population ratios, market tightness, and labor productivity affect reservation wages and labor force participation. These findings reveal the cyclical sensitivity of reservation wages and underscore the role of UI in influencing job acceptance and economic behavior, offering valuable insights for improving labor market efficiency and policy design.

Building on this work, I am currently expanding my research to examine the relationship between labor market concentration and reservation wages. Traditional economic theory suggests that increased market concentration depresses wages due to reduced competition and fewer employer options for workers. Given my earlier findings that reservation wages track closely with actual wages, this extension is timely and necessary. By integrating additional datasets with the BAM survey, I aim to estimate the causal impact of labor market concentration on workers' reservation wages. This research has substantial policy implications, especially as labor market concentration continues to rise across industries in the United States. Understanding how market power affects workers' wage expectations can help policymakers promote fairer labor practices and support a more competitive workforce.

In parallel, I am also pursuing an original research project exploring the effects of Medicaid expansion on urban crime. Existing studies in this area primarily rely on FBI crime statistics, which are limited in temporal frequency and fail to capture short-term effects. My research addresses this gap by leveraging high-frequency daily crime data from major U.S. cities—data sources previously untapped in Medicaid-related research. Although the project is still in progress, it holds significant promise for uncovering how healthcare access shapes public safety outcomes. The findings could meaningfully inform debates around Medicaid expansion, criminal justice reform, and the broader social returns of public health investment.

Contribution to the Summer Institute Community

As a scholar originally from a small village in northern Pakistan, I bring a unique and underrepresented perspective to applied microeconomic research. My journey—shaped by navigating

structural barriers and a non-traditional academic path—has deeply informed my research on labor market inequities, public health interventions, and crime. I currently serve as a professor at a technical college, a role that is not commonly represented at conferences like the Summer Institute. This position grounds my research in the real-world experiences of diverse and often overlooked student populations, sharpening my commitment to inclusive, policy-relevant inquiry. Coming from a non-elite institution and an underrepresented background, I aim to enrich the Summer Institute's research community with both personal and scholarly diversity.

What I Hope to Gain from the Experience

I hope to engage deeply with leading scholars in applied microeconomics, not only to receive constructive feedback on my current projects but also to contribute to and learn from ongoing conversations at the frontier of labor, health, and public economics. My research agenda focuses on understanding how public policies—such as unemployment insurance and Medicaid expansion—shape individual behavior and socioeconomic outcomes. Attending the Summer Institute would allow me to refine the causal methods I employ, explore new data strategies, and gain insight into how others are approaching similar questions. Additionally, I am eager to form long-term collaborative relationships with researchers who share an interest in applied policy-relevant economics. The opportunity to immerse myself in this intellectually vibrant environment would be especially valuable as I continue developing projects from a technical college setting, where such exposure to cutting-edge empirical work is rare but deeply impactful for both teaching and scholarship.

Preferred Sessions

- Labor Studies
- The Micro and Macro Perspectives of the Aggregate Labor Market
- Law and Economics
- Economics of Crime
- Economics of Health

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Academic Position

Economics Professor **July 2024 - Present**
Midlands Technical College

Education

PhD in Economics **Jun 2021 - June 2024**
University of Delaware
Dissertation Title: Essays on Unemployment Insurance and the Reservation Wage

MS in Economics & Applied Econometrics **Aug 2019 - May 2021**
University of Delaware
Cumulative GPA: 3.8/4.0

BS in Economics & Mathematics **Sep 2014 - Jun 2018**
Lahore University of Management Sciences
National Outreach Program Scholar (Fully Funded Scholarship)

Fields

Labor Economics, Development Economics, Household Finance

Research Papers

"Reservation Wages and Macroeconomic Conditions: Evidence from Benefit Accuracy Measurement Data"(Job Market Paper)
The reservation wage is an important element in equilibrium labor market models. In this paper, I use new government Benefit Accuracy Measurement (BAM) survey data on unemployment insurance (UI) claimants to study the relationships between reservation wages and labor market conditions. The direction of most measures is in accordance with the theory. While the layoffs rate coefficient aligns with the theory, the total separation rate deviates from it, due to the role of quits in the job separation rate. Among the main indicators, workers are most responsive to the employment-to-population ratio. Results also show that the aggregate employment indicators matter more than worker's group-specific measures, indicating that workers focus more on the aggregate market conditions. To introduce exogeneity, I include shift share measures in my specifications and find similar positive relationships between the reservation wage and the shift share measures. All results are robust to different sub-sample selections and specifications.

"Unemployment Insurance and Employment: Evidence from the Lost Wages Assistance Program"(Link)
In August 2020, the US government introduced the Lost Wages Assistance Program, the purpose was to provide relief to the unemployed workers. Under the program, $300 additional payments were provided in addition to regular UI benefits. Using the Household Pulse Survey, this paper attempts to study the employment effects of the program. I find that a 1associated with a 4study results that show a decrease in the working probability in the post period. To address treatment heterogeneity, I also include Callaway and Sant'anna estimator and find similar negative employment effects. The results are robust to various specifications and statistically significant among the sub-groups as well.

"How Does the Early Withdrawal from Pandemic UI Extensions Impact Housing Outcomes?"
In June 2021, 23 states decided to end pandemic-era UI extensions. In this paper, I exploit state-level variation to examine the impact of early withdrawal from FPUC (Federal Pandemic Unemployment Compensation) on housing outcomes. I find that withdrawal from FPUC increased evictions and foreclosures. These estimates imply that financial fragility remained elevated through the end of 2021 despite the resumption of growth in per capita incomes.

Work in Progress

"Medicaid Expansion and Crime" with Vikrant Vilas Kamble.

"Is Crime Rate Affected when People Voluntarily Opt Out of the Labor Market?" with Abubakr Ayesh.

"Does the Food Stamp Program Improve the School Performance of Children in Recipient Families?"

"Does a targeted Cash Transfer Program Effectively Assist Families in Coping with COVID-19?"

Teaching Experience

University of Delaware

Introduction to Macroeconomics - Econ 103 **Spring 2024**
Teaching Assistant for Professor Erin Yetter

Introduction to Microeconomics - Econ 101 **Fall 2023**
Teaching Assistant for Professor Jens Schubert

The Economics of Regulation - Econ 463 **Spring 2023**
Teaching Assistant for Professor Julianna M. Butler

Intermediate Microeconomics - Econ 300 **Fall 2022 - Spring 2023**
Teaching Assistant for Professor Julianna M. Butler

Contemporary Macroeconomic Policy - Econ 435 **Fall 2022**
Teaching Assistant for Professor Laurence Seidman

Introduction to Microeconomics - Econ 101 **Fall 2021, Spring 2022 & Summer 2022**
Adjunct Faculty in the English Language Institute

Work Experience

Punjab Healthcare Department **Feb 2019 - July 2019**
Research Assistant
Provided weekly updates on the vaccination status of the district hospitals. Performed daily data analysis using ambulance-related data. Worked closely with the research team to develop monthly performance reports.

World Bank **Aug 2018 - Jan 2019**
Research Intern
Compiled data using SurveyCTO. Performed data cleaning using Stata on large data-sets containing millions of observations. Collaborated with senior researchers to discuss research plans and methodologies. Presented weekly updates on the research findings.

Seminars and Presentations

Carolina Regional Empirical Economics Day - CREED **Oct 2023**
"Reservation Wages and Macroeconomic Conditions: Evidence from BAM Data"

PhD - Economics Virtual Seminar (EVS) **Oct 2023**
"Reservation Wages and Macroeconomic Conditions: Evidence from BAM Data"

International Conference on Economics, Finance & Business, Prague **Aug 2023**
"Reservation Wages and Macroeconomic Conditions: Evidence from BAM Data"

Fall Research Symposium - University of Delaware **Dec 2022**
"Reservation Wages and Macroeconomic Conditions: Evidence from BAM Data"

Computer Skills
Stata (Advance), R (Intermediate), SQL (Intermediate), Python (Intermediate), SurveyCTO (Intermediate), C++ (Intermediate), LaTeX(Advance)

Languages
English (Fluent), Urdu (Native), Hindko (Fluent)

Certificates

Data Science Bootcamp **Spring 2024**
Erdos Institute

Python Prep **Spring 2024**
Erdos Institute

References

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Medicaid Expansion and Crime:

Evidence from U.S. Cities

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Abstract

We examine the impact of the Affordable Care Act (ACA) Medicaid expansion on city-level crime rates. The ACA's Medicaid expansion began in 2014, with various states gradually opting in over time. Utilizing high-frequency, city-level data and variation in policy start dates, we provide strong causal evidence on the relationship between Medicaid expansion and crime rates. Our event study employs an advanced difference-in-differences estimator that accounts for treatment heterogeneity. Our findings reveal a statistically significant reduction in crime, including a noticeable decrease in specific types of crime. These results provide evidence that Medicaid expansion reduces crime. Possible mechanisms behind this reduction might include financial stability, improved access to substance abuse treatment, and an increased opportunity cost of crime.

Keywords: Affordable Care Act (ACA), Medicaid expansion, Crime

JEL Codes: I13, K14, K42

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1 Introduction

Crime rates in the United States have shown a consistent decline over the past two decades. According to FBI's Uniform Crime Reporting (UCR) data, the violent crime rate decreased by 49% between 1993 and 2022, with significant reductions in robbery (- 74%), aggravated assault (- 39%), and murder / non-negligent manslaughter (- 34%) Gramlich (2024). However, despite the overall downward trend, certain periods have experienced notable increases in crime. For example, during the COVID-19 pandemic, the murder rate recorded its largest single-year increase in history and remained substantially elevated in 2022 compared to pre-pandemic levels. As crime rates continue to fluctuate, it becomes increasingly important to identify the policies that have contributed to the decrease in crime in recent years.

While there is substantial evidence in the literature examining the impact of Medicaid on criminal activity (Finkelstein et al. (2011), Deck et al. (2009), Aslim et al. (2022), Jácome (2020), He and Barkowski (2020), Vogler (2020)), almost all previous studies have based their empirical strategy on the Two-Way Fixed Effects (TWFE) estimator. Recent econometric literature has raised concerns about the validity of the TWFE estimator in the presence of staggered treatment adoption. We extend the current literature by providing stronger and more credible causal evidence on the relationship between the 2014 staggered rollout of Medicaid expansion and crime. First, we employ the advanced difference-in-differences estimator proposed by Callaway and Sant'Anna (2021), which addresses the issue of negative weighting and produces more accurate estimates. Second, we use more granular, daily-level crime data, in contrast to previous studies that relied on less detailed data.

Our crime data comes from the Crime Open Database (CODE), which is publicly available through an open-source platform.[1] It has been used in previous studies to analyze crime trends in U.S. cities. Our paper is the first to employ this dataset for a causal analysis of the effects of health insurance on crime. The data include daily-level crime counts for 30 crime categories in the 21 largest U.S. cities. Exploiting this data, we are able to observe crime trends in US main cities for an extensive period of time.

Health insurance expansion could be a potential factor in reducing crime due to a variety of reasons. Under the Affordable Care Act (ACA) 2014, Medicaid expansion was carried out with the goal of reducing the costs associated with health care. Medicaid expansion also targeted young, poor, and childless adults, a group with historically low rates of health insurance coverage He and Barkowski (2020). Mostly, young and poor adults are involved in crime due to drug usage or financial stress. By targeting these vulnerable individuals, Medicaid could decrease crime through income transfer, which reduces the financial burden of health expenditure and lowers the debt associated with healthcare that might induce some individuals to

[1]The data can be found here, with more details given in Ashby (2022).

involve in criminal behavior Finkelstein et al. (2011). Another possible channel is the likelihood of treatment for those suffering from mental health issues or drug addiction. Most people avoid these treatments as they are expensive and require significant savings. In the presence of Medicaid expansion, we should expect more eligible individuals to receive these treatments, which could potentially reduce the crime levels.[2]

We exploit the variation in the timing of Medicaid expansion in cities in our sample. In our main specification, we include all the cities that participated in the ACA expansion, which introduces treatment heterogeneity due to the variation in the starting time. We use the new DiD estimator proposed in Callaway and Sant'Anna (2021). After including all the cities, our main results show a clear decline in crime after the Medicaid expansion. This effect is evident in both overall crime, as well as in violent and non-violent crime categories. We also find a clear drop in crime for most of the major crimes in our data, such as assault, robbery, etc. Our city-level results are consistent with the previous studies showing a decrease in crime due to health expansion at the state or county level (Deck et al. (2009), Finkelstein et al. (2011), He and Barkowski (2020), Simes and Jahn (2022)).

In the existing literature, there are various papers that focus on the relationship between Medicaid expansion and crime. Vogler (2020) investigated the impact of the 2014 Medicaid expansion on crime, similar to our study. However, their unit of analysis was the state. Annual, state-level crime data were obtained from the FBI's UCR for the years 2009 through 2018. Using a difference-in-differences design, they found that states that expanded Medicaid experienced a 5.3% reduction in annual reported violent crime rates relative to non-expansion states. He and Barkowski (2020) conducted similar analysis using 2014 Medicaid expansion including county-level crime data from 2010-2014 and 2016.[3] The results indicated a decrease in violent and property crime rates due to Medicaid expansion (burglary rates fell by 3.75 percent, motor vehicle theft reduced by 10.4 percent, robbery is reduced by 6.33 percent, etc.). Wen et al. (2017) focused on a different policy related to Medicaid expansion. The authors analyzed the impact of the 2001 Health Insurance Flexibility and Accountability (HIFA) waiver initiative, which expanded Medicaid access for low-income individuals by providing states with federal matching funds. The main data consisted of county-level crime counts from the Uniform Crime Reports (UCR) and the National Survey of Substance Abuse Treatment Services (NSSATS) between 2001 and 2008. Results showed that HIFA-waiver expansions led to a relative 2% reduction in the robbery rate, a 1% reduction in the aggravated assault rate, and a 0.6% reduction in the larceny-theft rate, primarily through increased substance abuse disorder treatment.

In comparison to Medicaid expansion, there are papers that focused on the effects of losing Medicaid on crime. Deza et al. (2024) leveraged one of the largest Medicaid disenrollments in US history, which happened

[2]In the literature, Bondurant et al. (2018), Campbell et al. (2007), Frank et al. (2010), and many others found a reduction in crime due to substance use and mental health treatment.

[3]2015 was excluded as it was not publicly available.

in Tennessee in 2005, where almost 190,000 non-elderly and non-disabled individuals lost coverage. Using difference-in-differences strategy, results found a 7.1% increase in the total crime rate post disenrollment. Similar results were observed for violent and non-violent crimes. Jácome (2020) utilized South Carolina data to examine the effects of Medicaid eligibility loss at age 19. By comparing men just above and below this age threshold, the study found that losing Medicaid coverage increases the likelihood of incarceration, with particularly pronounced effects among individuals with mental health disorders and those involved in non-violent offenses. Fone et al. (2023) also found similar results, indicating that arrest rates increased among young adults who aged out of eligibility for parental coverage at 26. Recent studies have also examined other crime-related outcomes in relation to Medicaid expansion (Simes and Jahn (2022), Packham and Slusky (2023), Burns and Dague (2023), and Aslim et al. (2022)).

This paper makes several contributions to the existing literature. Firstly, this study adds to the growing literature that focuses on the relationship between healthcare and crime. (Frank et al. (2010), Bondurant et al. (2018), Campbell et al. (2007), Deck et al. (2009), Lurigio (2000), Marsch (1998), Deza et al. (2024)). These papers focused on various health-related programs and found that access to healthcare led to lower levels of crime and arrests. We find similar results where crime rate decreases after the Medicaid expansion. Our analysis also extends the specific literature that study the impact of Medicaid expansion on crime (He and Barkowski (2020), Simes and Jahn (2022), Vogler (2020), Wen et al. (2017)). The existing papers such as Vogler (2020) and He and Barkowski (2020), employed TWFE to establish causality in the context of Medicaid expansion. However, these studies did not account for treatment heterogeneity in their TWFE specifications. As shown in Table A.1, most states adopted Medicaid expansion over a period of time, introducing treatment heterogeneity. This temporal variation in treatment adoption creates a bias in the TWFE estimates due to negative weighting, which undermines the validity of the findings in these earlier studies. To address this issue, we adopt the estimator proposed by Callaway and Sant'Anna (2021), which mitigates the problem of negative weighting and provides more reliable estimates than the previous studies.

Almost all of the previous papers used FBI's UCR data for crime. That data is available for each state and for some counties at the agency-year level. Some agencies also report monthly crime counts. Due to a lower frequency in the data, most of the current papers have very small sample size.[4] These papers also use shorter time periods.[5] In our paper, we use high frequency daily-level crime data that provides a larger sample size for an extensive period.[6]

[4]The sample size in He and Barkowski (2020) is 357 for states and 3,246 for border counties. Similarly, it is 3,035 in Simes and Jahn (2022), 306 for each state and 18,246 for counties in Vogler (2017), and 22,328 in Wen et al. (2017).

[5]He and Barkowski (2020) uses 2010-2016 time period. Simes and Jahn (2022) analyzes 2014-2016 period, Wen et al. (2017) focuses on 2001-2008, while Vogler (2017) uses 2010-2015 years.

[6]We aggregate our data to monthly level to reduce noise and computational burden. After aggregation, our sample is still considerably larger than the previous studies.

Our paper is also different from the existing papers as the unit of analysis is city. Through the existing papers, we already know that the Medicaid expansion had a negative effect on state and county crime rates. This paper further the analysis by studying the impact of the policy on cities, which provides valuable insights into the effects of Medicaid expansion on city-level crime. We also include a large number of crimes in our analysis. Previous studies focused only on major crimes such as robbery, assault, larceny, homicide, and vehicle theft. Our data includes nearly 30 different types of crime, including offenses not present in the UCR (e.g., fraud/counterfeiting, human trafficking, disorderly conduct). This broader range of crimes allows us to conduct a more comprehensive analysis by examining offenses beyond those reported in the UCR.[7]

The remainder of this paper is organized as follows. Section 2 provides background information on ACA Medicaid expansion. Section 3 outlines our empirical strategy. Section 4 describes our data sources and presents descriptive statistics. Section 5 presents our main results and discusses their implications. Section 6 conducts robustness checks and Section 7 concludes.

2 ACA Medicaid Expansion of 2014

The Affordable Care Act (ACA) is a federal and state partnership program aimed at providing and expanding access to health insurance for low-income individuals He and Barkowski (2020). A significant milestone in this effort came in 2014, when Medicaid eligibility was expanded in 28 states and the District of Columbia. This expansion allowed millions of previously uninsured individuals to obtain health insurance coverage. Over time, additional states also chose to expand their Medicaid programs, further increasing access to health care for low-income populations. The impact of this expansion has been profound, especially in terms of reducing the number of uninsured individuals. According to McMorrow et al. (2015), Medicaid expansion led to a notable increase in health insurance coverage among eligible adult individuals, contributing to improved health outcomes and greater access to necessary medical services.

There are several papers that study the direct effects of Medicaid expansion on postpartum hospitalizations, perinatal insurance continuity, perinatal mental health, substance use disorder, postpartum coverage and outpatient utilization , infant mortality, etc (Steenland and Wherry (2023); Daw et al. (2020); Margerison et al. (2021); Maclean and Saloner (2019); Gordon et al. (2020); Constantin and Wehby (2023)). A few studies also examine the indirect effects of Medicaid expansion on migration, crime, criminal behavior, recidivism, etc (Goodman (2017); He and Barkowski (2020); Vogler (2020); Gollu and Zapryanova (2022)).

In this paper, we focus on the indirect effects of Medicaid expansion on crime. We analyze data from 21 major cities in the USA, with the corresponding states and Medicaid expansion implementation dates listed

[7]National Incident Based Reporting (NIBRS) is another data source that provides information on almost 50 crime categories across states. However, it does not contain information on specific cities, which is the main focus of this paper.

in Appendix Table A.1.[8]

3 Empirical Strategy

First, we investigate the direct impact of Medicaid expansion on Medicaid enrollment. To do this, we use the following equation:

$$Medicaid\ Enrollment_{st} = \beta_0 Post_t + \beta_1 Medicaid\ Expansion_s + \beta_2 Medicaid\ Expansion_s * Post_t + \zeta_{st} \quad (1)$$

We use Current Population Survey (CPS) for this analysis. CPS is at the monthly level, but the insurance questions are only asked once a year. In Equation 1, the dependent variable is a dummy equal to one if a person is enrolled in Medicaid in state s during the year t. Medicaid expansion is equal to one for states that enrolled in the 2014 ACA expansion and zero otherwise. Post is also one for 2014 and later years and zero otherwise.

To examine the causal relationship between the Medicaid expansion of the Affordable Care Act (ACA) and crime, we employ the Medicaid expansion as a quasi-natural experiment. Our analysis focuses on data from 2010 to 2022, using a difference-in-differences methodology. We also exclude the COVID period in the robustness checks. The key temporal variation is the 2014 implementation of the Medicaid expansion. States (and thus cities) that adopted the Medicaid expansion in 2014 serve as the treatment group, while other cities function as the control group. The primary identifying assumption is that, in the absence of the Medicaid expansion, crime rates in the treatment and control cities would have followed parallel trends.

Our main model incorporates a staggered design by considering the staggered implementation of Medicaid expansion across different states and cities in different calendar months. We employ the estimator given in Callaway and Sant'Anna (2021) and aggregate our daily data to a monthly level to reduce noise, ensure computational feasibility, and produce accurate estimates. The estimated equation is the following.

$$y_{cmt} = \gamma_{mt} + \beta Program_{cmt} + \theta X_{c,2013} + \zeta_{cmt} \quad (2)$$

The dependent variable in Equation 2 represents crime in city c during month m and year t. The outcome variables in this analysis include overall crime, violent crime, non-violent crime, assault, vandalism, weapon-related offenses, robbery, motor vehicle theft, and larceny. The term γ_{mt} represents month-year fixed effects, respectively. $Program_{cmt}$ represents the Medicaid expansion and is equal to one if the state (and thus city

[8] We selected these cities because the OSF dataset includes data only for these locations. Further details on the data and cities are provided in the data section.

c) implemented the Medicaid expansion law in month m, calendar year t and zero otherwise. $X_{c,2013}$ is a vector that contains baseline characteristics at the city level.

4 Data

4.1 Outcome data

The outcome data used in this article is sourced from the Crime Open Database (CODE).[9] It is daily data on crime and offense type in the 21 large US cities. The data ranges from year 2007 to 2022. In this paper, we include data from 2010 to 2022. The CODE database is an extensive repository of crime data from 21 major cities in the United States, providing a comprehensive view of urban crime patterns. The data set includes some of the largest metropolitan areas in the country, such as New York City, Los Angeles, and Chicago, as well as other prominent cities such as Houston, San Francisco, and Boston. Additional cities featured in the database include Austin, Charlotte, Colorado Springs, Detroit, Fort Worth, Kansas City, Louisville, Memphis, Mesa, Minneapolis, Nashville, St. Louis, Tucson, and Virginia Beach. This diverse selection ensures that the CODE database reflects a representative sample of urban crime in varying demographic, economic, and cultural landscapes within the United States.

To be included in CODE dataset, cities must meet specific criteria: their data must be openly licensed, include incident locations (with some privacy safeguards allowed), specify dates, use consistent crime categorization, span at least four consecutive years, and pass quality checks. These requirements ensure a standardized, reliable dataset that allows for meaningful comparisons across various urban areas while maintaining a high level of detail and utility. Table 1 provides the summary statistics of the main variables of interest.

Crimes are categorized into three primary groups: offenses against persons, property, and society. Violent crimes include detailed classifications such as homicides, different forms of assault, and sexual offenses. Property crimes are thoroughly documented, with distinctions made between types of theft, burglary, and fraud. Societal offenses encompass drug-related crimes, weapons violations, and public order infractions.

We use the CODE dataset due to its advantages over the FBI data. First, the CODE dataset offers a more detailed perspective, documenting offense types that are both extensive and specific at the daily city level rather than as agency-wide aggregates. This approach not only increases sample size but also enhances variability and statistical power to detect meaningful effect in regression analysis. Second, the CODE dataset introduces finer distinctions, such as separating personal from commercial robberies and

[9] For technical detail on the data, see Ashby (2019).

distinguishing between residential and non-residential burglaries. Finally, this level of detail enables a more precise analysis of crime trends and patterns across diverse urban environments.

4.2 Treatment and covariates data

Data on Medicaid expansion dates are sourced from Kaiser Family Foundation (KFF), which provides detailed information about Medicaid expansion dates across states. Current Population Survey (CPS) provides information on Medicaid enrollment after the introduction of the health expansion. We use CPS data to detect the direct impact of Medicaid expansion on enrollment.

The county-level controls data are obtained from Griffith et al. (2021), which provides detailed information on county demographics, including age, race, ethnicity, income, insurance coverage, healthcare care demand, and more. Additional information on this data set is available in the Griffith et al. (2021) paper. In our analysis, we used variables such as Medicaid eligibility, population, unemployment rate, black population, and poverty. The summary statistics for both the outcome and control variables are shown in Table 1.

5 Results

In this section, we explain our results in detail. We start off by investigating the direct impact of Medicaid expansion on the enrollment (first stage). We use the specification given in Equation 1. Table 2 provides the result. Our results show that states with Medicaid exposure experienced an increase in enrollment by 0.01 percentage point.[10] Our point estimate is different from the existing studies. Vogler (2020) found that state-level uninsured rates decreased by 0.02 percentage point after the expansion, while Deza et al. (2024) reported coverage coefficient with a magnitude of -0.05 after the disenrollment in Tennessee. Our coefficient is lower as we are using a different time period. We are also conducting our analysis on CPS, which is a representative sample but very different from the data sources of mentioned studies.[11]

5.1 Staggered Treatment

This section provides the results from our main specification (Equation 2). With treatment heterogeneity, we employ the estimator given in Callaway and Sant'Anna (2021).[12] Figure 1 shows the results where there

[10] We run the specification at the state level. We also restrict the time period from 2010-2015. In this way, we are able to measure the direct short-term impact of the expansion on Medicaid enrollment.

[11] Vogler (2020) obtained uninsured rates from US Census Bureau. Deza et al. (2024) analyzed administrative data that included information on Medicaid coverage across various counties in Tennessee.

[12] According to Callaway and Sant'Anna (2021), TWFE often produces negative weights in the case of treatment heterogeneity. Due to this, the coefficients are biased and the true effect is not estimated. The new estimator solves this issue by identifying the group-time treatment effect in the presence of treatment heterogeneity. Further detail is provided in Callaway and Sant'Anna (2021).

is a significant drop in crime in the post-period. The effect is more pronounced for overall and violent crime. In all panels, the parallel trend assumption is satisfied. There is a slight increase in the crime rate just before treatment. However, it drops significantly at $t = 0$. This increase is in the opposite direction of the treatment effect, and it is also smaller in magnitude when compared with the post-period. After treatment, there is a clear trend break and a sharp decrease in crime. So, our estimates should still be considered as a lower bound of the true effect of the policy.

We also provide results for various crimes in the presence of treatment heterogeneity. We estimate Equation 2 for different types of crimes. To be consistent, we use the same types of crime that contribute at least 5% to the total crime in our data. Figure 2 includes the results. The crime rate goes down for almost all crimes. In terms of pre-trend, the coefficients are most stable for weapon law violations in panel (e). For the other panels, the pre-period crime rate is scattered and does not follow a regular trend. In the post-period, the treatment effect is downwards except for the weapon law violations, which also goes down in the long run. Overall, the results show a decrease in the various types of crime after expansion. All of these crimes are typically reported by victims, except for weapon law violations. Weapon law violations are almost exclusively recorded when an officer discovers someone illegally possessing a weapon. This means the number of violations depends on the level of police attention to detecting weapons offenses and the strictness of weapon laws in a given city. If those laws change over time, the trend in recorded violations should also change. We also provide an event study by excluding cities that experienced significant changes in weapon laws during our period of study.[13]

In terms of magnitude, our event studies show more pronounced results compared to earlier papers (Vogler (2020) and He and Barkowski (2020)). The main reason for this is the bias that arises from treatment heterogeneity. The estimator proposed by Callaway and Sant'Anna (2021) outperforms TWFE in the presence of treatment heterogeneity, making our estimates more accurate and robust. Our findings align with previous studies showing a decrease in crime due to expansion of health coverage at the state or county level (Deck et al. (2009), Finkelstein et al. (2011), He and Barkowski (2020), Simes and Jahn (2022)).

The reduction in various crimes due to Medicaid expansion can occur through multiple channels. In theory, crime rates should decline following the expansion of health insurance. The main mechanism behind this is the rising opportunity cost of criminal activities. When Medicaid expands, individuals are discouraged from engaging in crime because they would risk losing the benefits associated with the expansion. As a result,

[13]Giffords Law Center provides useful information on gun law strength and gun deaths across states. It also assigns a grade to each state depending on strength of gun laws and number of gun deaths per 100,000 people. We compare the grades from 2010 to 2019 grades. Out of the states to which our 21 cities belong, three states improved significantly during that time period (Illinois went from B- to A-, New York went from B to A-, while North Carolina received D grade from its previous F grade). We exclude cities from these three states. By doing this, we separate the effect of changing gun laws from the insurance effect. The results are given in the Appendix where the trend is similar to the main results (Figure 5b). This confirms that weapon law violations decrease because of Medicaid expansion in the post-period.

the utility of committing a crime decreases, while the utility of receiving health insurance increases.[14]

Access to health insurance can also improve health outcomes, which reduces crime. Through Medicaid expansion, individuals would be able to receive behavioral healthcare, such as mental health and substance abuse disorder treatment. This further reduces crime rates by improving mental health and substance use symptoms. There are already studies stating that better behavioral treatment led to lower crime rates (Heller et al. (2017),Deck et al. (2009), Bondurant et al. (2018)).

Health expansion can also reduce crime through the financial channel. Medical insurance reduces health-related costs, increasing disposable income and providing financial stability to recipients. This, in turn, reduces financially motivated crimes and violent crime stemming from financial stress. There is compelling evidence that positive income shocks and financial stability lead to a reduction in crime (Carr and Packham (2021), Arenberg et al. (2024)). Almost all of these mechanisms explain the reduction in crime in our results. We can also rely on these channels for the specific crime types, such as violent (assault, homicide, weapon law violations) and non-violent crimes (vandalism, fraud, disorderly conduct).

6 Robustness Checks

So far, we used the 2010-2022 period for our analysis. To check the robustness of our results, we restrict our time period to 2010-2019. The main reason behind this is to understand the role of COVID in the decrease in crime rates. In the existing literature, we have mixed findings about the crime rate during the pandemic period. Meyer et al. (2022) found out that homicide rate and auto thefts increased significantly throughout 2020, while robbery and larceny declined during the same period. Similarly, Boman and Gallupe (2020) stated that serious crimes that are generally committed with co-offenders (homicide and intimate partner violence) had remained constant or increased after the pandemic. According to Ashby (2020), there were no serious changes in assault, reductions in residential burglary, and a decrease in motor vehicle theft.

To separate the COVID effect from the insurance effect, we run the specification from Equation 2, while restricting our sample to pre-pandemic years. In Figure 3a, we show the results for overall crime where the effect is negative and significant in the post-period. The results are similar to the earlier results of the full sample (Figure 1). This confirms that the decrease in overall crime was due to Medicaid expansion and not to pandemic restrictions.

As an alternate specification, we use the log of overall crime as a dependent variable in our analysis. Through this, we are able to analyze the percentage change in monthly crime rate. Figure 3b provides the results, where the findings are similar to the main crime variable. The log of crime decreases significantly in

[14]See He and Barkowski (2020) for more explanation on the theoretical framework.

the post-period, showing a percentage decrease in crime due to Medicaid expansion. We also performed a placebo exercise by changing the timing of Medicaid expansion. Specifically, we employ the treatment three years earlier than the actual time.[15] As the Medicaid did not happen around our hypothetical time, we should not experience any significant change in crime. In Figure 3c, we can see that the crime rate does not change with the alternate timing. Although, there is a drop right around time zero, but the coefficients are still insignificant. This validates our main results and confirms the robustness of our specification.

With the hypothetical three years early treatment, we do not find any significant drop in crime. However, there is still possibility of contamination as the actual treatment started three years later within the same time frame. To counter this issue, we restrict our sample to 2007-2013. Then, we provide random treatment to cities where the actual treatment started in 2014.[16] In this way, we address the problem of contamination as no other treatment was provided to these cities during this time. Figure 3d shows that the results are insignificant and statistically indifferent from zero. This exercise further confirms the sensitivity of our analysis.

To further our analysis, we also include more types of crime to study their trend after the health expansion (Figure 4). In all panels, the crime rate goes down after the health expansion. This is similar to our main story and further provides evidence of crime reduction in the post-period.[17]

7 Conclusion

This paper investigates the effects of ACA Medicaid expansion on crime. Using daily-level crime data at the city level, we provide empirical evidence on the causal relationship between the Medicaid expansion and crime. We utilize timing variation in Medicaid expansion across cities to establish a causal relationship. To incorporate treatment heterogeneity, we use Callaway and Sant'Anna estimator. The estimator solves the negative weighting issue by identifying group-time treatment effects in the presence of treatment heterogeneity.

In contrast to the TWFE specification, our event studies accounting for treatment heterogeneity show a clear decline in crime rates during the post period. The reduction is particularly pronounced for non-violent crimes, while the decrease in violent crimes becomes evident only after the first few months. Additionally, we present results for specific categories of major crimes, such as assault, robbery, and vandalism, all of which exhibit a statistically significant decline following the implementation of the health expansion. We also

[15] For instance, Boston experienced expansion on Jan 1st, 2014 but we assigned the treatment to Boston on Jan 1st, 2011. We only use overall crime but the results are similar for violent and non-violent crime.

[16] We randomly put 2010, 2011, and 2012, as treatment years for the cities with 2014 Medicaid expansion.

[17] We employ the local projection based did estimator proposed by Busch and Girardi (2023) with time-varying controls and found a similar decrease in crime in the post period. The results are given in the Appendix.

include additional crime types (disorderly conduct, fraud / counterfeiting, trespassing of property). Overall, our findings suggest that Medicaid expansion had a substantial negative impact on crime rates in treated cities.

Our paper contributes to the existing body of research exploring the relationship between healthcare access and crime (Frank et al. (2010), Cameron et al. (2008), Lurigio (2000), etc). Previous studies have examined various health-related programs and found that access to healthcare can lead to reductions in crime. Our paper presents a similar analysis by studying the impact of Medicaid expansion on city-level crime. Our paper also extends the specific literature that study the impact of 2014 Medicaid expansion on crime levels (He and Barkowski (2020), Simes and Jahn (2022), Vogler (2020)). This paper is different from the existing research in several ways. First, we use a new estimator which outperforms TWFE in the presence of treatment heterogeneity due to negative weighting. Second, we utilize a novel crime dataset that provides daily crime counts for major U.S. cities, marking the first time this data has been used for causal analysis, as previous studies primarily relied on the FBI UCR dataset, which is aggregated at the agency-year level. By employing a dataset with greater frequency and spatial variation, we analyze a larger sample-size and cover an extended time period (2010-2022).

Additionally, while earlier research typically conducted analysis at the state or county level, our study offers city-level insights, providing a more localized perspective on the impacts of Medicaid expansion. Overall, our analysis is instrumental in enhancing our understanding of the role Medicaid expansion play in reducing crime and fostering economic well-being in cities.

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Table 1: Summary Statistics

	Mean	SD	Min	Max	N
Panel A: Crime					
Overall crime	21.10	15.98	1.95	69.04	1110200
Violent crime	49.70	26.15	1.64	69.70	1110200
Non-violent crime	41.09	26.95	2.10	82.51	1110200
Assault	69.57	2.35	51.87	91.15	1110200
Vandalism	67.38	9.03	25.11	69.70	1110200
Weapon	66.40	14.04	4.76	69.70	1110200
Robbery	66.50	13.20	7.78	69.70	1110200
Motor vehicle theft	66.34	13.07	10.97	69.70	1110200
Larceny	70.78	5.23	64.54	115.55	1110200
Panel B: Baseline Characteristics					
Medicare eligible	400,426.04	388,786.10	59,867.00	1,294,997.00	569623
Population	2,949,801.09	3,058,817.58	448,479.00	10,017,068.00	569623
Unemp Rate	7.57	1.61	5.20	10.50	569623
Black population (%)	15.04	9.99	3.50	40.50	569623
Poverty (%)	16.53	3.46	9.00	25.10	569623

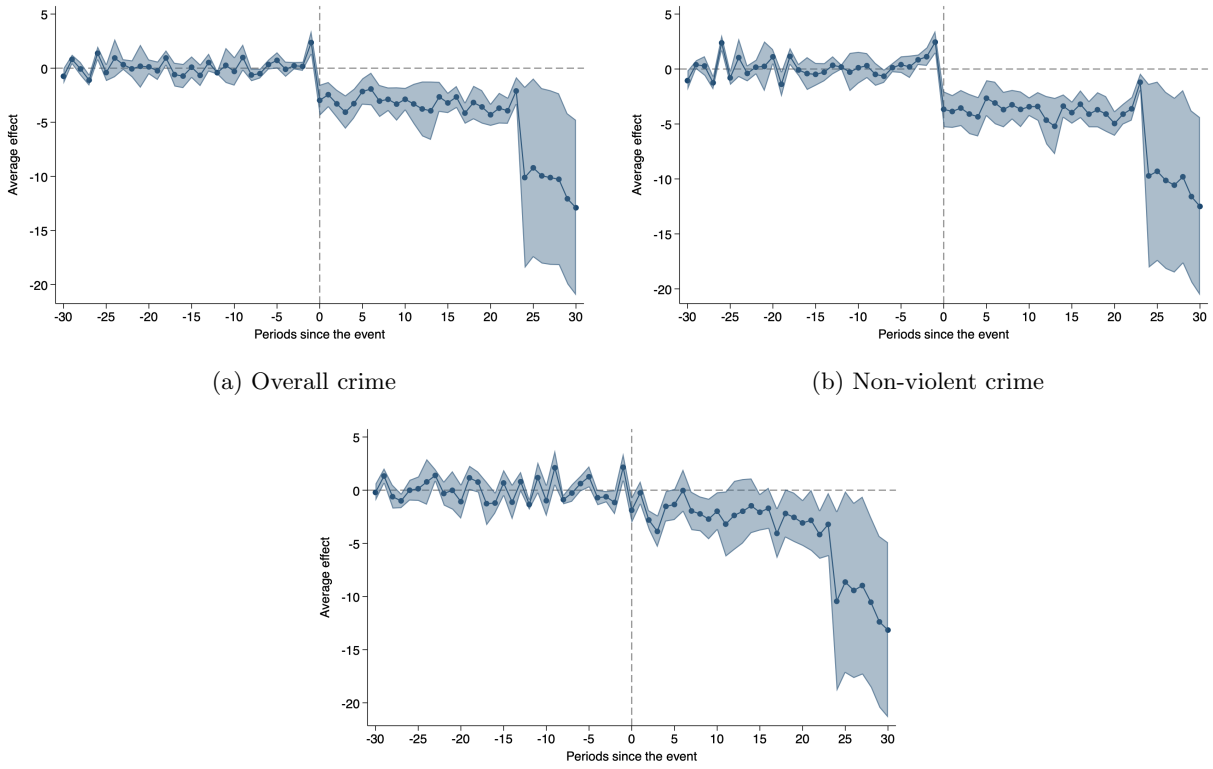
This table includes the summary statistics of the main variables of interest. Panel A shows various types of crime, while panel B has baseline characteristics.

Table 2: Estimated effect of Medicaid expansion on coverage

	(1) Medicaid Enrollment
Medicaid Expansion∗Post	0.0122*
	(0.00716)
N	1332466
adj. R^2	0.012

Source: CPS. This table shows the impact of Medicaid expansion on enrollment at the state level.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Figure 1: Impact of Medicaid expansion on crime



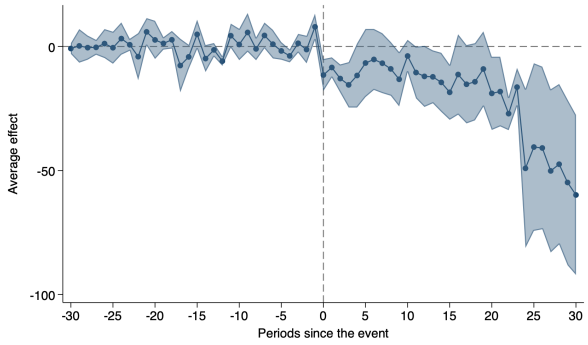
(a) Overall crime

(b) Non-violent crime

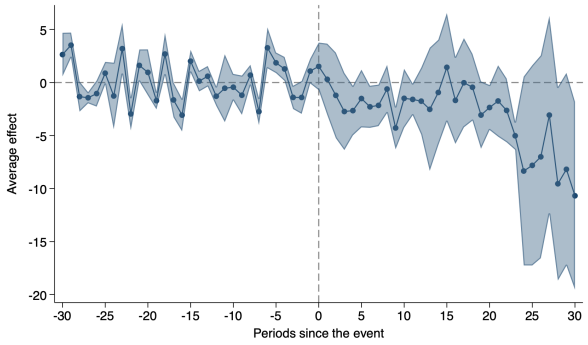
(c) Violent crime

Note: This figure shows the impact of Medicaid expansion on crime over time. In panel (a), we include the overall crime, while the other panels focus on non-violent and violent crimes.

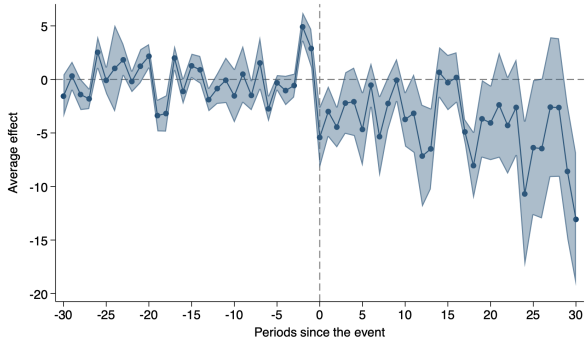
Figure 2: Impact of Medicaid expansion on major crimes



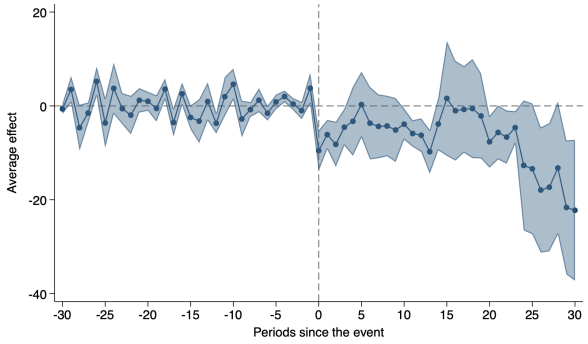
(a) Assault



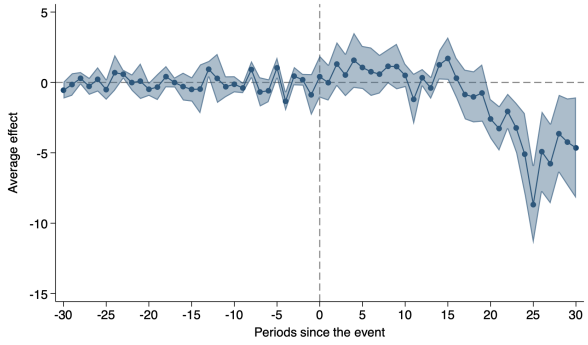
(b) Robbery



(c) Motor Vehicle theft



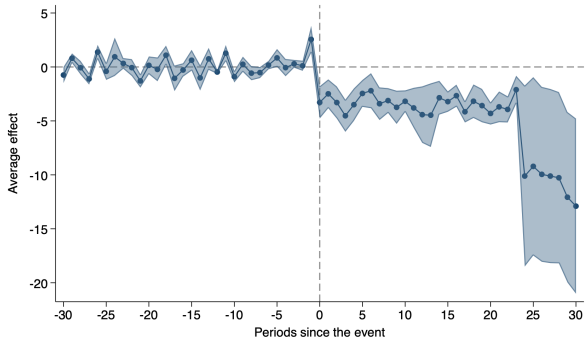
(d) Vandalism



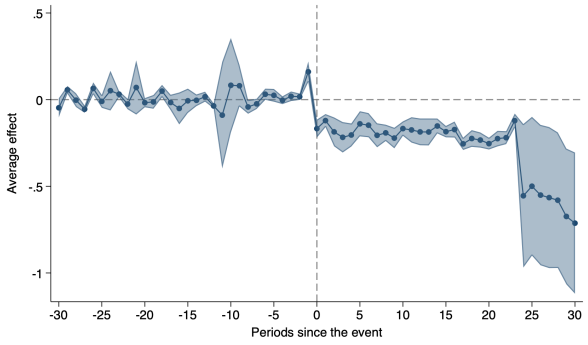
(e) Weapon Law Violations

Note: This figure shows the impact of Medicaid expansion on crime over time. Panel (a) shows the results for assault, panel (b) provides the event studies for robbery, while the remaining panels include results for motor vehicle theft, vandalism, and weapon law violations.

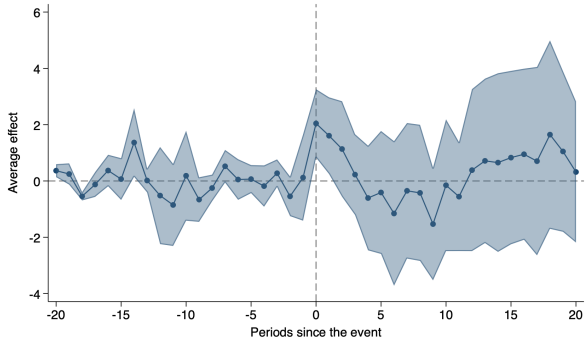
Figure 3: Impact of Medicaid expansion on crime - Placebo results



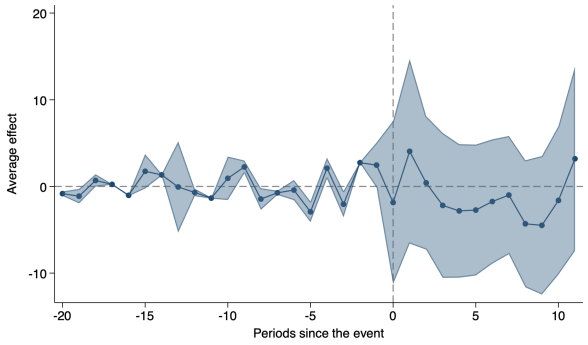
(a) Overall crime



(b) Log of overall crime



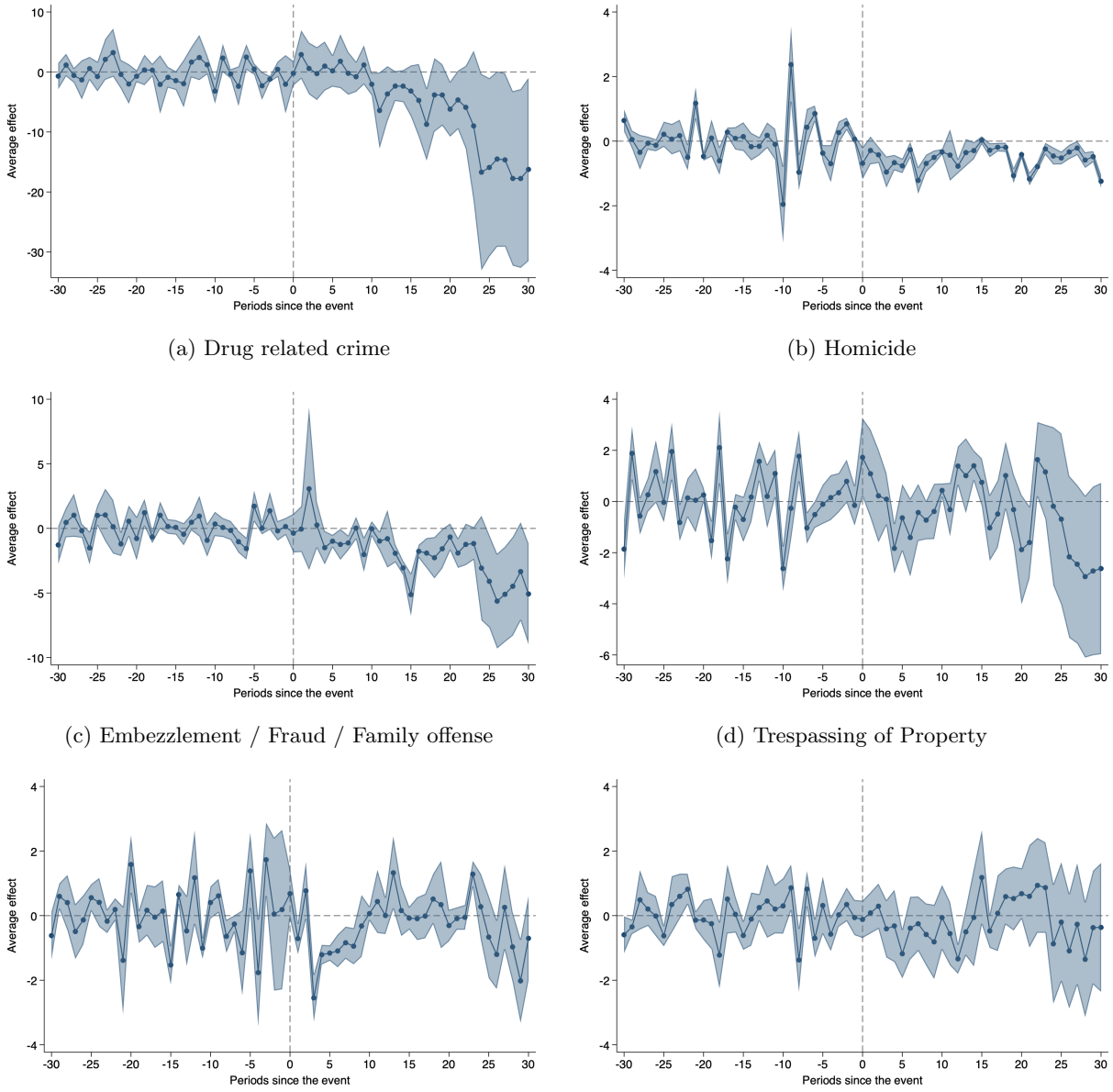
(c) Overall crime with alternate treatment timing



(d) Overall crime with alternate treatment timing (2007-2014)

Note: This figure provides alternate specifications. In panel (a), we restrict the time period to 2010-2019. Panel (b) includes log of overall crime as our dependent variable. For panel (c), we change the treatment time to 3 years earlier than the actual period. Panel (d) provides results for the random treatment in the pre-treatment years (2007-2013).

Figure 4: Impact of Medicaid expansion on additional crime types



(a) Drug related crime

(b) Homicide

(c) Embezzlement / Fraud / Family offense

(d) Trespassing of Property

(e) Disorderly Conduct

(f) Fraud / Counterfeiting

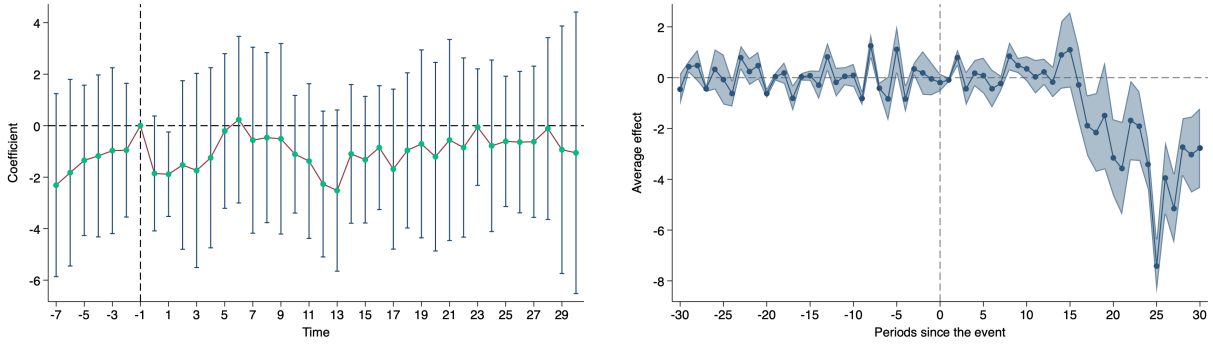
Note: This figure shows the impact of Medicaid expansion on crime over time. We restrict the time period to 2010-2019. In panel (a), we include drug-related crime, while the other panels focus on various other crimes, such as embezzlement, fraud, and homicide.

A Appendix

Table A.1: Medicaid expansion dates across the cities

City	**State**	**Medicaid Expansion**
Austin	Texas	No
Boston	Massachusetts	Jan 01, 2014
Charlotte	North Carolina	Dec 01, 2023
Chicago	Illinois	Jan 01, 2014
Colorado Springs	Colorado	Jan 01, 2014
Detroit	Michigan	Apr 01, 2014
Fort Worth	Texas	No
Houston	Texas	No
Kansas City	Missouri	Jul 01, 2021
Los Angeles	California	Jan 01, 2014
Louisville	Kentucky	Jan 01, 2014
Memphis	Tennessee	No
Mesa	Arizona	Jan 01, 2014
Minneapolis	Minnesota	Jan 01, 2014
Nashville	Tennessee	No
New York	New York	Jan 01, 2014
San Francisco	California	Jan 01, 2014
Seattle	Washington	Jan 01, 2014
St. Louis	Missouri	Jul 01, 2021
Tucson	Arizona	Jan 01, 2014
Virginia Beach	Virginia	Jan 01, 2019

Figure 5: Additional Results



(a) Overall crime

(b) Weapon Law Violations

Note: This figure provides additional results. Panel (a) includes an event study from the local projection estimator given in Busch and Girardi (2023). Panel (b) shows the findings of weapon law violation after excluding cities from states (IL, NY, and NC) that experienced significant changes in gun laws during our period of study.