The Effect of Health Insurance on Crime

Evidence from the Affordable Care Act Medicaid Expansion*

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Abstract

Little evidence exists on the Affordable Care Act (ACA) on criminal behavior, a gap in the literature that this paper seeks to address. Using a one period static model of criminal behavior, I argue we should anticipate a decrease in time devoted to criminal activities in response to the expansion, since the availability of public health insurance not only has a pure negative income effect on crime but also raises the opportunity cost of crime. This prediction is particularly relevant for the ACA expansion, because it primarily affects childless adults, the population that is most likely to engage in criminal behavior. I validate this forecast using a difference-in-differences approach, estimating the expansion's effects on a panel dataset of state- and county-level crime rates. My point estimates show that the ACA Medicaid expansion is negatively related to burglary, motor vehicle theft, criminal homicide, robbery, and aggravated assault. The value of this Medicaid expansion induced reduction in crime to expansion states is almost $10 billion per year.

Keyword: Health Insurance, The Affordable Care Act (ACA) Medicaid Expansion, Criminal Behavior.

JEL Classification: I13, K14, K42.

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I. Introduction

Increasing health insurance coverage and reducing crime rates are two important policy goals in the United States. According to the 2015 Uniform Crime Reports, property crimes (excluding arson) cost the US economy $14.3 billion and the estimated losses of violent crimes far exceed the cost of property crimes in 2015.[1] Among state prison inmates, 90 percent of them are uninsured and potentially qualify for Medicaid in the states that opted to expand Medicaid eligibility under the ACA (Yocom, 2014). Moreover, the population of low-income, childless adults is at high risk for delinquency and crime (Marr et al., 2014). Thus, the ACA Medicaid expansion has the potential to impact crime. Since this expansion not only significantly increased eligibility for parents and adults involved with the criminal justice system, but also ended the historic exclusion of childless adults from Medicaid.

Several studies estimate the effect of health insurance on criminal behavior. For example, Morrissey et al. (2007) found that higher enrollment in Medicaid before release from prison reduces the risk of re-arrest and re-incarceration among individuals with a severe mental disorder. Deck et al. (2009) indicate that Medicaid enrollees in both Oregon and Washington with higher access to methadone maintenance treatment (MMT) services are associated with much lower felony arrest rates than non-Medicaid counterparts. Wen et al. (2014) estimate the effect of expanding substance use disorder (SUD) treatment on crime by using HIFA-waiver expansions as instrument variable, they suggest that increasing SUD treatment rate has a significant reduction effect on robbery, aggravated assault and larceny-theft. However, there exists little reliable empirical evidence regarding the effect of the ACA Medicaid expansions on criminal behaviors.

In this paper, I introduce health insurance into a simple one period static economic model of criminal behavior to illustrate how the health insurance affects criminal behavior theoretically. The economic model predicts that the ACA Medicaid expansion will decrease the time allocated to illegal activities under some reasonable assumptions, since Medicaid coverage expansion not

[1]McCollister et al. (2010) estimated the social cost of various criminal activities, their finding suggests that the total tangible and intangible losses of violent crimes are much higher than property crimes.

only has a pure negative income effect on crime but also increases the opportunity cost of crime. I confirm this prediction empirically by using a difference-in-differences (DID) approach on both state- and county-level crime rates.

My findings indicate that the ACA Medicaid expansion reduced the burglary rate by 3.6 percent, the motor vehicle theft rate by 10 percent, the criminal homicide rate by 7.7 percent, the robbery rate by 6.1 percent, and the aggravated assault rate by 2.7 percent. These findings are robust to a variety of alternative specifications. A back-of-the-envelope calculation indicates the value of this ACA Medicaid expansion induced reduction in crime to expansion states is almost $10 billion a year.

This study is one of the two papers on the topic of the effect of the ACA Medicaid expansion on crime. This investigation and Vogler (2017) were performed concurrently but independently, and both use a state-level DID approach to estimate the effect on crime rates as a primary analysis.[2] These two studies differ along essential dimensions. First, I provide a theoretical explanation of how health insurance affects criminal behavior. Second, I perform an analysis using only contiguous border counties in the style of Dube et al. (2010), which addresses concerns about geographical heterogeneity. Third, in my state-level analysis, I include one more year of data which allows me to estimate the impact of the expansion over a more extended time period. Finally, there are several small differences in our DID empirical approaches,Vogler (2017) includes the number of law enforcement officers and state government expenditures in police protection and correction in his regression models, which I argue are inappropriate since these variables are endogenous with respect to crime rates (Levitt, 2002). Indeed, implementing his empirical specification on my data, the estimate is almost the same as his (see Table 9). However, when I use my preferred specification, which excludes these endogenous variables, the estimates report a weaker crime reduction effect than the estimates from his specification.

The rest of the paper is organized as follows. Section II provides background on ACA Medicaid expansion. Section III introduces the theoretical model of criminal behavior, Section IV discusses

[2]I was in the final stages of my paper draft when Vogler (2017) was posted, and his and my work were done independently without any knowledge of the other.

the data and how to construct the treatment and control groups, Section V presents empirical strategies, Section VI describes the various robustness checks, and Section VII reports the main results . Section VIII concludes.

II. Background

Medicaid is the most extensive public health insurance program in the United States that provides free or low-cost health coverage to low-income pregnant women, parents, the elderly, and people with disabilities. In 2010, Medicaid and the related Children's Health Insurance Program covered almost one-fifth of the population, over 60 million enrollees, at a cost to state and federal governments of nearly $427 billion (Bitler and Zavodny, 2014). Starting in 2010, the Affordable Care Act (ACA) was signed into law and intended to extend health coverage across the country by providing Medicaid to nearly all adults with household income at or below 138 percent of the Federal Poverty Level (FPL). Following the 2012 Supreme Court decision, states faced a decision about whether to opt to implement this ACA Medicaid expansion. However, there is no deadline for states to expand Medicaid under the ACA. This expansion became effective on January 1, 2014. As of January 2017, 31 states and Washington D.C. adopted the Medicaid expansion (see Table 1).

While the main goal of the ACA is to increase the health insurance coverage and improve the health of the population, this health insurance reform may also have effects on a broad range of non-health outcomes, such as welfare use and labor supply, marriage, fertility, savings, etc (Bitler and Zavodny, 2014). Most of the studies explore the ACA Medicaid expansion effect by using a difference-in-difference (DID) regression framework (Ghosh et al., 2017; Maclean et al., 2017; Slusky and Ginther, 2017). For instance, smoking cessation prescription increased by 36% and total expense for these medications increased by 28% after the ACA Medicaid expansion (Maclean et al., 2017). This expansion also decreased medical divorce and the prevalence of divorce among individuals between 50 and 64 reduced by 5.6% (Slusky and Ginther, 2017).[3]

[3] Medical divorce is a couple consider divorce due to the medical expenses of a spouse who need long-term medical care would force the couple to run out of their assets, making the another spouse destitute.

Currently, the only research on the effect of the ACA Medicaid expansions on criminal behaviors come from this study and that of Vogler (2017). In his paper, He finds this expansion has a statistically significant reduction effect on annual crime rate by 3.2 percent.

III. Theoretical Model of Criminal Behavior

There are several reasons why the Medicaid expansions may affect criminal behavior. Individuals who are newly eligible for Medicaid may reduce the time spent in criminal activities because Medicaid coverage practically eliminates their health insurance premiums and out of pocket medical costs, which not only allows an individual to work less to obtain the same amount of expenditure but also increases the opportunity cost of committing crimes.[4] Moreover, the expanding coverage for individuals involved with the criminal justice system would decrease the risk of re-arrest and re-incarceration among criminals with mental illness issues who, when they are released from prison, will be able to get the treatment they need to stay in a normal mental state and avoid committing crimes (Morrissey et al., 2007). Additionally, some individuals who were eligible for Medicaid before this expansion may decrease time spent in criminal activities since they can work more in legitimate jobs with less risk of being arrested than before the expansion and still gain Medicaid coverage, on account of the Medicaid income eligibility threshold increased.

However, individuals whose legitimate income are just higher than the new Medicaid expansion eligibility threshold may reduce working hours in legitimate work and increase in criminal activities to lower their legitimate income, and then become eligible for Medicaid. Furthermore, the Medicaid expansion may cause a moral hazard problem result in a higher crime rate. Ehrlich and Becker (1972) show that individuals who are newly eligible for health care may be more likely to engage in various risky health behaviors such as heavy alcohol consumption, substance abuse, heavy smoking, and risky sexual behaviors because they are less likely to suffer from the potential medical expenditures. Inmate drug reports and arrestee drug test results show that there is a

[4] If an individual failed in criminal activity and got imprisoned, this individual will no longer eligible for Medicaid coverage and will be suffering a very low level health care during imprisonment.

positive relationship between alcohol and substance abuse and crime (Wen et al., 2014). Among inmates convicted of violent crimes, fifty-two percent reported being under the influence of alcohol and other drugs at the time of the offense or reported committing the crime to finance their substance use habit. There was thirty-nine percent among those convicted of property crimes (Miller et al., 2006).

Becker (1968) proposes an economic framework to analyze criminal behavior rationally. Sjoquist (1973), Ehrlich (1973, 1977)), and Block and Heineke (1975) follow Becker's economic analysis and develop a one-period static model of criminal behavior. In this theoretical model, an individual chooses whether or not to commit a crime based on rationally weighing the benefits and costs of participating in legitimate works and illegal activities. Zhang (1997) incorporates welfare programs into the criminal behavior model to explore the effect of welfare payments on crime. In this paper, I follow the one-period static model setup and incorporate health insurance into the model to explain how the health insurance affects crime, especially the ACA Medicaid expansion.

Consider an individual who is eligible to receive health insurance coverage. This individual chooses how much time to spend on legitimate work and illegal activities. If this individual chooses to commit crimes and has not been imprisoned, he receives utility from the health insurance coverage plus utility from legitimate work wages and illegal activities gains. In the case of failure in an illegal activity, this individual is imprisoned. In this case, this individual loses health insurance coverage and receives a negative utility from imprisoned instead of positive utility from health insurance coverage.

Let H_l and H_c be the hours devoted to legal and illegal activities respectively, and T is total time available ($H_l + H_c = T$). w_l and w_c are the wage for legal and illegal activities and are assumed to be known and predictable ($w_l < w_c$). $P(H_c)$ is the probability of imprisonment ($P'(\cdot) > 0$ and $P''(\cdot) \geqslant 0$), which is positively related to hours of illegal activities and the marginal rate of imprisoned is constant or increasing. If an individual is successful in illegal activities (with probability $1 - P(H_c)$), this individual's utility would be $U_N = V(w_l H_l + w_c H_c) + M$, where $V(\cdot)$ represents a risk-averse utility function of income ($V'(\cdot) > 0$ and $V''(\cdot) < 0$), and M the utility of health insurance coverage. If the individual is imprisoned (with probability $P(H_c)$), the utility would be $U_A = V(w_l H_l + w_c H_c) + J$, where J represents negative utility of any sanctions ($J < 0$).

Thus, the individual's expected utility $E[u]$ is

$$
\begin{gathered}
E[u] = [1 - P(H_c)]U_N + P(H_c)U_A, \\
U_N = V(w_l H_l + w_c H_c) + M; U_A = V(w_l H_l + w_c H_c) + J, \\
s.t. H_l \geqslant 0, H_c \geqslant 0, \ and \ H_l + H_c = T.
\end{gathered} \tag{1}
$$

The individual chooses H_l and H_c to maximize $E(u)$ subject to $H_l \geqslant 0$, $H_c \geqslant 0$, and $H_l + H_c = T$. Let us focus on an interior solution, and substituting $H_l = T - H_c$ into $E[u]$, then

$$
E[u] = [1 - P(H_c)]\{V[w_l(T - H_c) + w_c H_c] + M\} + P(H_c)\{V[w_l(T - H_c) + w_c H_c] + J\}. \tag{2}
$$

We have the first-order condition with respect to H_c is

$$
\begin{aligned}
D_c = \frac{\partial E[u]}{\partial H_c} &= -P'(H_c)U_N + [1 - P(H_c)]V'(\cdot)(w_c - w_l) \\
&\quad + P'(H_c)U_A + P(H_c)V'(\cdot)(w_c - w_l) \\
&= P'(H_c)(J - M) + V'(\cdot)(w_c - w_l) = 0,
\end{aligned} \tag{3}
$$

so

$$
P'(H_c)(M - J) = V'(\cdot)(w_c - w_l), \tag{4}
$$

or

$$
\frac{P'(H_c)}{V'(\cdot)} = \frac{w_c - w_l}{M - J}. \tag{5}
$$

The second-order condition requires:

$$D_{cc} = \frac{\partial^2 E[u]}{\partial H_c^2} = P''(H_c)(J - M) + V''(\cdot)(w_c - w_l)^2 < 0. \tag{6}$$

It would be satisfied if individual is risk-averse ($V''(\cdot) < 0$) and the marginal rate of imprisoned is constant or increasing ($P''(\cdot) \geqslant 0$).

Equation (4) says that, at the optimal choice of H_c, the amount of hours spent in crime, the marginal gain from devoting one additional hour to crime equals the marginal cost from that one additional hour.

To consider the effect to H_c of changes in health insurance coverage M, equation (3) defines the implicit function of H_c in terms of M. Differentiating (3) with respect to M yields:

$$\begin{aligned} \frac{\partial^2 E[u]}{\partial H_c \partial M} &= P''(H_c)(J - M)\frac{\partial H_c}{\partial M} - P'(H_c) + V''(\cdot)(w_c - w_l)^2 \frac{\partial H_c}{\partial M} = 0 \\ &= D_{cc}\frac{\partial H_c}{\partial M} - P'(H_c) = 0, \end{aligned} \tag{7}$$

so

$$\frac{\partial H_c}{\partial M} = \frac{P'(H_c)}{D_{cc}} < 0. \tag{8}$$

The equation (8) shows that the sign of $\frac{\partial H_c}{\partial M}$ depends entirely on the probability of imprisonment toward the number of hours spent in crime and the individual's risk preference. If the individual is risk-averse and spends more time on criminal activities does not decrease the marginal probability of imprisonment, an increase in health insurance coverage would decrease the time devoted to illegal activities due to it increases the marginal cost of illegal activities. In other words, we can expect that individuals who are newly eligible for health insurance coverage and enrollees who have higher eligibility threshold would be less likely to commit crimes.

The pathway for the crime reduction effect is replacing the money ordinarily spent on health care, Medicaid coverage eliminates the insured's health insurance premiums and out of pocket medical expenses and is only eligible for individuals who have not been imprisoned. It means the eligibility for health insurance coverage not only has a pure negative income effect on criminal activities but also increases the opportunity cost of crime. Therefore, one might think that the crime reduction effect would be concentrated on burglary, motor vehicle theft, and robbery which are likely to be motivated by the acquisition of cash. However, larceny is typically a misdemeanor and is the least likely offense to result in prison. It then implies that the category of crime I would least likely expect to observe an effect is larceny in these crimes which can generate income. Moreover, there is reason to think effects could also be observed on arson, assault, homicide and rape that are unlikely to have a direct financial motivation. Since crimes like assault and homicide often occur during other theft type crimes or in combination with robbery. For instance, robbery is a crime that theft accomplished by force or the threat of physical security and most frequently leads to victim death (criminal homicide) and injury (aggravated assault). Moreover, armed robbery is almost always simultaneous with aggravated assault. FBI reports that almost 60 percent of all killings in time of other forcible felonies are caused by robbery (Zimring and Zuehl, 1986). Additionally, the variations in robbery rates are positively correlated with the variations in the murder rate (Altbeker, 2008).

IV. Data

Data Sources

The theoretical model in the preceding section forecasts that the ACA Medicaid expansion would decrease the time allocated to illegal activities. Ideally, the effect of the Medicaid expansion on crime should be examined by utilizing individual-level data. However, it is really hard to acquire a credible individual-level dataset on illegal activity. Therefore, this paper follows most empirical studies of criminal behavior which used aggregate state- and county-level data.

The crime data for this analysis come from the Uniform Crime Reports (UCR), but are gathered from two different data sources. State-level crime data are directly constructed by the UCR for year 2010-2016. However, the aggregated county-level crime data from 2010 to 2014 are obtained from the Inter-university Consortium for Political and Social Research UCR Program Data

Series (ICPSR). Since *Uniform Crime Reporting Program Data: County-Level Detailed Arrest and Offense Data* are only available in 2014.

My investigation into the crime rates and the ACA Medicaid expansion needs precise measures of both variables. For the former, I use measures of state- and county-level crime rates ($Crime\ Rate_{st}$ and $Crime\ Rate_{ct}$) using the UCR and the ICPSR crime data. These crime rates are all collected annually by the Federal Bureau of Investigation (FBI) and calculated as the number of crimes reported to all police agencies per 100,000 inhabitants within each given state s or county c over a calendar year t. UCR crime data provides eight categories of crime. However, the FBI does not publish arson data due to it did not receive data from many states. Moreover, the definition of rape was revised by the FBI in 2013. Thus, I use only six of eight crime categories: aggravated assault, criminal homicide, robbery, burglary, larceny-theft, and motor vehicle theft. The first three crime categories constitute violent crime, while property crime is composed of the latter three.

For the Medicaid expansion data, the information on the status of state action on the ACA Medicaid expansion decision is compiled by the Henry J. Kaiser Family Foundation's State Health Facts, a non-profit organization that collects a vast array of health policy information. The states' decisions about adopting the Medicaid expansion are expressed by a dummy variable $MedicaidDummy_{st}$ which equals one if state s adopted the Medicaid expansion at or after year t, and equals zero otherwise.

I use data from the American Community Survey (ACS) to generate state- and county-level covariates data. ACS is a nationwide survey administered by the Census Bureau asking detailed questions about population and housing characteristics. These control variables include demographic characteristics, economic conditions, and state government expenditures. Demographic characteristics consist of age distribution and racial proportion of the population,[5] which are (1) between the ages of 20 and 34,[6] (2) White, (3) Black, (4) Native, and (5) Asian. Economic con-

[5]Both are measured as the percentage of the population in state s

[6]$age2034$ represents percent of state s or county c population between the ages 20-34, young adults aged between 20 and 34 are more likely to participate in crimes (Wen et al., 2014).

ditions are measured as the state's or county's (6) Gini Index,[7] (7) per capita income,[8] (8) poverty rate,[9] and (9) unemployment rate.[10]

In addition, I include contemporaneous and one year lagged state government expenditures in a few key aspects to account for the government investment that may relate to crime and the Medicaid expansion. These state government expenditures are measured as the dollar per capita spending on: (10) hospital and health, (11) welfare program, and (12) education. The state government expenditures data is derived from the U.S. Census Bureau from the Annual Survey of State & Local Government Finances.

Sample Construction

There are two distinct samples have been used in my analysis: a sample of all states (AS) and a sample of contiguous border counties (CBC). The all AS sample is composed of the full set of all 50 states and Washington D.C. for the years 2010 through 2016. Since there might be some geographic conditions that affect crime, to account for geographic heterogeneity, I use the CBC sample which consists of all contiguous border counties that share a common state border between Medicaid expanded states and Medicaid unexpanded states (Dube et al., 2010).

There are 1,184 of 3,233 total counties located along a state boundary in the U.S. mainland and 567 of 1,184 border counties located along a common state boundary between Medicaid expanded states and Medicaid unexpanded states based on the states' Medicaid expansion decision in 2014. Then I have full (five years) set of crime data for all those border counties. Therefore, the total number of observations for contiguous border counties with balanced panel is 2,835.

[7]The Gini index is a measure of income inequality in each state and county. Ehrlich (1973) claims that income inequality is a good approximation for the wage from legitimate work (w_l). A lower income inequality implies a better legitimate work opportunity. Therefore, a decrease in income inequality would reduce crime rate.

[8]Per capita income measures the potential returns from illegal activity (w_c). A decline in income would result in fewer crimes which the purpose of crime is predominantly monetary. However, a lower income may make criminals more likely to commit crimes (pure income effect). Therefore, the net effect of per capita income on crime is uncertain (Zhang, 1997).

[9]Poverty rate measures the percent of state or county population whose family income lower than federal poverty level (FPL) based on household income, household size, and household composition.

[10]Unemployment rate is measured as the number of unemployed individuals as a percent of the total labor force (aged 16 and above).

Table 2 provides means and standard deviations of the dependent variable and covariates for the AS sample, including separately for the expanded and unexpanded states. According to Table 2, the average crime rates in expanded states are relatively larger in property crime categories and slightly smaller in violent crime categories. However, the covariates are quite similar between expanded and unexpanded states. Summary statistics for the CBC sample are reported in Table 3. Almost all average crime rates in expanded states are slightly higher than in unexpanded states, but the differences in all variables between them are much smaller in the CBC sample.

V. Methodology

Main Empirical Specification

In my main empirical specification, I estimate the effect of health insurance on crime rates by comparing the average change in reported crime rate for expanded states, compared to the average change for unexpanded states before and after the quasi-experimental ACA Medicaid expansion policy implementation. Therefore, the difference-in-difference (DID) specification is given by:

$$ln(Crime\ rate)_{st} = \beta_0 + \beta_1 MedicaidDummy_{st} + \mathbf{X_{st}}\lambda + \mathbf{Z_{st}}\delta + \rho_s + \tau_t + \epsilon_{st}, \tag{9}$$

where s indexes state, and t indexes year. The dependent variable $ln(Crime\ Rate)_{st}$ represents the natural logarithm of the number of crimes committed per 100,000 residents in the state s at year t. X_{st} represents the vector of state-level demographic variables.[11] Z_{st} represents the vector of state-level economic conditions.[12] ρ_s is a set of state fixed effects, and τ_t is a set of year fixed

[11] Demographic variables include $Age2034_{st}$, $white_{st}$, $black_{st}$, $native_{st}$, and $Asian_{st}$. $Age2034_{st}$ measures the ratio of state s population between the ages 20-34 at year t. $white_{st}$, $black_{st}$, $native_{st}$, and $Asian_{st}$ are the population as a percentage of state s population for each race at year t, separately.

[12] Economic conditions consist of $PCIncome_{st}$, $Gini_{st}$, $Poverty_{st}$, $Unemployment_{st}$, $ln(Health\ Care)_{st}$, $ln(Health\ Care)_{st-1}$, $ln(Welfare)_{st}$, $ln(Welfare)_{st-1}$, $ln(Education)_{st}$, and $ln(Education)_{st-1}$. $PCIncome_{st}$ is per capita income for state s at year t. $Gini_{st}$ is Gini index for state s at year t. $Poverty_{st}$ is the poverty rate of population for state s at year t. $Unemployment_{st}$ is the Unemployment rate for state s at year t. $ln(Health\ Care)_{st}$, $ln(Health\ Care)_{st-1}$, $ln(Welfare)_{st}$, $ln(Welfare)_{st-1}$, $ln(Education)_{st}$, and $ln(Education)_{st-1}$ are the natural logarithm of contemporaneous and one year lagged state government expenditure on Health care, Welfare program, and Education in the state s at year t.

effects. Standard errors are clustered at the state-level to correct for serial correlation. Regression results are weighted by $Population_{st}$ for state s at year t to estimate the effect on the average person in the population, it means I want more populous states weighed heavier.

Validity of The Research Design

The validity of DID approach depends on a critical identifying assumption, which is that crime rates would follow the same trend in treatment states (i.e., expanded state) and control states (i.e., unexpanded state) in the absence of treatment (i.e., ACA Medicaid expansion). In other words, the Medicaid expansion decisions should be exogenous to the crime rates. Many studies examine the factors influencing state decision to support or oppose ACA Medicaid expansion and reveal that the partisanship of governors and the composition of the legislature have the most explanatory power (Barrilleaux and Rainey, 2014; Hertel-Fernandez et al., 2016; Henley, 2016). To test the plausibility of this parallel trends assumption in my paper, I utilize an event study model that allows a complete set of interactions of the expanded states with years, with 2013 being the base year (Autor, 2003):

$$\begin{aligned} ln(Crime\ rate)_{st} = \alpha_0 &+ \alpha_1(Treatment_s * I2010_t) + \alpha_2(Treatment_s * I2011_t) \\ &+ \alpha_3(Treatment_s * I2012_t) + \alpha_4(Treatment_s * I2014_t) \\ &+ \alpha_5(Treatment_s * I2015_t) + \alpha_6(Treatment_s * I2016_t) \\ &+ \mathbf{X_{st}}\lambda + \mathbf{Z_{st}}\delta + \rho_s + \tau_t + \epsilon_{st}, \end{aligned} \tag{10}$$

where $I2010_t$, $I2011_t$, $I2012_t$, $I2014_t$, $I2015_t$, and $I2016_t$ are dummy indicators for whether year t is 2010, 2011, 2012, 2014, 2015, and 2016, separately. $Treatment_s$ are dummy indicators for whether state s is expanded. The null hypothesis for the validity test is the coefficients on the interactions between $Treatment_s$ and year dummies in years before ACA Medicaid expansion are equal to zero.

VI. Robustness Checks

Some Variants of Main Specification

I provide a number of variants of my preferred specification to check the robustness. First robustness check excludes several states that already had comprehensive Medicaid coverage for both parents and childless adults in prior to 2014 in expanded states, and few states that had limited Medicaid expansion before 2014 in unexpanded states.[13] Secondly, I use these contiguous border states that share a common state border between Medicaid expanded state and Medicaid unexpanded state. Finally, I add state-specific time trend $\theta_s t$ and treatment-specific time trend $Treatment_s t$ separately to the main specification to control for the exogenous linear trends in the crime rate which are not captured by other variables.

Empirical Specification Using Contiguous Border County Sample

Contiguous border counties sample provides a better control group for treated counties to estimate the effect of health insurance eligibility expansion on crime, since the demographic characteristics and economic conditions are more similar between two cross-state border neighboring counties. Using contiguous border counties sample, I estimate the DID specification similar to equation (9):

$$ln(Crime\ rate_{ct}) = \beta_0 + \beta_1 MedicaidDummy_{st} + \mathbf{X_{ct}}\lambda + \mathbf{Z_{ct}}\delta + \rho_c + \tau_t + \epsilon_{ct}, \tag{11}$$

where c indexes county. $ln(Crime\ rate_{ct})$ represents the natural logarithm of the number of crimes per 100,000 residents in the county c at year t. X_{ct} represents the vector of county-level demographic variables.[14] Z_{ct} represents the vector of county-level economic conditions.[15] ρ_c is a

[13] These excluded states are Maine, Tennessee, Wisconsin, Delaware, Washington, D.C., Massachusetts, New York, and Vermont (Kaestner et al., 2017). See Table 1.

[14] Demographic variables include $Age2034_{ct}$, $white_{ct}$, $black_{ct}$, $native_{ct}$, and $Asian_{ct}$. $Age2034_{ct}$ measures the ratio of county c population between the ages 20-34 at year t. $white_{ct}$, $black_{ct}$, $native_{ct}$, and $Asian_{ct}$ are the population as a percentage of county c population for each race at year t, separately.

[15] Economic conditions consist of $PCIncome_{ct}$, $Gini_{ct}$, $Poverty_{ct}$, $Unemployment_{ct}$, $ln(Health\ Care)_{st}$, $ln(Health\ Care)_{st-1}$, $ln(Welfare)_{st}$, $ln(Welfare)_{st-1}$, $ln(Education)_{st}$, and $ln(Education)_{st-1}$. $PCIncome_{ct}$ is per capita income for county c at year t. $Gini_{ct}$ is Gini index for county c at year t. $Poverty_{ct}$ is the

set of county fixed effects, and τ_t is a set of year fixed effects. Standard errors are clustered at the state-level, and regression results are weighted by $Population_c t$ for county c at year t.

There are two reasons I prefer to use this specification as a robustness check instead of my main specification: First, contiguous border county sample is just a sub-sample of the whole population, it can not adequately represent the whole population. Second, the data time period for this sample is only available from 2010 to 2014, only one-year observations after ACA Medicaid expansion might not capture the real impact of this policy.

VII. Main Result

Estimates of the Effect of ACA Medicaid Expansion On State-Level Crime Rates

In this section, I begin the discussion of results with the effect of expanding health insurance coverage on state-level crime rates by using the all states sample. Table 4 reports difference-in-difference (DID) estimates for the all states sample by using each crime category as the outcome variable in eight distinct models.[16] There are two panels that show results for property crime (top panel) and violent crime (bottom panel). Column (1) shows the estimates without any state demographic and economic covariates, and column (2) presents the preferred regression results from equation (9).

Estimates in the property crime category of Table 4 reveal that statistically significant crime reduction effects of the Medicaid expansion are shown in burglary and motor vehicle theft, but not in larceny-theft and overall property crime.[17] For this sample, the ACA Medicaid expansion decreases the burglary rate by 3.6 percent in expanded states compared with unexpanded states, or a decline of 20 offenses per 100,000 inhabitants of the 2013 mean of the burglary crime rate in all

poverty rate of population for county c at year t. $Unemployment_{ct}$ is the Unemployment rate for county c at year t.

[16]Eight dependent variables are Property Crime rate, Burglary rate, Larceny-Theft rate, Motor Vehicle Theft rate, Violent Crime rate, Criminal Homicide rate, Robbery rate, and Aggravated Assault rate.

[17]Total property crime rate consists mainly of larceny-theft.

expanded states.[18] The expansion of Medicaid is associated with a 9.95 percent reduction in motor vehicle theft rate, or approximately 23.04 offenses per 100,000 inhabitants. Figure 1 shows the effect of the ACA Medicaid expansion on property crime categories.

In the violent crime category of Table 4, the 2014 Medicaid expansion is associated with a statistically significant crime reduction in all violent crime subcategories and overall violent crime. Estimates related to aggravated assault are statistically insignificant in column (1), but significant at the 5 percent level in my preferred specification. Among the violent crimes, Medicaid expansion decreases criminal homicide rate by 7.71 percent (0.34 offenses per 100,000 inhabitants), robbery rate by 6.14 percent (7.16 offenses per 100,000 inhabitants), and aggravated assault rate by 2.72 percent (5.88 offenses per 100,000 inhabitants), respectively. Moreover, there is a significant decline in overall violent crime rate by 3.52 percent and correspond to 11.87 offenses per 100,000 inhabitants, which is mainly driven by the decline in both robbery rate and aggravated assault rate. The effect of the ACA Medicaid expansion on violent crime categories is reported in Figure 2.

The significant effect of the Medicaid expansion on burglary, motor vehicle theft, and robbery indicates that the ACA Medicaid expansion providing coverage for uninsured adults and higher eligibility thresholds for enrollees can decrease their motivation to commit money-related crimes. And my estimates are consistently smallest for larceny in Table 4, which corresponds to the theoretical expectation. As mentioned before, criminal homicide and aggravated assault often happen during robbery or in combination with other theft type crimes. The significant negative effect on criminal homicide and aggravated assault might be caused by the considerable decrease in burglary, motor vehicle theft, and robbery.

Estimates of Event Study Model

As noted above, the parallel trends assumption needs to be satisfied for the validity of difference-in-difference (DID) estimates in Table 4. To investigate the plausibility of this assumption, I estimate

[18]This reduction in burglary crime rate calculated by using total number of burglary crime and total population in all expanded states in 2013 (around 555.64 offenses per 100,000 inhabitants). See Table 8.

the event study model and report the regression estimates in Table 5. The event study estimates are consistent with the DID regression estimates. The estimated coefficients are relatively smaller in magnitude in pre-treatment periods than in post-treatment periods. Only the coefficient on larceny in 2010 is negative and marginally statistically significant, it might be the potential reason for why the Medicaid expansion has no statistically significant reduction effect on larceny in DID estimates. However, the p-value for F-tests of joint significance indicates that pre-treatment interaction terms are not jointly statistically significantly different from zero. Therefore, the event study model estimates support the parallel trends assumption and the estimates in Table 4 can be considered as representing the causal effects of the ACA Medicaid expansion on crime.

Robustness Checks

To check the robustness of the state-level estimation, I estimate several modifications of my preferred specification and results are reported in Table 6. Column (1) represents the base estimates from my preferred main specification. I drop several states that already expanded their Medicaid coverage in prior to 2014 in both expanded and unexpanded states and report the estimates in column (2). The estimates from this restricted sample are larger in magnitude in property crime categories and smaller in magnitude in violent crime categories than main estimates. Moreover, the reduction in overall property crime even becomes statistically significant at 10 percent level. However, the effect of the Medicaid expansion on aggravated assaults is no longer significant.

Column (3) shows that the estimates generated by using contiguous border state sample are very similar to column (1), although the standard errors from this sample are slightly higher. Column (4) and (5) report the regression estimates from the preferred specification with state-specific time trend and treatment-specific time trend, respectively. The estimates from column (4) have a higher crime reduction effect of the ACA Medicaid expansion on all crime categories, except for the coefficient on aggravated assault is a little bit smaller than in column (1). All regression estimated coefficients are highly statistically significant in column (5), even with higher standard errors. Overall, the estimates from my preferred specification broadly persist across a range of robustness checks.

Estimates of the Effect of ACA Medicaid Expansion On Border Counties' Crime Rates

Table 7 reports the estimated effect of the Medicaid expansion on border counties' crime rates by using the contiguous border county samples for year 2010-2014. This table is organized the same way as Table 4. In property crime estimates, the 2014 Medicaid expansion is associated with a 3.70 percent decrease in burglary rate and a 7.48 percent decline in motor vehicle theft rate. While the coefficient on larceny rate becomes positive, the magnitude of this effect is really small.

In the estimates of violent crimes, the sizable crime reduction effect of the Medicaid expansion is only present in robbery rate by 6.69 percent, but there is no statistically significant crime reduction effect on criminal homicide and aggravated assault. Since the primary unit of analysis in this specification is county-year and county is the smallest geographical identified in dataset, the reported crime rate in violent crime categories are very low and small variation in this sample. Specifically, there is zero variation in reported criminal homicide in many border counties between 2010 and 2014.

Overall, estimates of the effect of ACA Medicaid expansion on criminal behavior for border counties are largely consistent with corresponding estimates generated using the all states sample. The main difference is that the estimates from this specification are less precise than the preferred specification estimates, as the results in Table 4 present. The reason is restricted sample of contiguous border counties decreases the identifying variation in data (Neumark et al., 2014). Additionally, the statistically significant crime reduction effects of the Medicaid expansion on Burglary, motor vehicle theft, and robbery provide evidence that the Medicaid expansion is more likely to affect money-related crimes than other crimes.

VIII. Discussion and Conclusions

The Affordable Care Act (ACA) Medicaid expansion enhanced public safety through crime reduction. The ACA Medicaid expansion decreased the rate of burglary by 3.6 percent, decreased the rate of motor vehicle theft by 10 percent, decreased the rate of criminal homicide by 7.7 percent, decreased the rate of robbery by 6.1 percent, and decreased the rate of aggravated assault by 2.7 percent. The results are robust to a variety of alternative specifications.

To better evaluate the economic implication of the Medicaid expansion regarding crime, I estimate the social benefit of crime reduction based on the cost to society of crime which is calculated by McCollister et al. (2010). The cost of crime measures per-offense social cost of crime across all crime categories, which includes tangible costs to crime victims and criminal justice system, the opportunity social cost if an individual chooses to commit crimes as opposed to engage in legitimate activities, as well as the intangible cost to crime victims, such as pain and suffering, reduction in life quality, and mental impairment. According to McCollister et al. (2010), the total offense costs are about \$8.0 billion for burglary, \$5.5 billion for motor vehicle theft, \$87.6 billion for criminal homicide, \$11 billion for robbery, and \$51.4 billion for aggravated assault in all expanded states in 2013.[19] As of January 1, 2014, the ACA Medicaid expansion yields an average crime reduction benefit of almost \$10 billion from reducing crime rates in Medicaid expanded states a year.[20]

In July 2017, Senate has been starting to debate on repeal and replace the ACA Medicaid expansion by the American Health Care Act (AHCA), which would bring to an end the enhanced federal matching funds for the ACA Medicaid expansion and terminate the guarantee of federal government supporting state governments for all people insured by this program. This paper provides new evidence about the effect of the ACA Medicaid expansion on criminal activities. My findings suggest that a shrinkage in Medicaid coverage would bring back the level of crime rates

[19] All values are converted to 2017 dollars. See Table 8.

[20] The Medicaid expansion yields an average crime reduction benefit of \$0.29 billion from burglary, \$0.55 billion from motor vehicle theft, \$6.75 billion from criminal homicide, \$0.63 billion from robbery and \$1.40 billion from aggravated assault for all expanded states.

and endanger public security. Policymakers thinking about the impacts of repealing or replacing ACA Medicaid expansion should consider the effects on criminal behaviors. My findings are also valuable for these unexpanded states which are considering to expand Medicaid coverage and improve their social public safety.

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Table 1: Classification of States into Treatment and Control Groups as of January 2017

Control Groups (No Expansion After 2014)	
No Prior Expansion	**Prior Limited Expansions for Parents and/or Childless Adults**
Alabama	Maine
Florida	Tennessee
Georgia	Wisconsin
Idaho	
Kansas	
Mississippi	
Missouri	
Nebraska	
North Carolina	
Oklahoma	
South Carolina	
South Dakota	
Texas	
Utah	
Virginia	
Wyoming	

Treatment Groups (Expansion After 2014)		
No Prior Expansion	**Prior Limited Expansions for Parents and/or Childless Adults**	**Prior Full Expansions for Parents and Childless Adults**
Alaska[1]	Arizona	Delaware
Arkansas	California	Washington, D.C.
Kentucky	Connecticut	Massachusetts
Louisiana[1]	Colorado	New York
Michigan[1]	Hawaii	Vermont
Montana[1]	Illinois	
Nevada	Indiana[1]	
New Hampshire[1]	Iowa	
New Mexico	Maryland	
North Dakota	Minnesota	
Ohio	New Jersey	
Pennsylvania[1]	Oregon	
West Virginia	Rhode Island	
	Washington	

Note: All expanded states that have adopted the Medicaid expansion in January 1, 2014 except for the following: Michigan (4/1/2014), New Hampshire (8/15/2014), Pennsylvania (1/1/2015), Indiana (2/1/2015), Alaska (9/1/2015), Montana (1/1/2016), and Louisiana (7/1/2016).

Table 2: Summary Statistics of All States Sample 2010-2016

Summary Statistics	**All States**	**Expanded States**	**Unexpanded States**
	Mean (S.D.)	*Mean (S.D.)*	*Mean (S.D.)*
Dependent Variables:			
Crime Rate (per 100,000 residents)			
Property Crime	2,713.37 (662.09)	2,666.87 (701.24)	2,791.69 (584.51)
Burglary	580.32 (214.14)	555.44 (197.87)	622.22 (233.89)
Larceny Theft	1,922.97 (451.25)	1,891.58 (503.07)	1,975.82 (342.26)
Motor Vehicle Theft	210.08 (104.20)	219.85 (119.02)	193.64 (70.13)
Violent Crime	338.59 (176.32)	353.71 (197.97)	313.13 (128.83)
Criminal Homicide	4.59 (2.89)	4.62 (3.33)	4.54 (1.94)
Robbery	94.42 (84.91)	106.96 (101.34)	73.32 (37.13)
Aggravated Assault	239.58 (110.36)	242.14 (115.61)	235.27 (101.17)
Covariates:			
State Demographics & Economics			
$ Per Capita Income ($1,000)	28.40 (4.80)	29.80 (5.19)	26.05 (2.79)
% Gini Index	45.80 (2.19)	45.94 (2.34)	45.57 (1.91)
% Age 20-34	20.42 (1.95)	20.50 (2.25)	20.30 (1.30)
% White	76.95 (13.57)	76.02 (15.01)	78.52 (10.60)
% Black	11.14 (10.90)	10.01 (10.59)	13.05 (11.18)
% Native	1.58 (2.79)	1.64 (3.05)	1.48 (2.28)
% Asian	3.82 (5.49)	4.85 (6.66)	2.09 (1.20)
% Poverty Rate	14.27 (3.13)	13.81 (3.20)	15.03 (2.87)
% Unemployment Rate	6.65 (2.11)	6.83 (2.12)	6.35 (2.07)
State Government Expenditure ($ per capita)			
$ Healthcare	2,159.67 (655.64)	2,233.46 (717.22)	2,035.38 (515.26)
$ Welfare	758.82 (385.09)	879.01 (421.03)	556.40 (186.20)
$ Education	2,968.51 (602.49)	3,101.96 (585.38)	2,743.76 (564.79)
Observations	357	224	133

Source: The Uniform Crime Reports (UCR), The American Community Survey (ACS), the Henry J. Kaiser Family Foundation(KFF), and the U.S. Census Bureau from the Annual Survey of State & Local Government Finances.

Notes: Crime rates are from application the Uniform Crime Reports (UCR).
Demographic date is from the American Community Survey (ACS).
State government expenditures data is from the U.S. Census Bureau from the Annual Survey of State & Local Government Finances.

Table 3: Summary Statistics of Contiguous Border Counties Sample 2010-2014

Summary Statistics	**All Border Counties**	**Expanded Counties**	**Unexpanded Counties**
	Mean (S.D.)	*Mean (S.D.)*	*Mean (S.D.)*
Dependent Variables:			
Crime Rate (per 100,000 residents)			
Property Crime	1,828.37 (1203.71)	1,834.90 (1,194.93)	1,821.94 (1,212.75)
Burglary	456.05 (360.00)	473.81 (363.81)	438.60 (355.48)
Larceny Theft	1,277.07 (856.69)	1,268.38 (839.99)	1,285.61 (872.99)
Motor Vehicle Theft	95.24 (105.34)	92.71 (105.75)	97.73 (104.91)
Violent Crime	191.65 (214.60)	192.81 (206.96)	190.51 (221.91)
Criminal Homicide	2.78 (5.55)	2.57 (4.58)	2.99 (6.34)
Robbery	30.42 (61.83)	32.29 (62.11)	28.57 (61.53)
Aggravated Assault	158.45 (175.86)	157.95 (167.64)	158.94 (183.64)
Covariates:			
State Demographics & Economics			
$ Per Capita Income ($1,000)	23.64 (5.90)	23.89 (5.79)	23.38 (6.00)
% Gini Index	42.97 (3.49)	43.29 (3.28)	42.66 (3.65)
% Age 20-34	17.47 (3.87)	17.34 (3.67)	17.59 (4.05)
% White	87.44 (14.82)	87.90 (14.11)	86.99 (15.47)
% Black	6.19 (12.16)	5.96 (11.07)	6.41 (13.15)
% Native	1.90 (7.59)	1.71 (7.60)	2.09 (7.58)
% Asian	0.96 (1.62)	1.03 (1.51)	0.90 (1.72)
% Poverty Rate	15.40 (6.61)	15.47 (6.37)	15.33 (6.84)
% Unemployment Rate	8.02 (3.43)	8.33 (3.36)	7.71 (3.47)
State Government Expenditure ($ per capita)			
$ Healthcare	1,922.00 (429.88)	1,969.29 (486.08)	1,875.53 (360.55)
$ Welfare	721.12 (246.66)	771.13 (259.46)	671.98 (222.82)
$ Education	2,820.20 (371.57)	2938.83 (585.38)	2,703.64 (378.19)
Observations	2,835	1,405	1,430

Source: The Inter-university Consortium for Political and Social Research UCR Program Data Series (ICPSR), The American Community Survey (ACS), the Henry J. Kaiser Family Foundation(KFF), and the U.S. Census Bureau from the Annual Survey of State & Local Government Finances.

Notes: Crime rates are from application the Uniform Crime Reports (UCR).
Demographic date is from the American Community Survey (ACS).
State government expenditures data is from the U.S. Census Bureau from the Annual Survey of State & Local Government Finances.

Table 4: Estimated Effect of the Medicaid Expansion On State-Level Crime Rates: DID Result

DID Estimates	All States Sample	
	(1)	(2)
Dependent Variables:		
Natural Log of Crime Rate per 100,000 residents		
Property Crime	-0.0190	-0.0225
	(0.018)	(0.019)
Burglary	-0.0390*	-0.0360*
	(0.023)	(0.020)
Larceny Theft	-0.0034	-0.0098
	(0.018)	(0.019)
Motor Vehicle Theft	-0.1170***	-0.0995**
	(0.037)	(0.041)
Violent Crime	-0.0398***	-0.0352***
	(0.014)	(0.012)
Criminal Homicide	-0.103***	-0.0771**
	(0.035)	(0.032)
Robbery	-0.0876***	-0.0614**
	(0.029)	(0.025)
Aggravated Assault	-0.0198	-0.0272**
	(0.016)	(0.012)
Control Variables	No	Yes
#Observations	357	357

Note: This sample includes all states for the year 2010-2016.
$*p < 0.05$, $**p < 0.01$, $***p < 0.001$;
Standard errors in parentheses are clustered at the state-level.
Analytic weighted by population.
Year fixed effect and state fixed effect are included.
Each cell in table is a regression result.

Table 5: Estimated Effect of the Medicaid Expansion On State-Level Crime Rates: Event Study Result

Dependent variable:	**All States Sample**							
Natural Log of Crime	Property	Burglary	Larceny	Motor	Violent	Homicide	Robbery	Assault
Rate per 100,000 residents	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2010*Treatment	-0.0259	-0.0353	-0.0275*	0.0201	-0.00750	-0.00841	-0.0333	0.00817
	(0.018)	(0.030)	(0.015)	(0.044)	(0.024)	(0.051)	(0.030)	(0.032)
2011*Treatment	-0.00477	0.00549	-0.0103	0.0355	0.0143	-0.00138	0.0122	0.0200
	(0.024)	(0.035)	(0.020)	(0.049)	(0.021)	(0.043)	(0.034)	(0.025)
2012*Treatment	-0.00186	0.00799	-0.00449	0.00975	0.0000685	0.0197	0.00193	0.00136
	(0.014)	(0.022)	(0.012)	(0.027)	(0.014)	(0.030)	(0.021)	(0.014)
2014*Treatment	-0.0484*	-0.0505*	-0.0406	-0.100**	-0.0542**	-0.0929***	-0.0786***	-0.0397
	(0.028)	(0.028)	(0.028)	(0.043)	(0.024)	(0.034)	(0.024)	(0.026)
2015*Treatment	-0.00608	-0.0203	0.00736	-0.0840*	-0.0171	-0.0664	-0.0472	-0.00291
	(0.014)	(0.024)	(0.015)	(0.045)	(0.017)	(0.045)	(0.032)	(0.017)
2016*Treatment	-0.00552	-0.00769	0.000873	-0.0570	0.00957	-0.0509	-0.0148	0.0125
	(0.025)	(0.037)	(0.023)	(0.066)	(0.033)	(0.074)	(0.044)	(0.037)
p-value test of joint significance of pre-trend	0.1889	0.1453	0.2163	0.8414	0.5339	0.8823	0.5538	0.7685

Note: This sample includes all states for the year 2010-2016.

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$;

Standard errors in parentheses are clustered at the state-level.

Analytic weighted by population.

Control variable, year fixed effect, state fixed effect are included.

Table 6: Estimated Effect of the Medicaid Expansion On State-Level Crime Rates: Robustness Check Result

DID Estimates	Main	No Prior Expansion	Border State	State Trend	Treatment Trend
	(1)	(2)	(3)	(4)	(5)
Dependent Variables:					
Natural Log of Crime Rate per 100,000 residents					
Property Crime	-0.0225	-0.0374*	-0.0144	-0.0435**	-0.0456**
	(0.019)	(0.019)	(0.020)	(0.020)	(0.021)
Burglary	-0.0360*	-0.0460**	-0.0357	-0.0678***	-0.0655***
	(0.020)	(0.023)	(0.022)	(0.022)	(0.024)
Larceny Theft	-0.00975	-0.0259	0.00229	-0.0289	-0.0332*
	(0.019)	(0.017)	(0.020)	(0.019)	(0.019)
Motor Vehicle Theft	-0.0995**	-0.0975**	-0.0880*	-0.102***	-0.0932**
	(0.041)	(0.042)	(0.050)	(0.037)	(0.039)
Violent Crime	-0.0352***	-0.0294**	-0.0392**	-0.0441**	-0.0519***
	(0.012)	(0.014)	(0.015)	(0.019)	(0.017)
Criminal Homicide	-0.0771**	-0.0560*	-0.0933**	-0.101***	-0.0874***
	(0.032)	(0.031)	(0.041)	(0.035)	(0.031)
Robbery	-0.0614**	-0.0522*	-0.0567*	-0.0944***	-0.0922***
	(0.025)	(0.027)	(0.033)	(0.024)	(0.019)
Aggravated Assault	-0.0272**	-0.0214	-0.0244	-0.0210	-0.0359*
	(0.012)	(0.014)	(0.015)	(0.022)	(0.020)
#Observations	357	301	210	357	357

Note: This sample includes all states for the year 2010-2016.

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$;

Standard errors in parentheses are clustered at the state-level.

Analytic weighted by population.

Control variables, year fixed effect and state fixed effect are included.

Each cell in table is a regression result.

Table 7: Estimated Effect of the Medicaid Expansion On Border Counties' Crime Rates: DID Result

DID Estimates	**Contiguous Border Counties**	
	(1)	(2)
Dependent Variables:		
Natural Log of Crime Rate per 100,000 residents		
Property Crime	-0.0159	-0.0155
	(0.023)	(0.018)
Burglary	-0.0406	-0.0370*
	(0.030)	(0.019)
Larceny Theft	0.0080	0.0067
	(0.021)	(0.018)
Motor Vehicle Theft	-0.0824	-0.0748*
	(0.050)	(0.042)
Violent Crime	-0.0468	-0.0474
	(0.037)	(0.029)
Criminal Homicide	0.0080	0.0263
	(0.053)	(0.046)
Robbery	-0.0779**	-0.0669*
	(0.037)	(0.033)
Aggravated Assault	-0.0273	-0.0339
	(0.037)	(0.028)
Control Variables	No	Yes
#Observations	2835	2835

Note: This sample includes contiguous border counties for the year 2010-2014.
$*p < 0.05$, $**p < 0.01$, $***p < 0.001$;
Standard errors in parentheses are clustered at the state-level.
Analytic weighted by population.
Year fixed effect and state fixed effect are included.
Each cell in table is a regression result.

Table 8: Estimated Social Benefit Saving From Crime Reduction By ACA Medicaid Expansion

Crime	**Cost Per Offence**	**Total Offense**	**Crime Reduction**	**Total Estimated Cost**
Aggravated Assault	$121,675	422,798	2.72%	$1,399,275,348.88
Burglary	$7,347	1,086,067	3.60%	$287,256,032.96
Criminal Homicide	$10,213,002	8,574	7.71%	$6,751,360,122.31
Motor Vehicle Theft	$12,247	452,691	9.95%	$551,638,614.36
Robbery	$48,104	227,797	6.14%	$672,817,938.92
Total (In Expanded States)				$9,662,348,057.43

Note: Notes: All values are converted to 2017 dollars.

Cost per offense is calculated by McCollister et al. (2010) in 2008 dollars and then converted to 2017 dollars.

Total offense is the total crime rate for all expanded states in 2013.

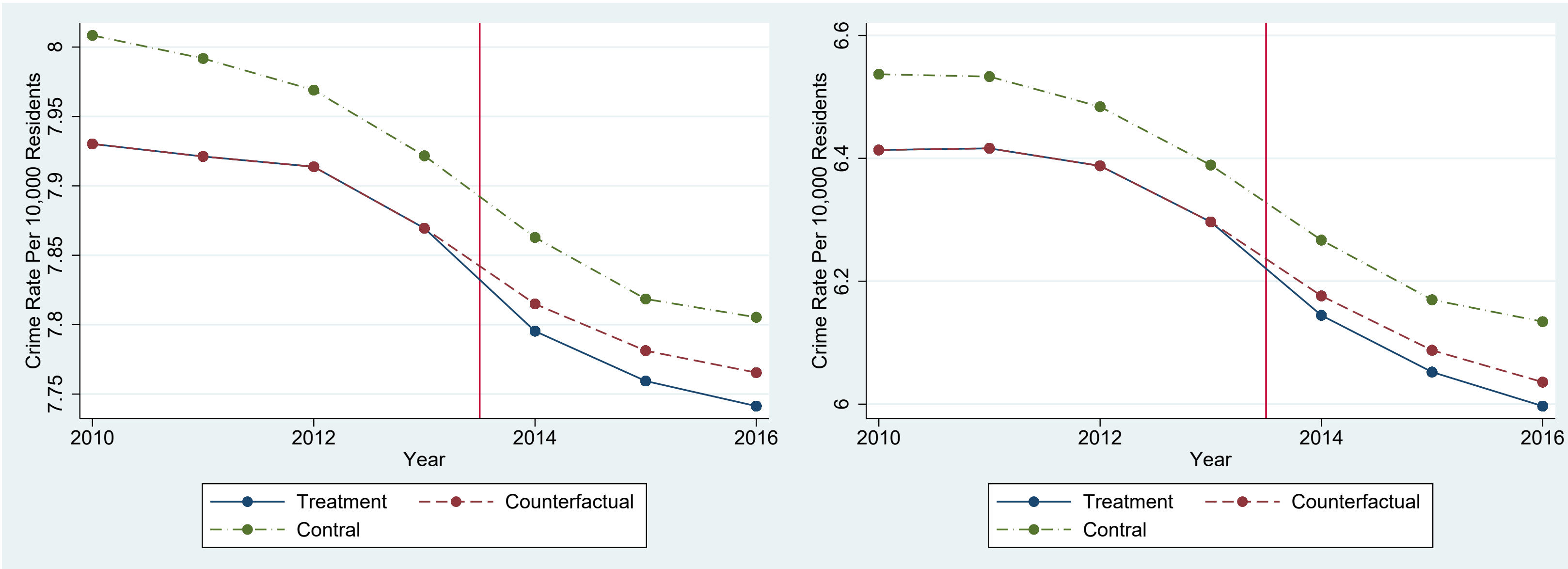
Crime reduction is gathered from my main specification results.

Table 9: Estimated Effect of the Medicaid Expansion On State-Level Crime Rates: Vogler (2017)'s Main Specification Replication

DID Estimates	All States Sample	
	(1)	(2)
Dependent Variables:		
Natural Log of Crime Rate per 100,000 residents		
Property Crime	-0.030*	-0.0264
	(0.018)	(0.018)
Burglary	-0.043**	-0.0514**
	(0.021)	(0.021)
Larceny Theft	-0.010	-0.00903
	(0.018)	(0.017)
Motor Vehicle Theft	-0.115***	-0.119**
	(0.041)	(0.046)
Violent Crime	-0.058***	-0.0565***
	(0.018)	(0.017)
Criminal Homicide	-0.116***	-0.127***
	(0.039)	(0.030)
Robbery	-0.082***	-0.0716**
	(0.028)	(0.027)
Aggravated Assault	-0.047***	-0.0415**
	(0.018)	(0.018)
#Observations	306	306

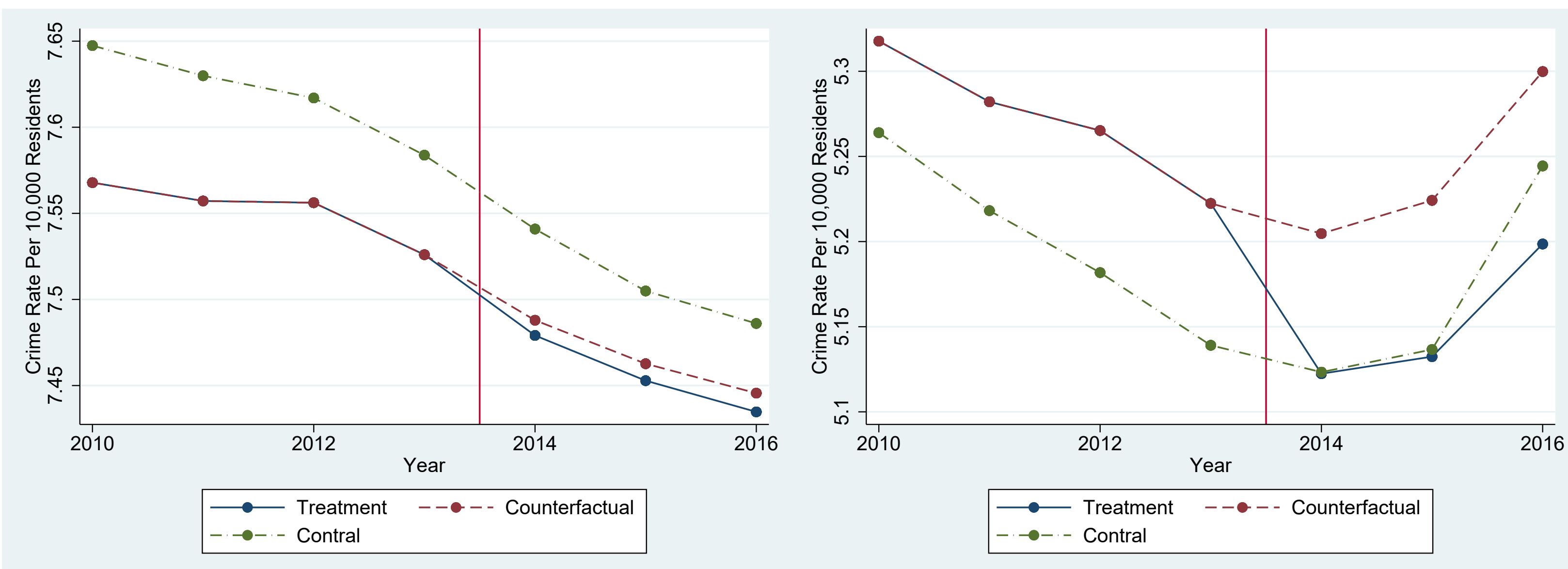
Note: Column (1) shows the estimates from Vogler (2017)'s paper, and Column (2) reports the replicated estimate by using Vogler (2017)'s specification and my dataset.
This sample includes all states for the year 2010-2015.
$*p < 0.05$, $**p < 0.01$, $***p < 0.001$;
Standard errors in parentheses are clustered at the state-level.
The number of law enforcement officers (per 100,000 inhabitants) and state government expenditures in police protection and correction are included.
Analytic weighted by population.
Year fixed effect and state fixed effect are included.
Each cell in table is a regression result.

Figure 1: The Effect of the Medicaid Expansion on Property Crime: DID Method



(a) Property Crime in State-Level

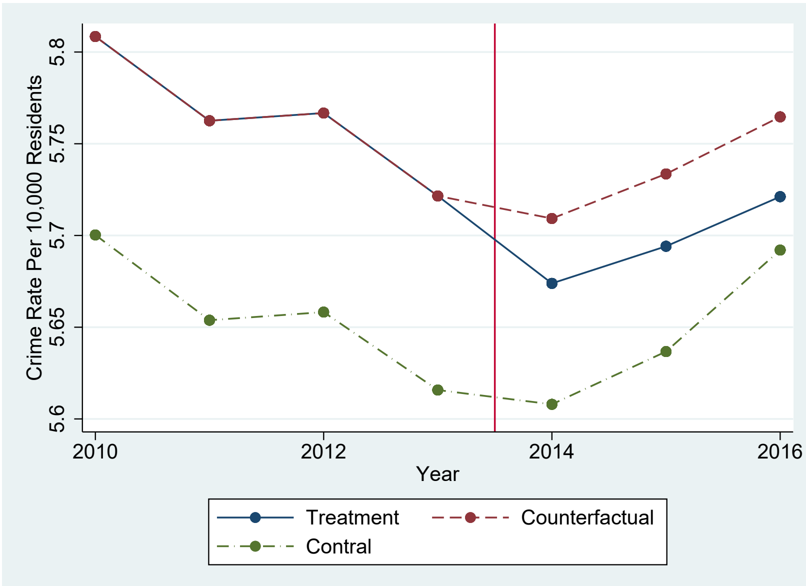
(b) Burglary Crime in State-Level



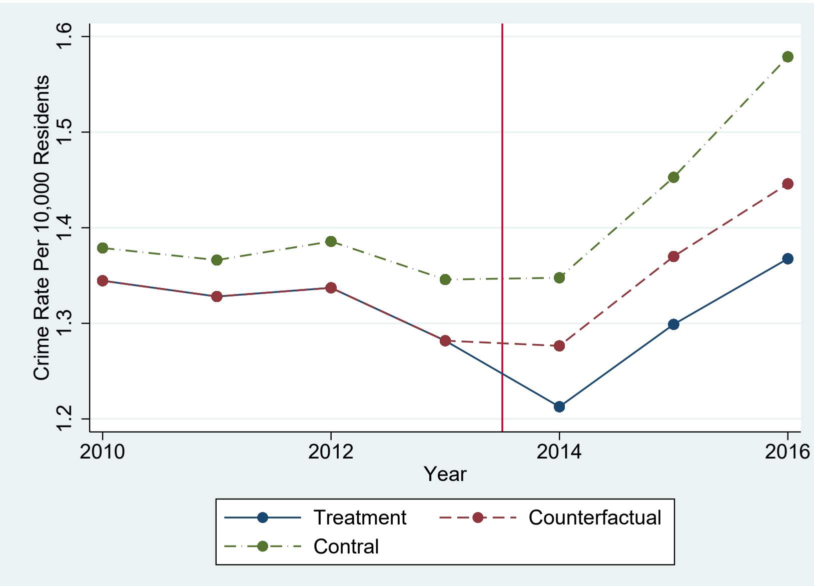
(c) Larceny Theft Crime in State-Level

(d) Motor Vehicle Theft Crime in State-Level

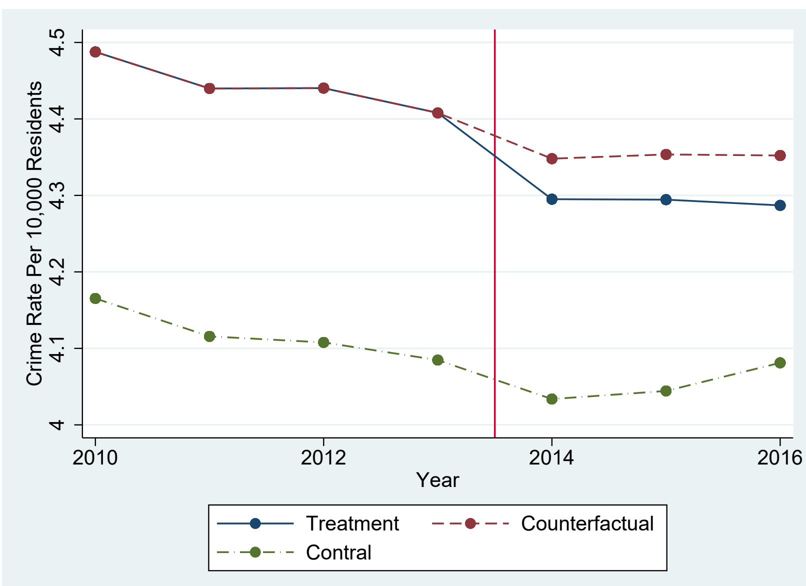
Figure 2: The Effect of the Medicaid Expansion on Violent Crime: DID Method



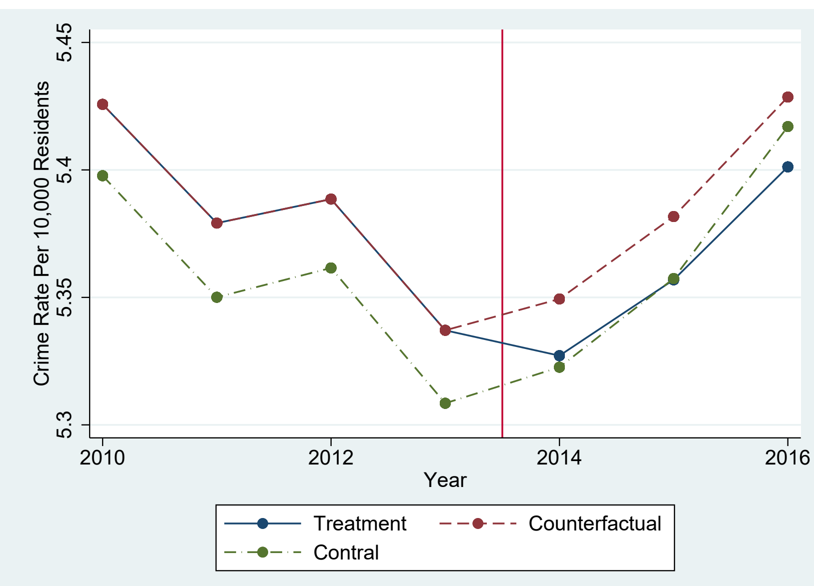
(a) Violent Crime in State-Level



(b) Criminal Homicide Crime in State-Level



(c) Robbery Crime in State-Level



(d) Aggravated Assault Crime in State-Level