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Health Insurance on Social Welfare

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Abstract

This dissertation examines the causal effects of health insurance on social welfare, especially Affordable Care Act (ACA) Medicaid expansion and state-dependent health insurance mandates.

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). This expansion became effective on January 1, 2014. As of January 2017, 31 states and Washington D.C. adopted the Medicaid expansion. 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. The first two chapters of this dissertation investigate the effects of health insurance on criminal behaviors in the United States. In first chapter, 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 the ACA Medicaid coverage not only has a negative income effect on criminal behavior but also raises the opportunity cost of crime. This prediction is particularly relevant for the ACA expansion, because it primarily affects low-income childless adults, the population that is most likely to engage in criminal behavior. I validate this forecast using a difference-in-differences (DID) approach, estimating the expansion's effects on a panel dataset of state- and county-level crime rates. My findings 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.

The second chapter, which is joint work with Scott Barkowski and Joanne Song McLaughlin, examines the negative effect of increasing health insurance coverage rates on arrest rates based on state-level panels of health insurance coverage and arrest data from 2000 to 2012 in the United States. To address the endogeneity of the health insurance coverage rates with respect to arrest rates, we use plausibly exogenous variation in the predicted health insurance coverage rate by using state-level health insurance mandates and the federal dependent coverage mandate in the Affordable Care Act (ACA). The instrumental variable (IV) approach estimates indicate that an increase in the health insurance coverage rate results in a statistically significant reduction in the arrest rates of aggravated assault, prostitution and commercialized vice, but an increase in the arrest rate for fraud. Overall, the state and federal dependent health insurance mandates are associated with a sizable reduction in arrest rates. Our findings suggest that the state and federal dependent health insurance coverage mandates are effective policy instruments to increase health insurance coverage for young adults, and the increased health insurance coverage reduces arrest rates.

The third chapter examines the effect of the Affordable Care Act (ACA) Medicaid eligibility expansion on the labor supply of low-income childless adults. In particular, I investigate that whether this effect is different between blacks and whites. I find that the Medicaid expansion decreased the labor force participation rate by approximately 3 percentage points for married whites and increased the labor supply of never-married blacks by 5.4 percentage points. However, expansion does not play a large role for other groups of blacks and whites. My finding suggests that the recent law change has different effects on the labor supply for blacks and whites.

Dedication

To my parents, Ms. Ping Xiong and Mr. Zhiwei He, who have always trusted, encouraged and supported me unconditionally.

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Contents

List of Tables

List of Figures

Chapter 1

Effect of Health Insurance on Crime: Evidence from the Affordable Care Act Medicaid Expansion

1.1 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

[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.

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 indirect effect of health insurance on criminal behavior through a variety of treatments for some population groups. 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 the Health Insurance Flexibility and Accountability (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, since the health insurance coverage rate is potentially endogenous to crime rates, there exists little reliable empirical evidence regarding the direct causal effect of health insurance on criminal behaviors for the entire eligible population, especially the ACA Medicaid expansion on crime.

In this paper, I introduce health insurance into a simple one-period static economic model of criminal behavior to illustrate how health insurance directly affects criminal behavior through negative financial incentives for all eligible individuals. The economic model predicts that the ACA Medicaid expansion will decrease the time allocated to illegal activities for the entire eligible population under some reasonable assumptions, since Medicaid coverage expansion not only has a negative income effect on criminal behavior but also increases the opportunity cost of crime. I confirm this prediction empirically by applying a difference-in-differences (DID) approach to both state- and county-level data in the United States.

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 potential 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 behav-

[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.

ior, Section IV discusses 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.

1.2 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]

Currently, the researches 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.

1.3 Theoretical Model of Criminal Behavior

There are several reasons why the Medicaid expansions may affect criminal behavior. 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). Moreover, 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 behav-

[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 another spouse destitute.

iors 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 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).

These explanations mainly focus on the effect of health insurance on crime for some subgroups of the entire population, and the expected effect of ACA Medicaid expansion on criminal behavior is ambiguous. Therefore, it is worth to develop a theoretical model to investigate the effect of health insurance on crime for the entire population. 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 change in health insurance coverage directly affects crime through negative financial incentives for all eligible individuals. This model predict that individuals who are eligible for the ACA Medicaid would 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]

[4]If an individual is imprisoned due to criminal activity, Medicaid will no longer pay for most medical care

Consider an individual who is eligible to receive health insurance coverage. This individual chooses how much time to devote to legitimate work and criminal 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. If this individual is imprisoned due to criminal activity, this individual will no longer be eligible for health insurance coverage, will only obtain minimal medical care level in prison, and will receive a negative utility from imprisoned instead of positive utility from health insurance coverage [4].

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 succeeds in criminal 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 is the utility of the difference between the healthcare quality under health insurance and the healthcare quality in prison. 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

$$
\begin{gathered}
E[u] = [1 - P(H_c)]U_N + P(H_c)U_A, \\
U_N = V(w_l H_l + w_c H_c) + M; U_A = V(w_l H_l + w_c H_c) + J, \qquad (1.1) \\
s.t. H_l \geqslant 0, H_c \geqslant 0, \ and \ H_l + H_c = T.
\end{gathered}
$$

for this individual while this individual has stayed in jail or prison as a result of the federal inmate exclusion policy (Gates et al., 2014).

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

$$E[u] = [1 - P(H_c)]\{V[w_l(T - H_c) + w_c H_c] + M\} + P(H_c)\{V[w_l(T - H_c) + w_c H_c] + J\}. \tag{1.2}$$

The first-order condition with respect to H_c is

$$\begin{aligned} D_c = \frac{\partial E[u]}{\partial H_c} &= -P'(H_c)U_N + [1 - P(H_c)]V'(\cdot)(w_c - w_l) \\ &\quad + P'(H_c)U_A + P(H_c)V'(\cdot)(w_c - w_l) \\ &= P'(H_c)(J - M) + V'(\cdot)(w_c - w_l) = 0, \end{aligned} \tag{1.3}$$

so

$$P'(H_c)(M - J) = V'(\cdot)(w_c - w_l), \tag{1.4}$$

or

$$\frac{P'(H_c)}{V'(\cdot)} = \frac{w_c - w_l}{M - J}. \tag{1.5}$$

The second-order condition requires:

$$D_{cc} = \frac{\partial^2 E[u]}{\partial H_c^2} = P''(H_c)(J - M) + V''(\cdot)(w_c - w_l)^2 < 0. \tag{1.6}$$

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

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

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

$$\begin{aligned}\frac{\partial^2 E[u]}{\partial H_c \partial M} &= P''(H_c)(J-M)\frac{\partial H_c}{\partial M} - P'(H_c) + V''(\cdot)(w_c - w_l)^2 \frac{\partial H_c}{\partial M} = 0 \\ &= D_{cc}\frac{\partial H_c}{\partial M} - P'(H_c) = 0,\end{aligned} \tag{1.7}$$

so

$$\frac{\partial H_c}{\partial M} = \frac{P'(H_c)}{D_{cc}} < 0. \tag{1.8}$$

The equation (8) says that the sign of $\frac{\partial H_c}{\partial M}$ all hinges 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 Medicaid coverage not only has a 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 a negative effect is larceny among these crimes which can generate income. Moreover, there is a 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). Additionally, 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).

1.4 Data

1.4.1 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 in and 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 ongoing survey administered by the U.S. Census Bureau providing detailed information 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 conditions are measured

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

[6]$age2034$ represents the 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).

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 of state government spending 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) hospitals and health, (11) public welfare, 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.

1.4.2 Sample Construction

There are two distinct samples have been used in my analysis: a state sample and a border county sample. The state 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 border county 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 be-

[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 the 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 (income effect). Therefore, the net effect of per capita income on crime is uncertain (Zhang, 1997).

[9] Poverty rate measures the percent of the 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).

tween 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 the balanced panel is 2,835.

Table 2 provides means and standard deviations of the dependent variable and covariates for the state 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 border county 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 border county sample.

1.5 Methodology

1.5.1 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:

$$ln(Crime\ rate)_{st} = \beta_0 + \beta_1 MedicaidDummy_{st} + \mathbf{X_{st}}\lambda + \mathbf{Z_{st}}\delta + \rho_s + \tau_t + \epsilon_{st}, \quad (1.9)$$

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 effects. I cluster the standard errors at the state-level to account 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.

1.5.2 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). Unlike DID approach which the estimated crime reduction effect is constant over time after the ACA Medicaid expansion, event study model can flexibly trace changes in crime rates before and after the expansion every year. To test the plausibility of this parallel trends assumption in my paper, I utilize

[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.

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):

$$\begin{aligned} ln(Crime\ rate)_{st} = \alpha_0 &+ \alpha_1(Treatment_s * I2010_t) + \alpha_2(Treatment_s * I2011_t) \\ &+ \alpha_3(Treatment_s * I2012_t) + \alpha_4(Treatment_s * I2014_t) \\ &+ \alpha_5(Treatment_s * I2015_t) + \alpha_6(Treatment_s * I2016_t) \\ &+ \mathbf{X_{st}}\lambda + \mathbf{Z_{st}}\delta + \rho_s + \tau_t + \epsilon_{st}, \end{aligned} \tag{1.10}$$

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 jointly equal to zero.

1.6 Robustness Checks

1.6.1 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

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

control for the exogenous linear trends in the crime rate which are not captured by other variables.

1.6.2 Empirical Specification Using Border County Sample

The Border county 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 the border county sample, I estimate the DID specification similar to equation (9):

$$ln(Crime\ rate_{ct}) = \beta_0 + \beta_1 MedicaidDummy_{st} + \mathbf{X_{ct}}\lambda + \mathbf{Z_{ct}}\delta + \rho_c + \tau_t + \epsilon_{ct}, \tag{1.11}$$

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 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 $Population_ct$ 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, the border county sample is just a sub-sample of the whole population, it can not adequately represent the whole population. Second, the data time

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

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.

1.7 Main Result

1.7.1 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 state sample. Table 4 reports difference-in-difference (DID) estimates for the state 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 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.

[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.

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

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.

Figure 1 and 2 show the effect of the ACA Medicaid expansion on both property and violent crime categories from DID estimates. The solid line represents the predicted crime rates in Medicaid expanded states, dash line represents the predicted counterfactual crime rates in Medicaid expanded states in the absent of the expansion, dash-dot line represents the predicted crime rates in Medicaid unexpanded states, and the vertical solid line represents the 2014 Medicaid expansion. Both figures reveal that the predicted crime rates in all crime categories are declined in Medicaid expanded states after the expansion in comparison with the counterfactual, which means the expansion has a negative effect on all crime categories in expanded states from DID estimates. The DID approach compares the average reported crime rate before the expansion with the average reported crime rate after that in each crime category and finds a crime reduction effect of the Medicaid expansion. Figure 3 and 4 report the time trend of difference in the predicted crime rates between expanded and unexpanded states (Treatment minus control) in all crime categories. Figure 3 shows that the predicted crime rates in expanded states are rising relative to the unexpanded states in prior to the expansion in all property crime categories, however, the differences in predicted crime rates show a sizeable decrease after the Medicaid expansion in all property crimes but larceny theft. Even there is a decrease in the larceny theft in 2014, the difference in the predicted crime rate of larceny theft still keep increasing after 2014. Figure 4 indicates that the predicted crime rate gaps between are relatively constant before 2014 and keeping decrease after the expansion in all violent crime categories. Both Figure 3 and 4 show that the Medicaid expansion has the largest crime reduction effect in 2014 and this effect is gradually weakened in 2015 and 2016 in expanded states relative to unexpanded states.

The significant negative 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 a 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.

1.7.2 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 the event study model and report the estimated flexible event study coefficients 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 for pre-treatment coefficients indicates that I fail to reject the null hypothesis that the pre-treatment coefficients are jointly equal to zero. Therefore, the event study model estimates support the parallel trends assumption that crime rates would follow the same trend in both expanded and unexpanded state in absence of the Medicaid expansion, and the estimates in Table 4 can be considered as representing the causal effects of the ACA Medicaid expansion on crime. Moreover, the estimates also reveal that the ACA Medicaid expansion has a significant crime reduction effect for all crime categories except larceny theft and aggravated assaults in 2014, but the negative effect of the expansions on crime rates is diminishing in 2015 and 2016. The p-value for F-tests of joint significance for post-treatment coefficients indicates that the post-treatment coefficients are jointly significantly different from zero in motor vehicle theft, criminal homicide, and robbery.

Figure 5 and Figure 6 present plots of the event study estimates for property and violent crime categories separately. Both figures show how the difference in reported crime rates between expanded and unexpanded states changed over time in the time period before and after the ACA Medicaid expansion for all crime categories. All plots reveal that the estimated coefficients exhibit a relatively smooth trend around zero before the Medicaid expansion became effective, which supports the DID identifying assumption. A sharp decline in all kinds of crime rates is associated with the Medicaid expansion in 2014 in expanded states in comparison with unexpanded states. However, the crime reduction effect of the expansion is fading away and even stalled in the period after 2014, especially on larceny theft and aggravated assault. One potential reason for the diminishing crime reduction effect is that the Medicaid utilization expansion causes health care services shortage for these low-income eligible individuals. The shortage of health care services weakens the crime reduction effect of the Medicaid expansion.

1.7.3 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 the 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.

1.7.4 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 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 the 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 state 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.

1.8 Discussion and Conclusions

This paper extends a one-period static criminal behavior model with health insurance to illustrate how health insurance directly affects criminal activity for all eligible individuals. Under risk-aversion and other reasonable assumptions, the model forecasts an adverse effect of the ACA Medicaid expansion on criminal behavior. A difference-in-difference approach is then used and applied to both state- and county-level data in the United States. My findings suggest that the Affordable Care Act (ACA) Medicaid expansion enhances public safety through crime reduction. The estimates show that the ACA Medicaid expansion decreases the rate of burglary by 3.6 percent, decreases the rate of motor vehicle theft by 10 percent, decreases the rate of criminal homicide by 7.7 percent, decreases the rate of robbery by 6.1 percent, and decreases the rate of aggravated assault by 2.7 percent. These results all remain similar across a wide range of robustness checks.

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 the 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

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

states a year.[20]

In July 2017, the 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 the 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 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.

[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.

Table 1.1: 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 1.2: 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 1.3: 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 1.4: 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 Indicated 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
Year Fixed Effect	Yes	Yes
State Fixed Effect	Yes	Yes
#Observations	357	357

Note: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Analytic weighted by population. This sample includes all states and Washington D.C. for the year 2010-2016. Standard errors in parentheses are clustered at the state-level. Each of the reported cells correspond to a separate DID regression.

Table 1.5: 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 of Jointly Pre-treatment	0.1889	0.1453	0.2163	0.8414	0.5339	0.8823	0.5538	0.7685
P value of Jointly Post-treatment	0.2422	0.1623	0.2384	0.0754	0.0113	0.0201	0.0040	0.3232

Note: $*p < 0.10$, $**\,p < 0.05$, $***p < 0.01$. Standard errors in parentheses are clustered at the state-level. This sample includes all states and Washington D.C. for the year 2010-2016. Analytic weighted by population. Control variable, year fixed effect, state fixed effect are included in each regression.

Table 1.6: 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 Indicated 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: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Standard errors in parentheses are clustered at the state-level. This sample includes all states and Washington D.C. for the year 2010-2016. Control variables, year fixed effect and state fixed effect are included in each regression. Analytic weighted by population. Each of the reported cells correspond to a separate DID regression.

Table 1.7: Estimated Effect of the Medicaid Expansion On Border Counties' Crime Rates: DID Result

DID Estimates	Contiguous Border Counties		Main
	(1)	(2)	(3)
Dependent Variables:			
Natural Log of Indicated Crime Rate per 100,000 residents			
Property Crime	-0.0159	-0.0155	-0.0225
	(0.023)	(0.018)	(0.019)
Burglary	-0.0406	-0.0370*	-0.0360*
	(0.030)	(0.019)	(0.020)
Larceny Theft	0.0080	0.0067	-0.00975
	(0.021)	(0.018)	(0.019)
Motor Vehicle Theft	-0.0824	-0.0748*	-0.0995**
	(0.050)	(0.042)	(0.041)
Violent Crime	-0.0468	-0.0474	-0.0352***
	(0.037)	(0.029)	(0.012)
Criminal Homicide	0.0080	0.0263	-0.0771**
	(0.053)	(0.046)	(0.032)
Robbery	-0.0779**	-0.0669*	-0.0614***
	(0.037)	(0.033)	(0.025)
Aggravated Assault	-0.0273	-0.0339	-0.0272**
	(0.037)	(0.028)	(0.012)
Control Variables	No	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
State Fixed Effect	Yes	Yes	Yes
#Observations	2835	2835	357

Note: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Analytic weighted by population. This sample includes contiguous border counties for the year 2010-2014. Standard errors in parentheses are clustered at the state-level. Year fixed effect and state fixed effect are included in each regression. Each of the reported cells correspond to a separate DID regression.

Table 1.8: 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

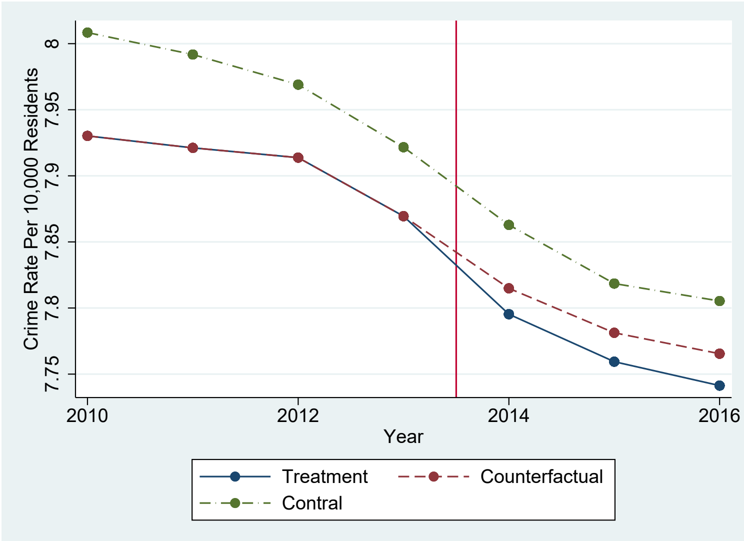
Note: Notes: All values are converted to 2017 dollars. Cost per offense is calculated by McCollister et al. (2010) in 2008 dollars and then converted to 2017 dollars. Total offense is the total crime rate for all expanded states in 2013. Crime reduction is gathered from my main specification results.

Table 1.9: Estimated Effect of the Medicaid Expansion On State-Level Crime Rates: Vogler (2017)'s Main Specification Replication

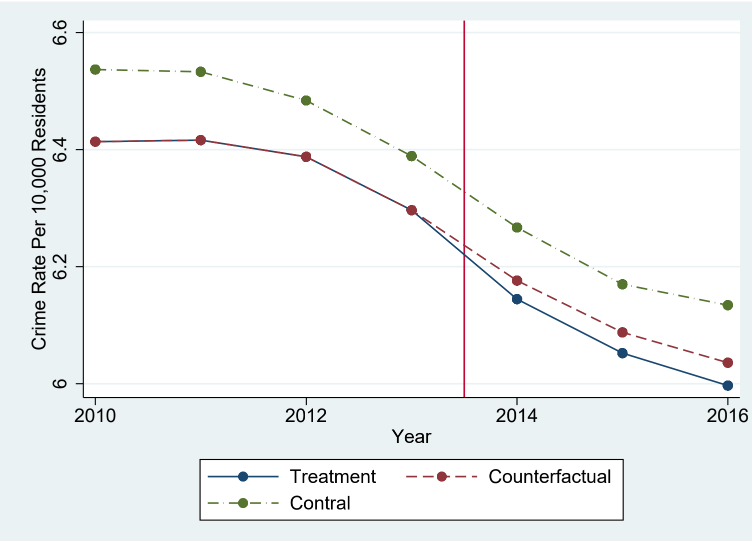
DID Estimates	All States Sample	
	(1)	(2)
Dependent Variables:		
Natural Log of Indicated Crime Rate per 100,000 residents		
Property Crime	-0.030*	-0.0264
	(0.018)	(0.018)
Burglary	-0.043**	-0.0514**
	(0.021)	(0.021)
Larceny Theft	-0.010	-0.00903
	(0.018)	(0.017)
Motor Vehicle Theft	-0.115***	-0.119**
	(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: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Analytic weighted by population. Column (1) shows the estimates from Vogler (2017)'s paper, and Column (2) reports the replicated estimate by using his specification and my dataset. This sample includes all states and Washington D.C. for the year 2010-2015. 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. Year fixed effect and state fixed effect are included in each regression. Each of the reported cells correspond to a separate DID regression.

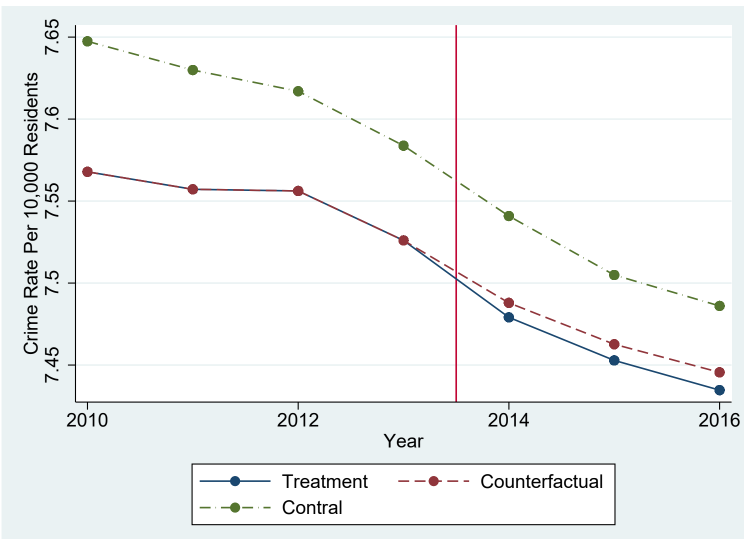
Figure 1.1: The Effect of the Medicaid Expansion on Property Crime: DID Method



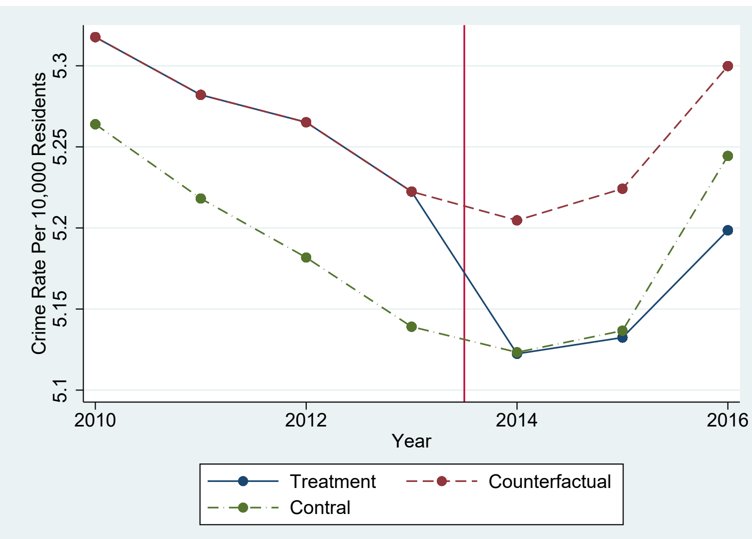
(a) Property Crime in State-Level



(b) Burglary Crime in State-Level

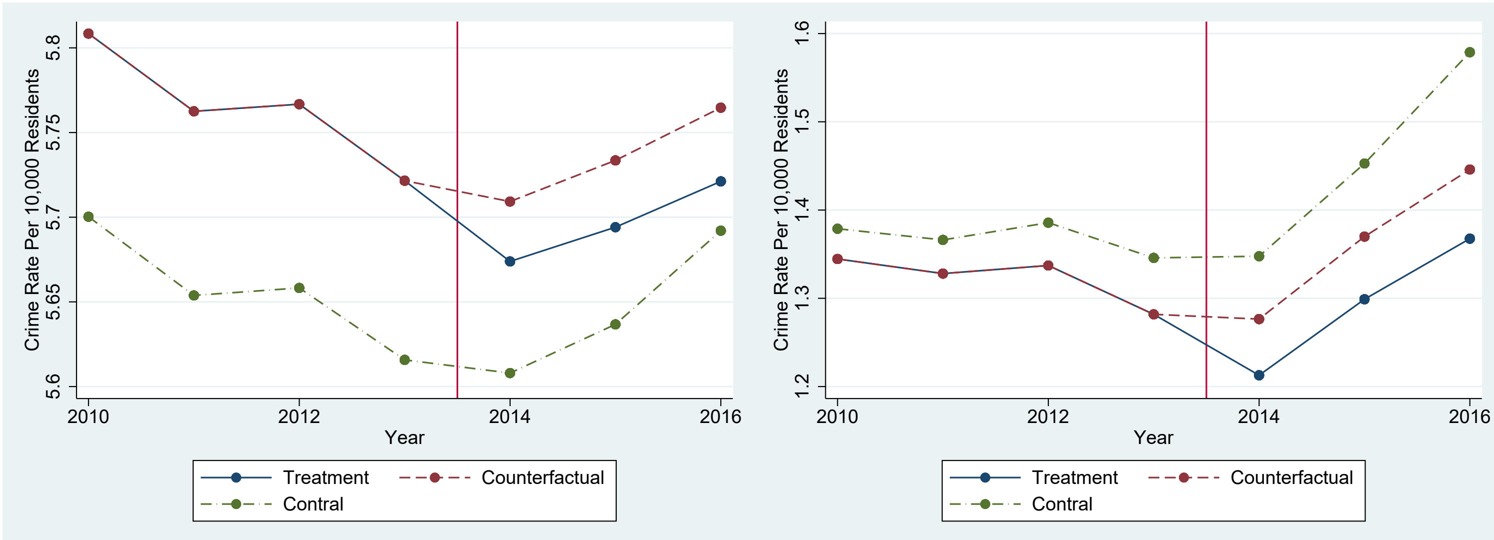


(c) Larceny Theft Crime in State-Level



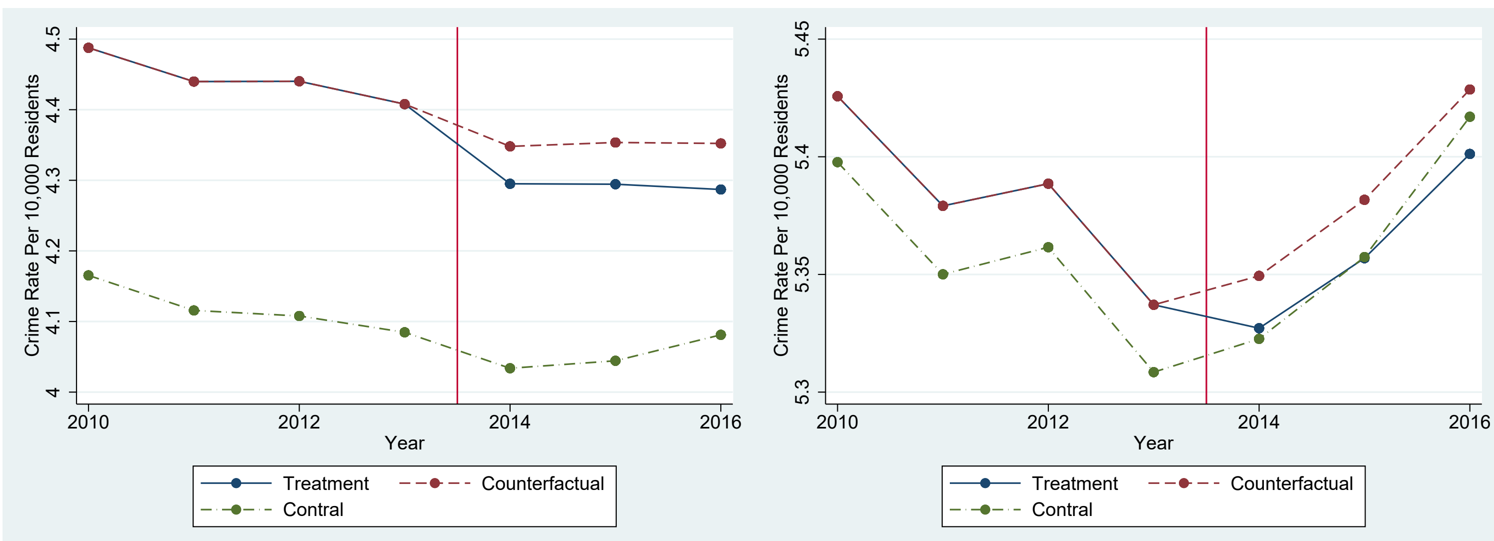
(d) Motor Vehicle Theft Crime in State-Level

Figure 1.2: The Effect of the Medicaid Expansion on Violent Crime: DID Method



(a) Violent Crime in State-Level

(b) Criminal Homicide Crime in State-Level

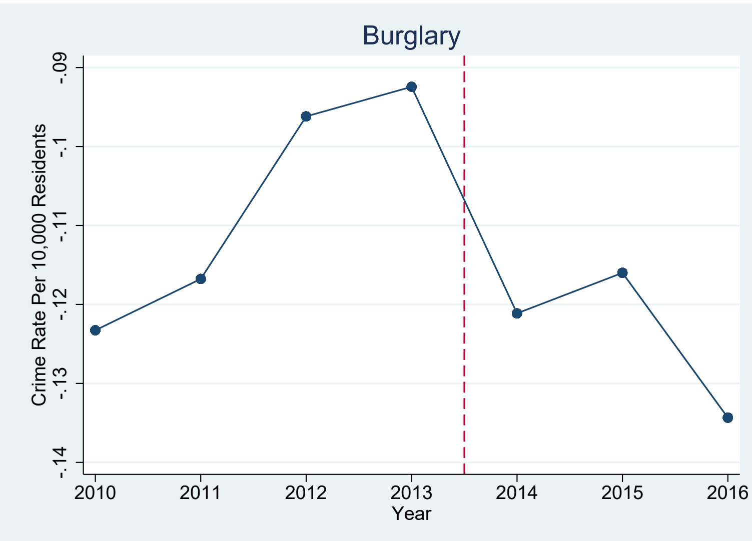


(c) Robbery Crime in State-Level

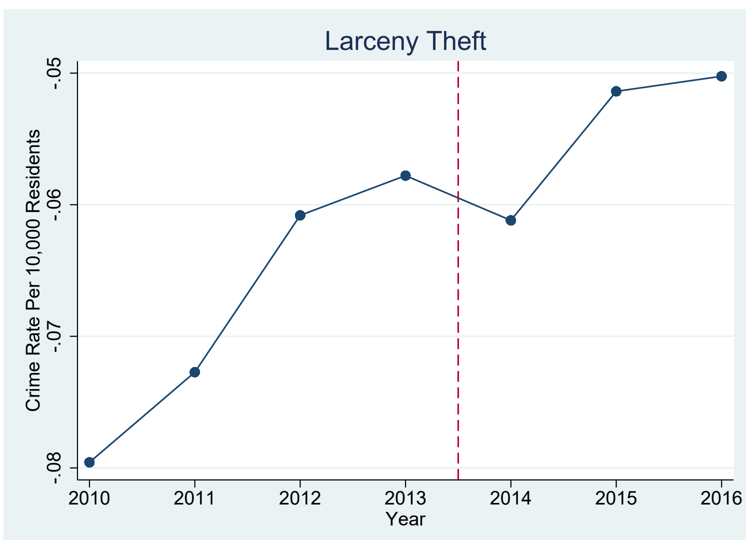
(d) Aggravated Assault Crime in State-Level

Figure 1.3: The Effect of the Medicaid Expansion on Property Crime: Difference between Treatment and Control Groups

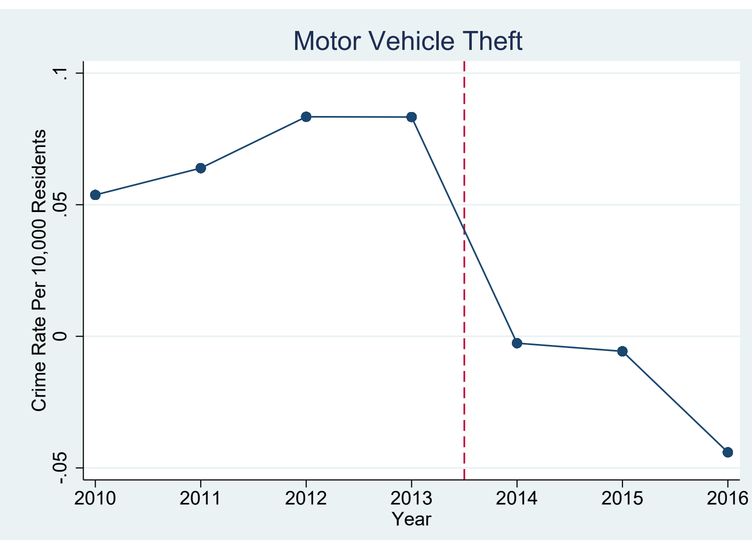
(a) Property Crime in State-Level



(b) Burglary Crime in State-Level

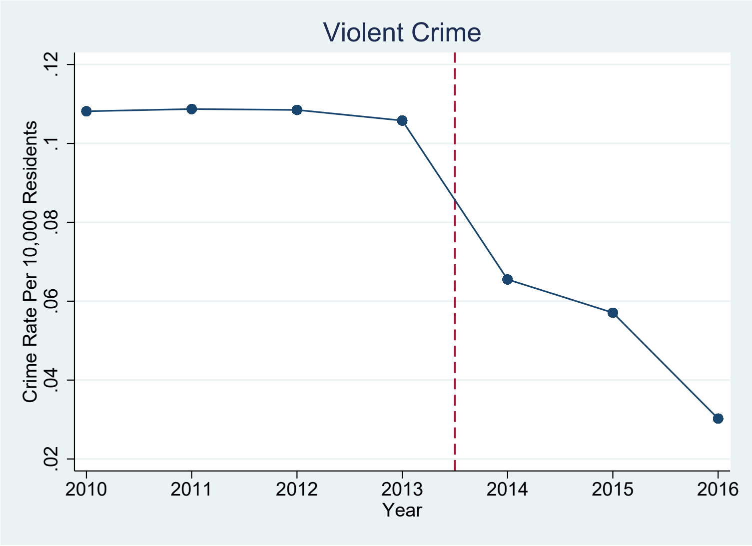


(c) Larceny Theft Crime in State-Level

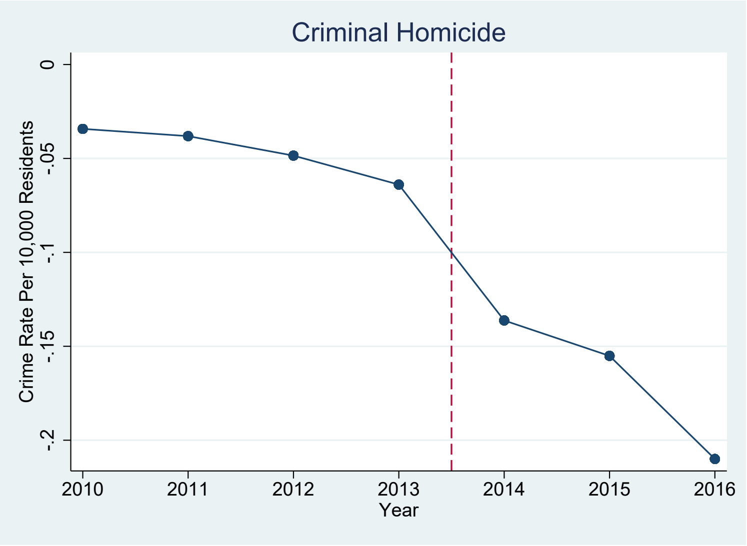


(d) Motor Vehicle Theft Crime in State-Level

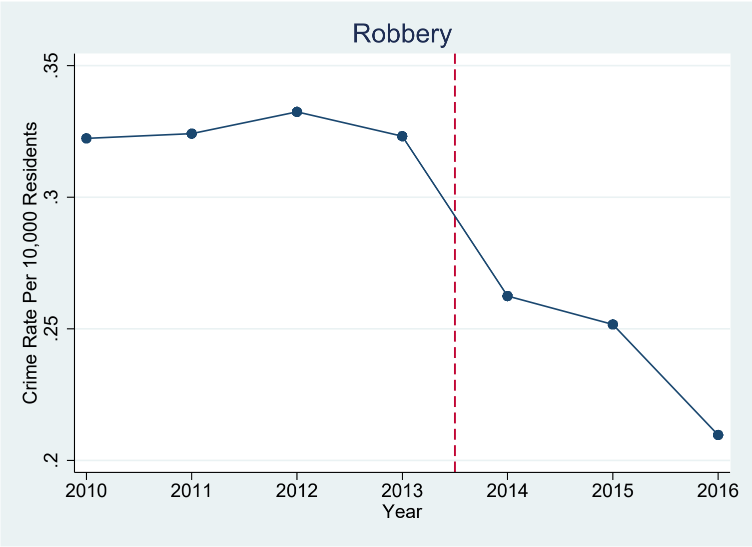
Figure 1.4: The Effect of the Medicaid Expansion on Violent Crime: Difference between Treatment and Control Groups



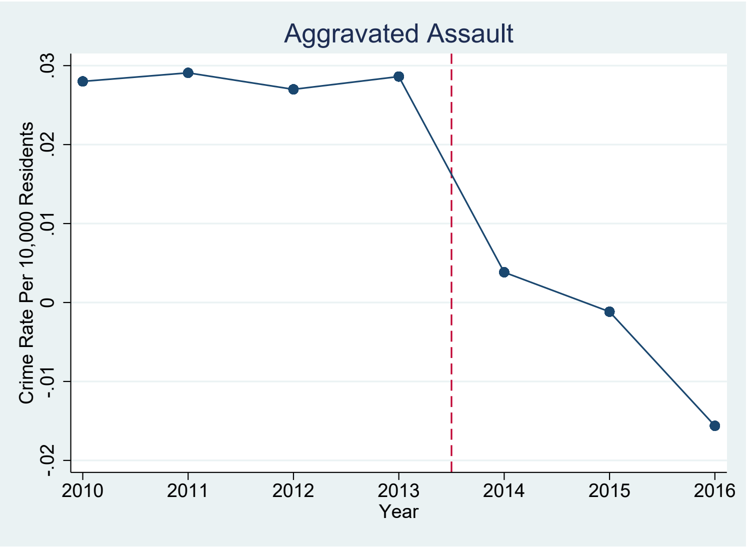
(a) Violent Crime in State-Level



(b) Criminal Homicide Crime in State-Level



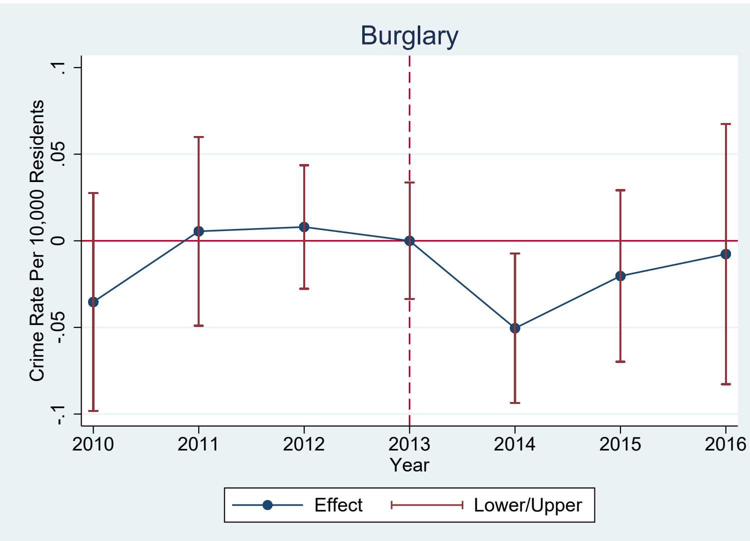
(c) Robbery Crime in State-Level



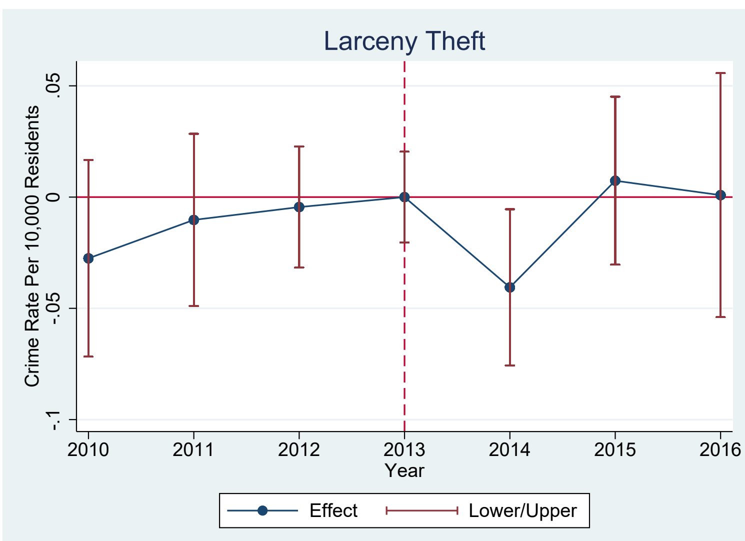
(d) Aggravated Assault Crime in State-Level

Figure 1.5: The Effect of the Medicaid Expansion on Property Crime: Event Study Estimates

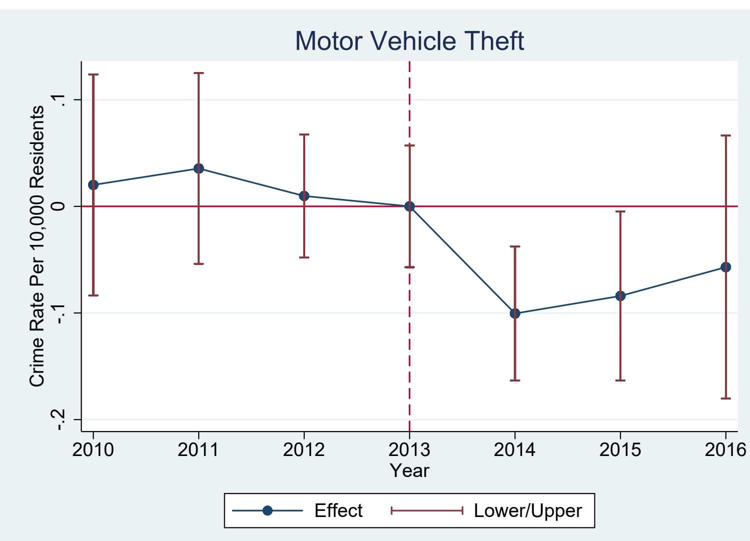
(a) Property Crime in State-Level



(b) Burglary Crime in State-Level

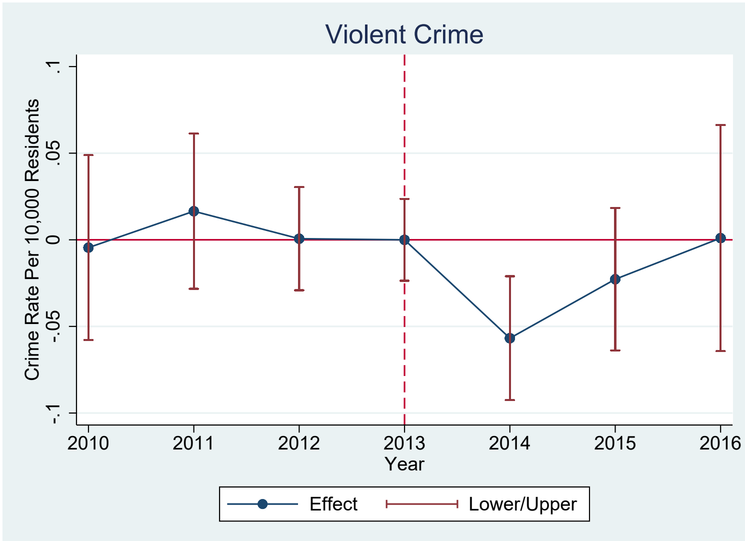


(c) Larceny Theft Crime in State-Level

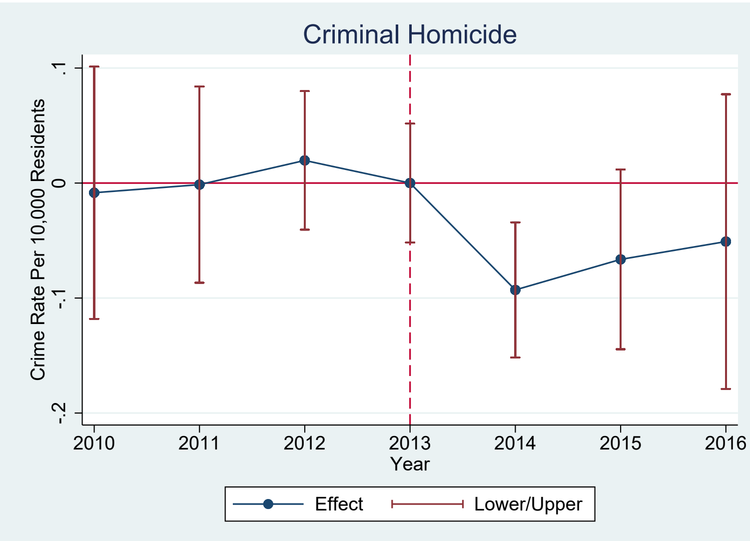


(d) Motor Vehicle Theft Crime in State-Level

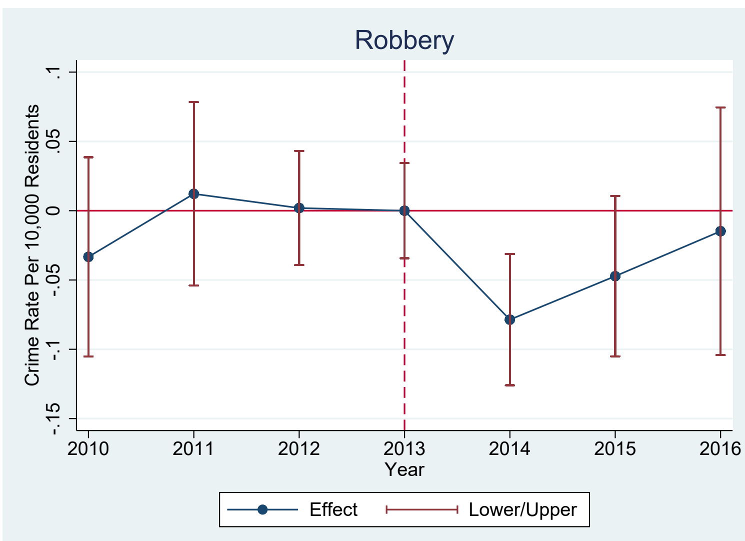
Figure 1.6: The Effect of the Medicaid Expansion on Violent Crime: Event Study Estimates



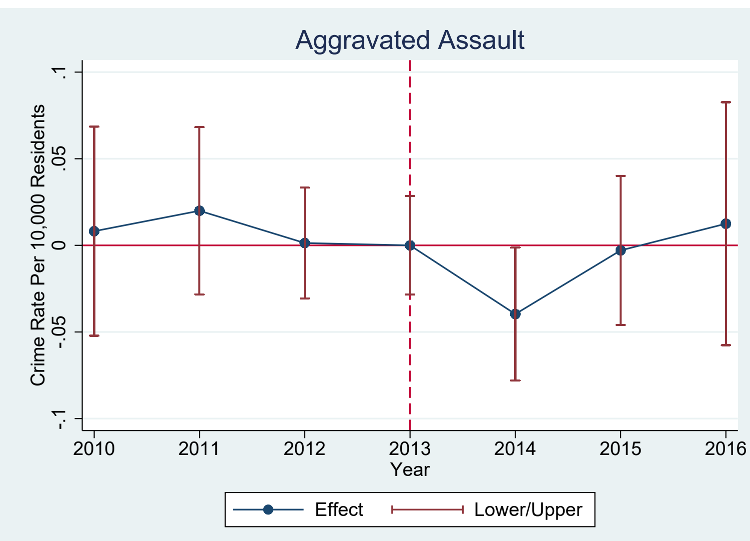
(a) Violent Crime in State-Level



(b) Criminal Homicide Crime in State-Level



(c) Robbery Crime in State-Level



(d) Aggravated Assault Crime in State-Level

Chapter 2

Health Insurance Effects on Arrest Rates of Young Adults

2.1 Introduction

In the U.S., young adults historically have been less likely to be covered by health insurance than other age groups. Nearly one in three, or almost 10 million, young adults aged 19-24 lacked health insurance coverage in 2008 (DeNavas-Walt et al., 2009). Young adults have the lowest health insurance coverage rates because high school or college graduation frequently leads to loss of dependent coverage under a parent's health insurance plan. Meanwhile, they have limited access to employer-sponsored coverage and subsidized public health insurance. In order to address this critical concern, 33 states enacted a dependent coverage mandate of their own, which require health insurers to increase the eligibility age limit and permit young adults to remain on their parent's health plan, prior to the enactment of the Patient Protection and Affordable Care Act (ACA) (Barkowski and McLaughlin, 2018). Evidence suggests that these state-based mandates have successfully increased the proportion of young adults with insurance coverage (Levine et al., 2011;

Monheit et al., 2011; Depew, 2015).

In 2010, the ACA was implemented, and the federal government adopted its own dependent health insurance mandate, which extended the age of dependency to 26 so that young adults can be enrolled in their parents' insurance plan. This federal mandate led to significant increases in health insurance coverage for young adults (Cantor et al., 2012; Sommers et al., 2012; Akosa Antwi et al., 2013).

These federal and state coverage mandates may have implications for the criminal behavior of young adults. There are two main factors driving such a result. First, both crime and arrest rates in the USA have been historically higher for young adults than for any other age group (Synder et al., 2012; Uniform Crime Report, 2003). Second, 90% of state prison inmates are uninsured and over half of them have a mental health disorder (Yocom, 2014; James et al., 2006). Thus, the health insurance mandates created disincentives for criminal behavior by providing appropriate treatments for young patients and by increasing the opportunity cost of committing crimes (He, 2017)[1].

Many studies investigate the relationship between health insurance and crime for all populations. Morrissey et al. (2007) use a quasi-experimental design to estimate the effect of receiving Medicaid benefits on re-arrest rates for prison inmates with severe mental illness, and find that having Medicaid health services was associated with a reduction in recidivism. Wen et al. (2014) instrument for substance use disorder (SUD) treatment by using Health Insurance Flexibility and Accountability (HIFA) waivers and their results suggest that HIFA-waiver expansions result in a sizable reduction in robbery, aggravated assault and larceny theft through increasing the SUD treatment rate. Vogler (2017) and He (2017) explore the effect of health insurance on criminal behavior, specifically the effect of the ACA Medicaid expansion. Both find the Medicaid expansions significantly reduces

[1] If an individual is imprisoned due to criminal activity, Medicaid will no longer pay for most medical care for this individual while this individual is stayed in jail or prison as a result of the federal inmate exclusion policy (Gates et al., 2014).

crime rates by using a difference-in-difference approach. However, there have been no investigations into the effect of health-insurance access on young adults' criminal behavior.

In this paper we examine the effect of increasing the health insurance coverage rate on reducing arrest rates for young adults, aged 19-22, based on state-level panels of health insurance coverage and arrest data from 2000 to 2012. Since the Federal Bureau of Investigation (FBI) does not provide crime data by age, we use arrest data to approximate the number of crimes committed by young adults in this study. However, a main empirical concern in estimating the effect is that the health insurance coverage rate is potentially endogenous to arrest rates. To address this concern, we leverage plausibly exogenous variation in the predicted health insurance coverage rate by using state-level health insurance mandates and the ACA dependent coverage mandate. The IV estimates show that an increase in the health insurance coverage rate results in a statistically significant reduction in arrest rates of aggravated assault,and prostitution and commercialized vice, but an increase in the arrest rate of fraud. Overall, the state and federal dependent health insurance mandates are associated with a sizable reduction in arrest rates for young adults.

The remainder of the paper proceeds as follows. Section 2 describes the empirical framework and data. In section 3, I provide a detailed description of the results. Finally, I present my concluding remarks in section 4.

2.2 Empirical Framework and Data

2.2.1 Empirical Analysis

To estimate the effect of health insurance coverage rates on arrest rates, we first use the following ordinary least squares (OLS) econometric model:

$$ArrestRate_{i,s,t} = \eta_0 + \eta_1 HISHR_{s,t} + X_{s,t}\eta_3 + \theta_s + \gamma_t + u_{s,t}, \tag{2.1}$$

where $ArrestRate_{i,s,t}$ is the arrest rate of offense i for young adults aged 19 to 22 in state s and year t, $HISHR_{s,t}$ is the share of the population aged 19 to 22 in state s during year t that is covered by health insurance, $X_{s,t}$ represents a vector of state-level demographic variables, and θ_s and γ_t represent state and year fixed-effects, respectively. The estimated coefficient η_1 shows the relationship between a state's health insurance coverage rate and its arrest rate.

However, OLS estimators for this model may be biased because the health insurance coverage rate is potentially endogenous, as $HISHR_{s,t}$ is not independent of the error term in Equation 1, in other words, both the arrest rate and the health insurance coverage rate are jointly affected by potentially unobserved demographic factors.

2.2.1.1 Instrumental Variable Approach

To properly identify the causal effect of health insurance, we use a two-stage least square (2SLS) instrumental variable (IV) approach to examine the pathway effect of health insurance coverage rates on the arrest rate. We use the federal and state dependent health insurance coverage mandates for young adults as an instrument for health insurance coverage. One option for an IV would be to use the share of young adults aged 19 to 22 who were eligible for the health insurance mandate under the state's law during a given year.

An important drawback to this approach is that, if we use the features of the laws that reflect personal characteristics like age, student, or marital status, then the resulting share of young adults eligible for the mandate would reflect the unobserved demographic and societal characteristics of a state in a given year. Our instrument would, therefore, potentially suffer from a similar problem as $HISHR_{s,t}$ would suffer from.

We solve this problem by creating a state-by-year measure of the extent/reach of the government health insurance mandates. This measure would not reflect the demographics of a particular state and year, but only the scope of the state's mandate in a year. To do this, we adopt the "simulated instrument" introduced by Currie and Gruber (1996a,b); Cutler and Gruber (1996) and used by Gruber and Yelowitz (1999), Ham and Shore-Sheppard (2005), Gruber and Simon (2008), and Barkowski (2015), among others. These papers used the stimulated instrument to adjust for endogeneity in Medicaid eligibility. We adapt this concept to the health insurance mandates.

The instrument $ELIGIV_{s,t}$ is imputed as the share of population aged 19-22 of *all other states* in year 2000 eligible for insurance coverage under the state s's mandate laws in year t. More precisely, let $\sim s$ indicate *not* state s, and $f_{s,t}(x_{i,g,t})$ reflect a function that maps from an individual i in geography g and year t to eligibility under the laws of state s in year t. $I_{g,t}$ measures the total number of people in a geography g in a year t. This yields the following equation:

$$ELIGIV_{s,t} = \frac{1}{I_{\sim s,t}} \sum_{i,\sim s,t} f_{s,t}(x_{i,\sim s,t}). \tag{2.2}$$

We calculate this using all individuals between the ages of 19 and 22 (inclusive). $ELIGIV_{s,t}$ is an instrumental variable for $HISHR_{s,t}$ in our model. Hence, identification comes from changes in the mandates, not demographics in the state.

The first-stage regression measures the relationship between health insurance mandates and health insurance coverage by the equation:

$$HISHR_{s,t} = \alpha_0 + \alpha_1 ELIGIV_{s,t} + X_{s,t}\alpha_3 + \theta_s + \gamma_t + \varepsilon_{s,t}, \tag{2.3}$$

where $ELIGIV_{s,t}$, the health-insurance mandate eligibility rate, is calculated by Equation 2. The coefficient of interest is α_1, which is expected to be positive since the health insurance coverage rate in a state should increase as the eligible population in all other states increases under this state's mandates. Using the predicted values for health insurance coverage $\widehat{HISHR}_{s,t}$ from Equation 3, we estimate the causal effect of heath insurance coverage on the arrest rate with the following second stage:

$$ArrestRate_{i,s,t} = \beta_0 + \beta_1 \widehat{HISHR}_{s,t} + X_{s,t}\beta_3 + \theta_s + \gamma_t + \mu_{s,t}. \tag{2.4}$$

The values of β_1 provide the causal estimate of health insurance availability on the arrest rate.

2.2.2 Data Sources

Our data consist of a panel of annual, state-level observations between 2000 and 2012. The data come from the American Community Survey (ACS), the Current Population Survey (CPS), and the Inter-university Consortium for Political and Social Research Uniform Crime Report (UCR) Program Data Series (ICPSR).

2.2.2.1 Dependent variables: arrest rates

State-level arrest rates ($ArrestRate_{s,t}$) are collected annually by the Federal Bureau of Investigation (FBI) and reported by the ICPSR in *Uniform Crime Reporting Program Data [United States]: Arrests by Age, Sex, and Race, Summarized Yearly* 2000-2012, and are measured as the number of arrests in the population aged 19 to 22 reported to police agencies within a given state s over an entire calendar year t ($ArrestRate_{s,t}$: number of arrests of young adults, aged 19 to 22, reported by the police of all law enforcement agencies per 100,000 residents).

ICPSR state-aggregate arrest reports provide information on the number of arrests on 43 sub-categories of offenses and the counts of arrests by age, sex, and race for each particular offense in a given year. Our sample uses 23 categories of offenses including criminal homicide, forcible rape, robbery, aggravated assault, burglary, larceny, motor vehicle theft, arson, other assaults (simple), forgery and counterfeiting, fraud, embezzlement, stolen property, vandalism, weapons, prostitution and commercialized vice, sex offenses, drug abuse violations, offenses against family and children, driving under the influence, liquor laws, disorderly conduct, and all other offenses. The first eight offenses are collectively referred to as Part I offenses, while the rest are refereed to as Part II offenses. Since Gambling, Drunkenness, Vagrancy, Suspicion, curfew, and runaways have a less than 600 observations, we drop them from the sample. There are total 10 sub-categories of drug related offenses, but we only use the aggregate drug offense category - Total drug abuse violations. Moreover, our sample include all states and Washington D.C. except Florida since it did not provide arrest data during our sample period, and only 35 states in our sample provided a balanced panel arrest dataset for all listed offenses.

2.2.2.2 Instrumental variable: health insurance mandates eligibility rate

Health insurance mandates eligibility rate ($ELIGIV_{s,t}$) are the share of young adults aged 19 to 22 in *all other states* in the year 2000 who are eligible for the health insurance coverage mandate under state s's mandate in effect during a given year t. The mandate dataset is gathered by Barkowski and McLaughlin (2018). Each state with a mandate has a set of eligibility requirements. If we impute average eligibility rates for a state s

in a given year t, this average would reflect the demographic features of the state s, which might be correlated with unobserved determinants of the arrest rate in the state. We therefore use ACS 2000 5% population sample data for the population of *all other states* in the year 2000 to calculate the average eligibility rate between the ages of 19 and 22 in state s and year t, using the state s's laws in year t. This measure only reflects the scope of the law, but not the demographics of a particular state s and year t.

2.2.2.3 Pathway variables: health insurance coverage rate

The variable on the pathway from the health insurance coverage mandates to arrest reductions is the health insurance coverage rate. We derived the state-level health insurance coverage rates ($HISHR_{s,t}$) from individual-level information on annual health insurance coverage in the CPS dataset.

CPS data are available on health insurance coverage from 2000 to 2012. All surveyed persons are requested to report whether respondents had any health insurance coverage during the previous year. The individual-level health insurance coverage dichotomous indicators of young adults aged 19 to 22 are then aggregated to each state s in each year t to calculate the state-level health insurance coverage rate ($HISHR_{s,t}$: the share of the population age 19 to 22 in state s during year t that was covered by health insurance).

2.2.2.4 Other controls

State-level covariates $X_{s,t}$ includes demographic characteristics for young adults aged 19-22 and all other age groups. Demographic characteristics for individuals between the ages of 19 and 22 consist of the racial, gender, and poverty proportions of the population, which were (1) White, (2) Black, (3) Asian, (4) Hispanic, (5) Male, (6) 75% poverty level or less, (7) 100% poverty level or less, (8) 125% poverty level or less, and (9) 150% poverty level or less. Demographic characteristics for all other age groups include (10) the proportion of the population who was employed, and the percentage of residents who were (11) high-school dropouts, and (12) high-school graduates or equivalent.

2.2.3 IV Validity

2.2.3.1 Balance Tests

For the instrument to be valid, the excluded instrument can only affect the outcome variable through the included endogenous regressor, this is called the exclusion restriction. In our case, it means the health insurance mandate eligibility rates can affect the arrest rate only indirectly through the health insurance coverage rate. However, the validity of the exclusion restriction cannot be tested as the condition involves an unobservable residual. If the health insurance mandates were randomly assigned, the health insurance mandate eligibility rate would be unrelated to both observable and unobservable characteristics, conditional on state and year fixed-effects. We provide a balance test to show whether the excluded instrument is correlated with any of the observable variables.

We regress each observable characteristic on the excluded instrument and other categories of controls individually, with state and year fixed effects using the following model:

$$Observable_{i,s,t} = \varphi_0 + \varphi_1 ELIGIV_{s,t} + \varphi_2 Others_{\sim i,s,t} + \theta_s + \gamma_t + u_{s,t}, \qquad (2.5)$$

where $Observable_{i,s,t}$ represents observable characteristic i in state s in year t, $ELIGIV_{s,t}$ is the excluded instrument variable for state s in year t, and $Other_{\sim i,s,t}$ represents all other categories of observable characteristics (control variables), which excluded the category of $Observable_{i,s,t}$[2].

[2]We have six categories of observable characteristics, i.e., Race, Hispanic, Gender, Poverty Levels, Ed-

Table 3 reports the regression results for the observable demographic characteristics of the individuals in the states. The proportion of the population who were Hispanic is only marginally significant coefficients. The state aggregate education levels, employment status, races, gender, and poverty levels show no significant relationship with the excluded instrument.

2.3 Empirical Results

The results for the effect of the health insurance coverage rate on arrest rates are reported in Table 4. The estimates with only state and year fixed effects are reported in Columns (1) - (3); the estimates including all covariates are presented in Columns (4) - (6). Moreover, Columns (1) and (4) show the OLS regression results from Equation 1; Columns (2) and (5) present the IV regression estimates from Equation 4; Columns (3) and (6) report the F-statistics for the excluded instrument from the first stage estimates (Equation 3). In Columns (3) and (6), all F statistics are larger than 6.636 (square of 2.576), which means all first stage coefficients are statistically significant at the 1% significance level.

In Part I offenses, we report property crime categories and violent crime categories separately. For the property crimes, the OLS estimates show that the arrest rates of all offenses are negatively associated with an increase in health insurance coverage except arson. Only motor vehicle theft has significant coefficients in both columns. In IV regression results, almost all the coefficients of interest become negative and statistically insignificant. This is due to the standard deviations of each IV estimates being much higher than for OLS estimates. However, the magnitude of coefficients is also higher than OLS, especially, for Burglary and Larceny. For violent crime, there are no statistically significant estimates in

ucation Levels, and Employment Status. For instance, if we run a regression of percent of individuals who were white on the excluded instrument, we will include Hispanic, Gender, Poverty Levels, Education Levels, and Employment Status into the model.

the OLS regression results. However, the IV estimates in both column (2) and (4) report that the coefficient of aggravated assault is negative and statistically significant on the margin at a 10% significance level. In other words, a 1 percentage point increases in health insurance coverage led to 8.31 fewer offenses of aggravated assault per 100,000 residents, which is a relative 2.7 percent reduction in the aggravated assault arrest rate.

In Part II offenses, most of the coefficients are negative, but none of them are statistically significant in the OLS estimates. Once we instrument for the health insurance coverage rate, the IV regression result show that an increase in the health insurance coverage rate of 1 percentage point reduced the arrest rate of prostitution and commercialized vice by 4.21 per 100,000 residents. Moreover, we also found a significant increase in the arrest rate of fraud at the 5% significance level. An increase of 31.72 per 100,000 residents was associated with a 1 percentage point increase in the health insurance coverage rate. Translating the estimated marginal effects into percentage change, a 1 percentage point increases in the health insurance coverage rate resulted in a relative 8.33 percent decrease in the arrest rate of prostitution and commercialized vice, and a relative 12.4 percent increase in the arrest rate of fraud. In general, the coefficients and standard deviations of IV estimates are larger than OLS estimates.

Even though we present estimates and standard deviations for individual regressions, our main hypothesis is not about a particular outcome, but the set of outcomes. In particular, we want to test a null hypothesis in which the effect of health insurance on each arrest category is jointly equal to zero against an alternative where at least one of the categories has a non-zero effect. To do this, we use a binomial sign test. In this test, the sign of the coefficient estimate for each arrest category is observed. If the null hypothesis is true, the expected number of negative coefficient estimates would be 11.5, but if many more or many fewer are observed, this is evidence against the null. The binomial distribution is used to quantify how many more or less need to be observed before rejecting the null. In the language of the binomial distribution, we will call a negative coefficient estimate as a success and each regression represents a trial. In the context of the binomial distribution, our null hypothesis would be stated as the probability of a success is equal to 0.5 for all trials, and the alternative is that it is not 0.5 for at least one of the trials. In our analysis, therefore, we have 23 trials (due to 23 arrest categories), and we reject the null for a 5% significance level if we have six or fewer successes (since six is the 0.0173 quantile of the binomial distribution) or sixteen or more successes (the 0.9827 quantile). Since the binomial distribution is symmetric under the null hypothesis, we calculate the associated p-value as $2 * (1 - F(x, 0.5, 23))$, where F is the binomial CDF, and 0.5 and 23 represent the relevant parameters. Table 4 reports the number of successes (negative estimates) and the p-value of binomial two tail test for each specification, the estimates in all specifications show that we have enough evidence to reject the null hypothesis at a 10% significant level. In particular, in our main specification, we can reject the null at a 5% significant level in which the effect of health insurance coverage on each arrest category is jointly significantly different from zero. In other words, the estimates reveal that the increase in health insurance coverage has resulted in a significant decrease in the overall arrest rates at the 10% significance level.

2.4 Conclusion

State and federal governments have enacted dependent coverage mandates requiring health insurers to extend health insurance coverage to young adults. These mandates not only significantly increased health insurance coverage for young adults, but also held the potential to promote public safety through a sizable reduction in the arrest rate. By instrumenting with state-level dependent health insurance coverage mandates and the ACA coverage mandate, we can address the potential endogeneity of the health insurance coverage rate with respect to arrest rates. Our findings suggest a statistically significant negative effect of the increasing health insurance coverage rate on overall arrest rates for young adults.

The IV estimates show that a 1 percentage point increases in health insurance coverage rates can reduce the arrest rate of aggravated assault by 2.7 percent, reduce the arrest rate of prostitution and commercialized vice by 8.33 percent, but increase the arrest rate of fraud by 12.4 percent. Our findings indicate that enacting state and federal dependent health insurance coverage mandates are effective policy instruments to improve health insurance coverage for young adults, and a higher level of health insurance coverage rate can reduce overall arrest rates.

Table 2.1: Summary Statistics: Part I and II Offenses Categories

Dependent Variables	Mean	Standard Deviations	Observations
Part I Offenses			
Property Crime			
Arson	9.70	6.78	636
Burglary	275.64	136.80	641
Larceny Theft	1111.84	424.76	648
Motor Vehicle Theft	99.49	80.53	648
Violent Crime			
Assault	304.17	170.15	648
Criminal Homicide	15.80	10.83	636
Forcible Rape	24.15	13.61	637
Robbery	113.84	74.29	648
Part II Offenses			
Disorderly Conduct	657.15	512.79	648
Driving Under The Influence	1268.28	673.35	647
Embezzlement	26.69	31.70	631
Forgery And Counterfeiting	97.83	61.61	646
Fraud	256.26	307.77	647
Liquor Laws	1746.67	1692.36	648
Offense Against Family And Children	85.56	74.38	635
Other Assaults	1072.47	478.74	648
Other Offenses	3962.79	2142.04	648
Prostitution And Commercialized Vice	50.52	133.06	631
Sex Offenses	54.75	33.73	640
Stolen Property-Buy, Receive, Poss.	115.77	83.18	642
Total Drug Abuse Violations	1793.54	762.29	648
Vandalism	278.28	149.40	648
Weapons-Carry, Posses, etc.	156.17	91.01	648

Note: This sample includes all states and Washington D.C., but Florida for the year 2000-2012. Sample restricted to young adults ages 19 through 22 who were not disabled. All offenses measured as number of arrest per 100,000 residents in a state and a given year.

Table 2.2: Summary Statistics: Instrumental, Pathway, and Control Variables

	Mean	Standard Deviations
Instrumental Variable		
Health Insurance Mandates Eligibility Rate	0.351	0.426
Pathway Variable		
Health Insurance Coverage Rate	0.733	0.084
Covariates *for young adults aged 19-22*		
White	0.746	0.147
Black	0.127	0.124
Asian	0.037	0.058
Male	0.510	0.023
Hispanic	0.119	0.115
75% Poverty or less	0.186	0.044
100% Poverty or less	0.239	0.053
125% Poverty or less	0.292	0.062
150% Poverty or less	0.343	0.070
Covariates *for other age groups*		
High school dropout	0.368	0.039
High school graduate	0.376	0.044
Employed	0.473	0.033

Note: This sample includes all states and Washington D.C., for the year 2000-2012. Sample restricted to young adults ages 19 through 22 who were not disabled. ACS 2000 census person weights and CPS insurance weights used in calculations.

Table 2.3: Balance Test

Dependent Variables:	(1) Mandate Eligibility Rate
Percent of individuals who were high school dropout	0.000807
	(0.002)
Percent of individuals who were high school graduate	-0.00242
	(0.002)
Percent of individuals who were employed	-0.000497
	(0.003)
Percent of individuals who were white	-0.0111
	(0.007)
Percent of individuals who were black	0.00497
	(0.004)
Percent of individuals who were Asian	-0.000196
	(0.002)
Percent of individuals who were Hispanic	-0.00679*
	(0.004)
Percent of individuals who were male	-0.00343
	(0.004)
Percent of individuals whose income was below 75 % poverty	-0.000329
	(0.007)
Percent of individuals whose income was below 100 % poverty	0.00156
	(0.007)
Percent of individuals whose income was below 125 % poverty	0.00180
	(0.008)
Percent of individuals whose income was below 150 % poverty	0.000442
	(0.009)

Note: $*p < 0.10$, $**\,p < 0.05$, $***p < 0.01$. This sample includes all states and Washington D.C. for the year 2000-2012. And sample restricted to young adults ages 19 through 22 who were not disabled. Standard deviations in parentheses are clustered at the state-level. Year fixed effect and state fixed effect are included. Each cell in table is a regression result.

Table 2.4: *IV Estimated Effect of the Health Insurance Coverage On Young Adults' Arrest rates*

	OLS	IV	First Stage	OLS	IV	First Stage
Outcome Variables:						
Arrest Rate per 100,000 residents			**F-stat**			**F-stat**
Part I Offense						
Property Crime						
Arson	3.185	-3.032	8.06	3.409	0.053	8.03
	(5.854)	(25.112)		(5.772)	(25.597)	
Burglary	-62.72	-188.7	7.98	-52.94	-273.8	8.03
	(43.608)	(365.898)		(47.170)	(340.703)	
Larceny Theft	-258.5	-1761.7	7.97	-238.2	-1838.8	8.32
	(170.205)	(1526.128)		(160.692)	(1469.631)	
Motor Vehicle Theft	-85.06**	-93.13	7.97	-87.14**	-166.3	8.32
	(41.196)	(304.356)		(39.815)	(269.090)	
Violent Crime						
Aggravated Assault	-87.33	-987.9*	7.97	-79.26	-831.2	8.32
	(76.763)	(548.506)		(75.141)	(506.356)	
Criminal Homicide	3.725	20.59	7.57	4.703	26.19	7.57
	(5.503)	(33.481)		(5.508)	(31.894)	
Forcible Rape	3.839	-67.23	7.97	3.399	-53.22	7.81
	(7.570)	(65.151)		(7.207)	(61.508)	
Robbery	-57.84	3.976	7.97	-39.28	-2.018	8.32
	(43.734)	(200.828)		(38.220)	(189.741)	
Part II Offense						
Disorderly Conduct	-325.9	-839.7	7.97	-299.7	-433.4	8.32
	(224.630)	(1328.260)		(214.331)	(1223.330)	
Driving Under The Influence	-199.9	-2454.5	7.87	-304.8	-2158.2	8.17
	(230.517)	(1977.528)		(218.843)	(1683.568)	
Embezzlement	-11.77	-49.03	7.24	-12.00	-6.022	7.30
	(12.347)	(75.923)		(12.669)	(78.472)	
Forgery And Counterfeiting	23.02	358.2	8.14	22.44	381.3	8.29
	(32.427)	(279.036)		(30.033)	(254.820)	
Fraud	318.1	3139.2**	8.10	265.3	3171.5**	8.35
	(198.281)	(1540.464)		(195.390)	(1469.868)	
Liquor Laws	-456.9	1245.6	7.97	-397.4	2911.3	8.32
	(787.922)	(6192.979)		(789.769)	(4790.159)	
Offenses Against Family And Children	7.558	46.23	8.13	22.81	-23.26	8.02
	(34.550)	(206.914)		(28.923)	(189.974)	
Other Assaults	-83.03	-1458.9	7.97	-147.1	-1250.9	8.32
	(245.383)	(1551.139)		(238.236)	(1443.379)	
Other Offenses	-1033.3	-6628.0	7.97	-941.2	-7047.2	8.32
	(987.154)	(7258.180)		(869.103)	(7262.604)	
Prostitution And Commercialized Vice	-28.86	-453.6**	7.98	-20.42	-421.1**	7.91
	(48.360)	(194.811)		(40.367)	(192.027)	
Sex Offenses	-8.499	-94.48	7.54	-4.678	-109.9	7.92
	(16.394)	(106.084)		(15.812)	(98.768)	
Stolen Property-Buy, Receive, Poss.	5.398	3.815	7.33	3.764	66.35	7.73
	(40.195)	(362.220)		(36.895)	(347.805)	
Total Drug Abuse Violations	-669.6	-2440.2	7.97	-629.1	-1932.5	8.32
	(466.989)	(2476.119)		(433.102)	(2322.119)	
Vandalism	-31.84	-785.1	7.97	-31.05	-686.3	8.32
	(59.293)	(574.494)		(56.852)	(523.876)	
Weapons-Carry, Posses, etc.	-45.57	-351.3	7.97	-51.29	-302.9	8.32
	(34.453)	(299.573)		(31.836)	(268.215)	
Number of Successes (Negative Estimates)	16*	16*		16*	17**	
P-value	0.093	0.093		0.093	0.035	
Control Variables	No	No	No	Yes	Yes	Yes

Note: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. This sample includes all states and Washington D.C., but Florida for the year 2000-2012. And sample restricted to young adults ages 19 through 22 who were not disabled. Standard deviations in parentheses are clustered at the state-level. Year fixed effect and state fixed effect are included. Each cell in table is a regression result.

Chapter 3

The Effect of Medicaid Expansions on Labor Supply of Low-Income Childless Adults: Black-White Differentials

3.1 Introduction

The United States health insurance market is closely linked with the labor market. For instance, the evidence shows that approximately 80% of full-time, year-round workers bought health insurance through their own employment in 2010 (Barkowski, 2017). The main reason for this is that employment-based health insurance is usually provided at a much lower cost than coverage through other sources due to preferential tax treatment, economies of scale for groups, and the control of adverse selection. Public health insurance programs only cover the elderly, permanently disabled, and low-income parents, but most other groups of adults, in particular, low income childless adults, are not eligible for public coverage. As such, adults who are not covered through public or employment-based insurance have difficulty purchasing a health insurance through non-group market, one reason for this is that the market is suffering from serious adverse selection. As a result, the Medicaid expansions have a direct effect on the labor market. Moreover, previous studies have documented that race/ethnicity and fertility have an intricate effect on the life-time labor supply (Troske and Voicu, 2011). Thus, this paper investigates whether the effect of the Affordable Care Act (ACA) Medicaid expansion on the labor supply of low-income childless adults is different for different races.

As of January 1, 2014, the ACA has expanded Medicaid to all adults with an income level at or below 138% of Federal Poverty Level (FPL) in 26 states. This expansion not only increased eligibility for parents, but also ended the historic exclusion of childless adults from Medicaid. This paper will explore the effects of this Medicaid expansion on the labor supply for adults without dependent children. Using the Current Population Survey (CPS) Basic Monthly Data, I find new evidence that the Medicaid reform has had different effects on the labor supply for different races. My results suggest that the phased-in Medicaid expansions decreased the probability of participating in the labor force by 2.90 percentage points among white married adults and increased the labor supply of never-married black adults by 5.41 percentage points. However, the Medicaid expansion does not play a large role for other groups of black and white adults.

The remainder of the paper proceeds as follows. Section 2 describes the Medicaid program and the particular reforms used to identify Medicaid's effect. Section 3 discusses the previous literature. Section 4 shows the theoretical effects of Medicaid for childless adults. Section 5 describes the data extraction and sources used in my analysis. Section 6 provides reduced-form evidence of Medicaid's impact on labor force participation. Section 7 concludes.

3.2 The National Health Care Reform

On March 23, 2010, The Patient Protection and Affordable Care Act of 2010 (PPACA, PL 111-148) was signed into law by President Obama. This law was intended to reform the US health care system, control health care costs and extend health coverage to uninsured adults across the country (Bhole and Curto, 2016). Starting January 1, 2014, the Affordable Care Act (ACA) expanded Medicaid eligibility to nearly all adults with family income at or below 138% of the Federal Poverty Level (FPL) ($15,856 for an individual, $26,951 for a family of 3 in 2014) (KFF State Health Facts, 2013). This Medicaid expansion vastly increased eligibility in many states for low-income parents and other adults without dependent children.

Although the Medicaid expansion was designed to be implemented in the entire country, individual states could choose whether or not to participate. As of January 1, 2014, there were 25 states and Washington D.C. that planned to move forward with the Medicaid expansion in the first place (KFF State Health Facts, 2013). As of January 1, 2016, a total of 30 states and Washington D.C. had adopted the Medicaid expansion (KFF State Health Facts, 2018).

In the states that expanded Medicaid, many low-income childless adults and parents become eligible for coverage for the first time. In the 25 states and Washington D.C.that first adopted the expansion, the median eligibility threshold increased from 0% to 138% FPL for childless adults and from 106% FPL to 138% FPL for parents. However, there is a wide range of variation in the threshold change across states.

In 21 of the 25 states that did not move forward with the expansion, Medicaid only covers those parents up to 100% FPL, and almost all 25 states provide no coverage for childless adults, regardless of income level.

Table I illustrates the Medicaid eligibility thresholds for childless adults by state for the years 2011 through 2015. All eligibility thresholds are calculated as the percent of the Federal Poverty Level (FPL). The threshold data are based on a national survey conducted by the Kaiser Commission on Medicaid and the Uninsured with the Georgetown University Center for Children and Families.

3.3 Literature Review

In theory, the aim of Medicaid expansion was to expand health insurance coverage for families and individuals with low income and limited resources. However, the income-based eligibility criteria of Medicaid could have unintentional impacts on the labor supply of enrollees. The impacts of Medicaid expansion on the work effort can be broadly divided into three categories (Kaestner et al., 2015). First, people who lack employment-based health insurance and earn an annual income just higher than Medicaid eligibility threshold may decrease work effort or quit the job in order to lower income and become eligible for Medicaid. Second, some people newly eligible for Medicaid may reduce work effort or quit the job because Medicaid coverage directly reduces out-of-pocket medical expenses and eliminates the premium of health insurance, which allows individuals to work less but gain the same amount of consumption as before. Third, some people who are already eligible for Medicaid before expansion may increase work effort or look for a new job because the newly expanded eligibility threshold allows individuals work more and get a higher income than before and still remain eligible for Medicaid. Therefore, the Medicaid expansions may have either a positive or negative effect on the labor supply for different groups of people.

A number of researchers have explored the relationship between health insurance eligibility and labor supply, but most of them found a weak relationship. Moffitt and Wolfe (1990) examine the labor supply behavior after changes in Medicaid eligibility. They conclude that increasing the expected benefits of Medicaid would reduce the Labor Force Participation (LFP) rate of single mothers. Similarly, Yelowitz (1995) estimates the effect of Medicaid earnings eligibility limits on labor supply and finds a small increase in the probability of labor force participation and a decrease in the participation of Aid to Families with Dependent Children (AFDC) among divorced and separated women caused by expansions in Medicaid eligibility for children. Recently, Congressional Budget Office (2014) concludes that the ACA Medicaid expansion would reduce 1.7 percent of total work hours or 2 million full-time workers in the labor market, which is a relatively small negative effect on labor supply. Although those authors have found a weak effect of health insurance eligibility on labor supply, they also state that new sources of variation in Medicaid eligibility might provide a better way to estimate the relationship between public health insurance eligibility and labor supply.

Earlier studies investigating the relationship were mainly based on the effect of "Medicaid notch" in enrollees' budget sets, which means previous Medicaid enrollees would lose their coverage completely once their income exceeds the particular threshold. For instance, Dave et al. (2013) estimate the labor supply impact of Medicaid eligibility expansions for pregnant women in the 1980s and 1990s. These authors report that gaining Medicaid coverage is associated with a decrease in the employment of women who just gave birth within one year.

There are few studies that focus on the effect of expanding Medicaid to childless adults, and the conclusions of these studies are mixed. Baicker et al. (2013) use an experimental research design to estimate the impacts of the Oregon Medicaid expansion on adults without dependent children in 2008, and find that there is a 3 percent statistically insignificant change in labor supply and incomes after Medicaid expansion. Another innovative research design used by Dague et al. (2014) investigate the expansion of Medicaid in Wisconsin to childless adults in 2009. They find that the expansion of Medicaid enrollment decreases employment by a range from 2 to 18 percent. Moreover, Garthwaite et al. (2013) use a difference-in-difference approach to examine the Tennessee rollback of the Medicaid eligibility threshold in 2005. The authors report that the change in Medicaid eligibility increases the labor supply by 25 percent among low-educated adults without dependent children, but they do not find other statistically significant effects among other educational classes.

The question of potential racial differences in labor supply has been studied for decades, but few studies focus on the effect of Medicaid expansion on the labor supply for different racial groups. Troske and Voicu (2011) report that race/ethnicity, education level and fertility all have statistically significant impacts on the female's labor supply. Specifically, the negative effects of children are larger for white females than for other racial females. Pabilonia and Ward-Batts (n.d.) find different effects on a male's labor supply for different racial groups depending on the sex of his child. The results show that immigrants work more weeks and hours per year if they have a daughter than a son.

In this paper, I use recent data from the Current Population Survey (CPS) to investigate whether the effect of the latest Medicaid reform on labor force participation for low-income childless adults, who generally are not eligible for Medicaid coverage before this expansion, is different between blacks and whites. Moreover, I will take job search theory, the income effect and the permanent income hypothesis as potential explanations of the effect. My hypothesis is for there to be, in general, a negative impact from the Medicaid threshold on labor supply.

3.4 Theoretical Effects of Medicaid

To analyse the effect of Medicaid expansion on the labor supply of childless adults, I use a traditional kind of the static labor supply model. Assume that each adult maximizes their utility, $U = u(Consumption, Leisure)$. The budget constraint is linear and the slope is a constant after-tax wage, w. At zero hours of work, adults cannot receive any level of benefits, since there are few subsidies and assistance for childless adults.

Figure 1 shows the change in the optimal point of the consumption-leisure trade off for childless adults after Medicaid expansion. Before the expansion, adults choose a H_b and C_b to maximize their utility. H_e and C_e is the optimal point after the expansion. Since states have expanded eligibility for Medicaid by increasing the income limit, the budget constraint under the income eligible threshold shifts outward, and hence childless adults are able to choose a higher level of leisure and consumption for the same level of after-tax wage. This illustrates that Medicaid expansion decreases labor supply and increases consumption for childless adults.

3.5 Data

The dataset for this analysis derives from the Current Population Survey (CPS) Basic Monthly Data, from the January 2011 to December 2015. This time period covers the time-frame of the Medicaid expansion. The CPS is a monthly, nationally representative survey of approximately 50,000 households and it is the primary data set which includes retrospective information on labor force participation and welfare participation of the US civilian, non-institutionalized population in the U.S.. Table II provides descriptive statistics for all of my sample. The sample contains 473,365 adults between the age of 20 and 55. I exclude those with children in their family, since this paper investigates the effect of Medicaid expansion on the low-income childless adults who become newly eligible for coverage. I further limit my sample to adults whose family incomes were below 150% of the FPL (Federal Poverty level) when I first observe them in the data, since this range of adults is most likely to be affected by Medicaid expansion. Table III and Table IV provide descriptive statistics for childless white and black adults respectively. The labor force participation rate of all groups of whites are relatively higher than blacks except for married females. Approximately 52.1% of white married female are employed at the time of the interview, compared to approximately 53.7% of black married females. While these rates are relatively low, one should keep in mind that married women are less likely to enter the labor force than other demographic groups. The mean age are very similar for whites and blacks in each group. Moreover, whites, on average, receive more education than blacks.

Previous studies on labor force participation often focus on the entire population, since they assume that the Medicaid expansions affect the labor supply decisions of whites and blacks similarly. However, I expect the Medicaid expansion would have different effects on the labor supply for different races, gender, and marital status. Therefore, I choose a more flexible approach which divides the sample of adults into married male, never-married male, married female, never-married female, all married, and all never-married for blacks and whites separately. These detailed estimates will help us better understand whether marital status and gender have different impacts on the labor supply between white and black people.

In this paper, I use the CPS data to estimate a model of labor force participation rate, and suppose that varying the Medicaid eligible threshold could change the reservation threshold for an adult leaving the labor force. Even though I am not able to observe these reservation thresholds, I can estimate the variations in labor force participation in the aggregate which might be affected by the Medicaid expansion.

To estimate the effect of the Medicaid expansion on labor supply, I use a linear probability model. The model is specified as:

$$LFP_{ist} = \beta_0 + \beta_1 M_{ist} + \beta_2 X_{ist} + \rho_s + \tau_t + \rho_s * t + \epsilon_{ist} \tag{3.1}$$

where i indexes adults, s indexes states, and t indexes time. The dependent variable, LFP_{ist}, is a dummy variable representing Labor Force Participation (LFP), which equals one if adult i living in state s stayed in the labor force (employed & unemployed) at time t, and zero otherwise. X_{ist} is a vector of adult demographics (including race, age, education, and age-education interaction term). The variable ρ_s is a set of state fixed effects, τ_t is a set of month and year fixed effects, and $\rho_s * t$ is a set of state-specific linear time-trends.

The key variable is the Medicaid threshold variable, M_{ist}, which is defined as the monthly Medicaid eligibility threshold for adult i in state s at month t, and this threshold is assigned based on household size. Aizer and Grogger (2003) denote the Medicaid eligible threshold as a binary "Medicaid expansions" indicator, which equals one if the threshold expanded after Medicaid policy changes, and zero otherwise. This method is reasonable when studying the change in expansion size, and it can represent multiple expansions in the model easily. However, unlike their work, I code the eligible threshold as the percent of the FPL, since I attempt to answer a more specific question, "How does the labor force participation rate change in response to one percentage point change in the Medicaid threshold?"

The within-and-across states Medicaid expansions allow me to distinguish the effects of variation in Medicaid eligible thresholds from other more general effects of adults living in a specific state at a specific time. In my model, I adopt state fixed effects to control for all time independent differences across states, time fixed effects to account for the national monthly time trends and seasonal effects, and the $\rho_s * t$ term to refer to particular state specific linear time trends (by month). The adoption of these fixed effects allows me to identify the effect of Medicaid eligible threshold expansion on labor supply decisions. Moreover, the Medicaid expansion is clearly targeted at all adults with incomes below 138% of the federal poverty level. Even though approximately half of the states have not expanded Medicaid, I treat the Medicaid expansion as exogenous.

3.6 Results

3.6.1 Estimates of the Effect of Medicaid Expansions on Labor Supply-White

Table V summarizes the linear probability model regression results about the effect of the ACA Medicaid expansions on the labor supply for whites. The measures of labor supply are examined by labor force participation rate. The result indicates that white females are more likely to leave the labor force than white males (omitted), irrespective of marital status. Since there are age and education interaction terms in the model, the age dummies show that higher ages mainly have a negative effect on the labor supply for white males with an education level less than high school (omitted), and education dummies report that high school and college education are principally associated with a higher labor supply for whites with age between 20 to 25 (omitted): e.g., the labor force participation rate of white married adults with a high school education is 7.61 percentage points higher than high school dropout (omitted) on average with an age between 20 and 25. This result is consistent with the expectation that more-educated adults are more productive and that higher wages induce them to enter the labor force.

The Medicaid threshold has a strong explanatory power for the labor force participation of all white married childless adults, especially white married females. Since the negative effect of the 2014 medicaid expansion on all married white adults is statistically significant at the 5% significance level and on married white females at the 10% significance level. However, the expansions have no effect on the labor supply of childless never-married white adults. Moreover, the coefficients for the sample of married adults are consistent with expectation. These estimates indicate that white married adults are more likely to leave the labor force in the presence of a higher Medicaid threshold. There are a few potential reasons for this negative effect. First, if health insurance is relatively important compared to other job attributes such that it induces some adults to work, the public coverage expansion could reduce the incentive to work for those adults. Second, eligibility for public coverage virtually eliminates out-of-pocket medical expenses and premiums of health insurance (which is similar to an increase in total income), an outward movement of the budget constraint stimulates adults to consume more, leisure more and work less. In other words, adults will leave the labor force when the Medicaid threshold is greater or equal to the reservation threshold. Third, some adults without employment-based health insurance who have an annual income just higher than the new Medicaid eligibility threshold may decrease work effort or quit the job in order to lower income and become eligible for Medicaid. Conversely, the result also shows that the Medicaid expansion has a small positive (but statistically insignificant) effect on never-married white adults.

Even though the estimates for never-married white females and all white males are relatively small and statistically insignificant, the estimates indicate that the labor force participation rate for white married males decrease by 0.02 percentage points as the medicaid threshold increases one percentage point. The overall increase in the Medicaid threshold for childless adults is 138 percentage points after the Medicaid expansion, so this change in the threshold would decrease in the probability of labor force participation rate by $0.02 * 138 = 2.76$ percentage points on average for white married males, which is a more than 5% decrease relative to the average labor force participation rate. Similarly, the overall change in the labor force participation rate for white married females, white never-married females, white never-married males, all white married, and all white never-married are -2.64, 0.51, 1.63, -2.90 and 1.28 percentage points, respectively. The estimation result of the effect of the Medicaid expansion for whites only shows that childless white married adults have experienced a meaningful reduction in labor supply, but Medicaid expansion does not play a large role for never-married white males and females without children.

3.6.2 Estimates of the Effect of Medicaid Expansions on Labor Supply-Black

I also examine the effect of Medicaid expansions on the labor supply for blacks only. Table VI presents linear probability model estimates. The dummy variable for sex indicates that the labor force participation rate of black married females is 5.37 percentage points lower than black married males (omitted), but there is no significant difference between never-married black females and males. The age dummies report that higher ages only have significant negative effects on the labor supply for blacks who are older than 40 year-old who received less than a high school educational level (omitted). Moreover, educational dummies report that more educated blacks with an age between 20 and 25 (omitted) are generally associated with higher labor force participation rate, similar to whites.

Estimates of the Medicaid eligible threshold are all positive for blacks, but only two are statistically significant. Among them, there is a statistically significant (at the 10% significant level) positive effect on all never-married black adults and a statistically significant (at the 5% significant level) positive effect on never-married black males. The threshold variables indicate that the ACA Medicaid expansions are associated with a remarkable increase in labor supply for never-married black childless adults, particularly never-married males. This result may be explained by any one or more of the following reasons. First, the Medicaid coverage expansion improves physical or mental health for some young adults, making them more likely to work. Second, employers may offer more jobs or higher wages in the labor market, since they no longer need to offer employment-based health insurance for workers. Third, since black adults have relatively lower lifetime income on average than whites, the 2014 Medicaid expansion becomes a relatively higher jump in their income, inducing those young black people to look for a job directly after high school or drop out from college to work. Lastly, Medicaid expansion may reduce the crime rate of black young males and thus increase their labor supply. In contrast to married white adults, married black adults are shown to have no large response to the Medicaid expansion in their labor supply decision.

Likewise, the overall change in the labor force participation rate associated with the ACA Medicaid expansion for black married females, black never-married females, black married male, black never-married males, all black married, and all black never-married are 1.39, ,3.22, 2.57, 7.29, 1.97 and 5.41 percentage points, respectively. The estimates of the effect of the Medicaid expansions on the labor supply of blacks show that childless black married adults show indifference to the Medicaid expansion; on the other hand, the increase in Medicaid eligibility thresholds provides an incentive to increase labor supply among never-married black adults without dependent children.

3.6.3 Potential Problem of the Estimation

There are a few potential reasons for the relatively small impact on the labor supply from the Medicaid expansions predicted by my model. First, my data focus on near-poor adults, who are a relative small subset of the population, and this might make it difficult to obtain precise estimates of the effect. Second, my dataset contains less than twenty-four months of data for the period after the Medicaid expansion policy was enacted. In this period, some newly eligible childless adults may not realize that they are now eligible for Medicaid coverage, or they there may be a lag in their response to the policy change. Third, the variation in the dependent variable (LFP) is relatively small, creating a potential problem in estimating the effect of the expansions.

3.7 Conclusion

With the passage of The Patient Protection and Affordable Care Act(PPACA), some states expanded their health coverage to previously uninsured parents and childless adults. Using the ACA Medicaid health insurance expansion for childless adults, I investigate whether the spillover effect of the latest Medicaid reform on labor force participation for near-poor childless adults is different between blacks and whites. I show that the effect of Medicaid coverage on the labor supply is different between black and white childless adults. For whites, the Medicaid eligibility reduces the probability of labor force participation rate by 2.90 percentage points for all white childless married adults, and it does not play a large role for white childless never-married adults. The estimates of blacks are the opposite of whites; the Medicaid expansions are associated with a 5.41 percentage points increase in labor supply among never-married, low-income, childless black adults, and with a 7.29 percentage points for never-married black males without children in particular. There is little evidence that the Medicaid expansions impacted the labor supply of all married black childless adults. These results suggest that the recent law change has different influences on the labor supply for blacks and whites. The reasons for different responses in labor supply are mainly based on different lifetime income distributions and crime rates between blacks and whites, which will be investigated in my next paper.

Table 3.1: Medicaid eligibility thresholds for childless adults by state, 2011-2015

State	Jan-2011	Jan-2012	Jan-2013	Jan-2014	Jan-2015
Alabama	0	0	0	0	0
Alaska	0	0	0	0	0
Arizona	110	110	100	138	138
Arkansas	0	0	0	138	138
California	0	0	0	138	138
Colorado	0	0	20	138	138
Connecticut	73	72	70	138	138
Delaware	110	110	110	138	138
District of Columbia	211	211	211	215	215
Florida	0	0	0	0	0
Georgia	0	0	0	0	0
Hawaii	100	100	100	138	138
Idaho	0	0	0	0	0
Illinois	0	0	0	138	138
Indiana	0	0	0	0	0
Iowa	0	0	0	138	138
Kansas	0	0	0	0	0
Kentucky	0	0	0	138	138
Louisiana	0	0	0	0	0
Maine	0	0	0	0	0
Maryland	0	0	0	138	138
Massachusetts	0	0	0	138	138
Michigan	0	0	0	138	138
Minnesota	0	75	75	205	138
Mississippi	0	0	0	0	0
Missouri	0	0	0	0	0
Montana	0	0	0	0	0
Nebraska	0	0	0	0	0
Nevada	0	0	0	138	138
New Hampshire	0	0	0	0	138
New Jersey	0	0	0	138	138
New Mexico	0	0	0	138	138
New York	100	100	100	138	138
North Carolina	0	0	0	0	0
North Dakota	0	0	0	138	138
Ohio	0	0	0	138	138
Oklahoma	0	0	0	0	0
Oregon	0	0	0	138	138
Pennsylvania	0	0	0	0	138
Rhode Island	0	0	0	138	138
South Carolina	0	0	0	0	0
South Dakota	0	0	0	0	0
Tennessee	0	0	0	0	0
Texas	0	0	0	0	0
Utah	0	0	0	0	0
Vermont	160	150	160	138	138
Virginia	0	0	0	0	0
Washington	0	0	0	138	138
West Virginia	0	0	0	138	138
Wisconsin	0	0	0	100	100
Wyoming	0	0	0	0	0

Note:Reflects income eligibility limits for coverage that provides full Medicaid benefits. Eligibility limits for waiver programs that provide more limited benefits or for fully state-funded programs are not included. Sources: Based on a national survey conducted by the Kaiser Commission on Medicaid and the Uninsured with the Georgetown University Center for Children and Families, 2011-2016.

Table 3.2: Descriptive statistics

	Married Female	Married Male	Never-married Female	Never-married Male
LFP	52.49	65.89	61.26	65.20
	(49.94)	(47.41)	(48.72)	(47.63)
Age	44.91	43.679	30.6	31.034
	(9.32)	(9.52)	(10.86)	(10.42)
White	0.841	0.855	0.744	0.787
	(753.84)	(736.35)	(572.50)	(769.97)
Black	0.159	0.145	0.256	0.213
	(142.79)	(125.16)	(197.42)	(208.49)
Less than high school	0.219	0.257	0.137	0.196
	(173.68)	(178.63)	(133.69)	(197.64)
High school	0.574	0.581	0.622	0.641
	(380.72)	(357.55)	(431.00)	(535.58)
College degree	0.182	0.14	0.213	0.145
	(154.74)	(122.44)	(174.77)	(165.09)
Graduate school	0.025	0.022	0.029	0.018
	(52.84)	(45.35)	(58.08)	(54.23)
Sample Size	107,641	92,165	113,024	160,535

Note: Data from the January 2011 to December 2015 Current Population Survey (CPS) Basic Monthly files. Sample is limited to childless adults between ages 20-55 with family incomes were below 150% of the FPL (Federal Poverty level).

Table 3.3: Descriptive statistics for whites

	Married Female	Married Male	Never-married Female	Never-married Male
LFP	51.76	66.35	63.33	68.37
	(49.97)	(47.25)	(48.19)	(46.50)
Age	44.711	43.528	29.396	30.64
	(9.45)	(9.60)	(10.23)	(10.24)
Less than high school	0.221	0.265	0.123	0.188
	(160.09)	(168.64)	(108.47)	(171.22)
High school	0.568	0.568	0.609	0.633
	(344.60)	(321.93)	(362.13)	(466.33)
College degree	0.186	0.144	0.236	0.16
	(143.64)	(115.01)	(160.94)	(155.01)
Graduate school	0.026	0.023	0.032	0.019
	(49.29)	(42.87)	(52.86)	(49.85)
Sample Size	90,499	78,775	84,043	126,328

Note: Data from the January 2011 to December 2015 Current Population Survey (CPS) Basic Monthly files. Sample is limited to childless white adults between ages 20-55 with family incomes were below 150% of the FPL (Federal Poverty level).

Table 3.4: Descriptive statistics for blacks

	Married Female	Married Male	Never-married Female	Never-married Male
LFP	54.16	60.48	58.60	58.58
	(49.83)	(48.89)	(49.26)	(49.26)
Age	45.957	44.564	34.09	32.489
	(8.57)	(8.96)	(11.85)	(10.94)
Less than high school	0.209	0.21	0.176	0.223
	(67.39)	(59.58)	(78.77)	(99.04)
High school	0.607	0.657	0.657	0.673
	(162.83)	(160.19)	(235.79)	(265.34)
College degree	0.162	0.117	0.147	0.091
	(57.66)	(42.16)	(70.54)	(58.50)
Graduate school	0.021	0.016	0.02	0.013
	(19.07)	(14.82)	(24.16)	(21.38)
Sample Size	17,142	13,390	28,981	34,207

Note: Data from the January 2011 to December 2015 Current Population Survey (CPS) Basic Monthly files. Sample is limited to childless black adults between ages 20-55 with family incomes were below 150% of the FPL (Federal Poverty level).

Table 3.5: *Effect of Medicaid expansions on labor force participation rate for whites*

	Married female	Never-married female	Married male	Never-married male	All married	All never-married
Medicaid eligible threshold (%)	-0.0191*	0.00366	-0.0236	0.0118	-0.0210**	0.00926
	(0.0110)	(0.0118)	(0.0162)	(0.0102)	(0.0094)	(0.0082)
Female					-13.96***	-5.974***
					(1.1383)	(0.5117)
Age dummy from 26 to 30	8.514**	3.044	-3.041	4.574***	5.415**	5.002***
	(3.3204)	(3.5071)	(2.8956)	(1.2811)	(2.6232)	(1.5230)
Age dummy from 31 to 35	12.81***	-3.854	-6.631**	-0.438	5.019	-0.0505
	(4.4131)	(4.3085)	(3.1152)	(2.1522)	(3.2853)	(2.4726)
Age dummy from 36 to 40	8.091*	2.800	-6.645***	-4.253	2.127	-1.946
	(4.6767)	(6.0496)	(2.3481)	(3.0127)	(2.7294)	(3.5248)
Age dummy from 41 to 45	8.769**	-5.460	-14.94***	-10.32***	-4.022*	-9.407***
	(3.4004)	(4.8860)	(2.3768)	(2.6887)	(2.2968)	(2.6376)
Age dummy from 46 to 50	5.047	-6.998	-22.14***	-23.93***	-9.127***	-18.98***
	(3.9517)	(4.4377)	(3.7001)	(2.2177)	(3.2089)	(2.6969)
Age dummy from 51 to 55	0.0177	-14.33***	-29.94***	-30.71***	-15.70***	-25.74***
	(2.8859)	(3.4723)	(2.6098)	(3.0450)	(2.3514)	(2.4855)
High school	23.31***	18.62***	-6.506**	-1.935	7.607***	4.723***
	(3.0090)	(1.2580)	(2.5441)	(1.6658)	(2.2429)	(1.1751)
College degree	31.58***	25.64***	-9.792**	2.512	11.45***	11.04***
	(3.6596)	(1.4742)	(4.2384)	(1.9600)	(2.1562)	(1.5216)
Graduate school	20.45*	20.10***	-7.167	-6.424	7.541	4.577
	(10.1860)	(4.2625)	(9.4487)	(3.8569)	(7.0950)	(3.2828)
State Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
State-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Age&Edu Interaction Term	Yes	Yes	Yes	Yes	Yes	Yes
Observations	90,499	84,043	78,775	126,328	169,274	210,371
Average LFP	51.76	63.33	66.35	68.37	58.58	66.36

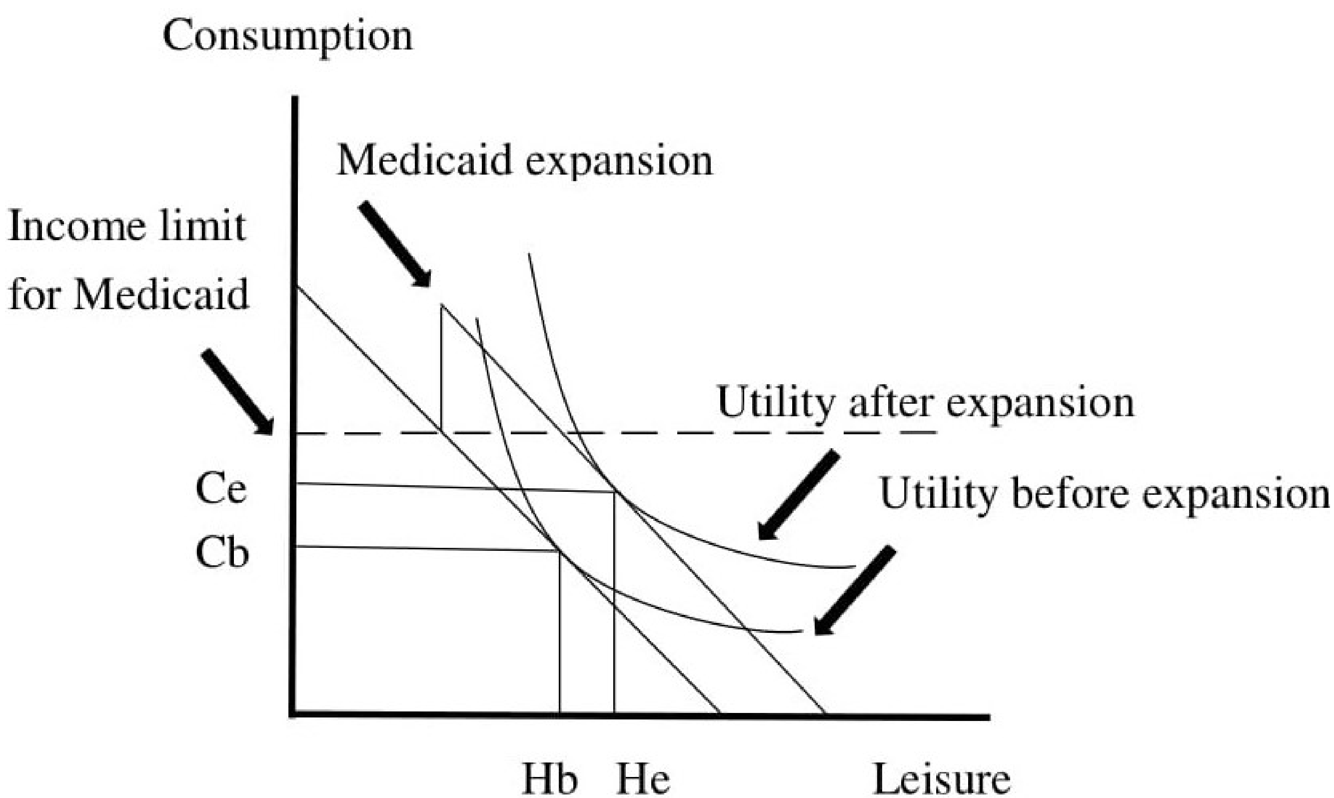
Note:$*p < 0.10$, $**p < 0.05$, $***p < 0.01$. The omitted groups are Male, Age dummy from 20 to 25 and Less than high school. Data from 2011-2015 Current Population Survey. Estimates report the regression results for white only. Sample is limited to childless adults between ages 20-55 with family incomes were below 150% of the FPL (Federal Poverty level). Regressions are adjusted using indicators for state, year, state-specific time trend, sex, age dummy, education and age-education interaction term. All standard errors are clustered on state.

Table 3.6: *Effect of Medicaid expansions on labor force participation rate for blacks*

	Married female	Never-married female	Married male	Never-married male	All married	All never-married
Medicaid eligible threshold (%)	0.0101 (0.0326)	0.0233 (0.0348)	0.0186 (0.0292)	0.0528** (0.0209)	0.0143 (0.0208)	0.0392* (0.0228)
Female					-5.368*** (1.2570)	0.320 (0.7869)
Age dummy from 26 to 30	-6.555 (14.0661)	-8.524 (5.1677)	6.659 (11.9649)	3.788 (3.4126)	-0.816 (9.7485)	-0.0261 (2.8923)
Age dummy from 31 to 35	-11.35 (9.1794)	-7.456 (7.6023)	5.847 (11.9741)	-3.239 (4.3776)	2.417 (7.5522)	-4.534 (3.9870)
Age dummy from 36 to 40	-0.455 (10.1027)	-4.090 (5.0629)	-8.517 (9.5725)	-2.408 (3.5331)	-3.173 (6.5763)	-2.902 (2.5451)
Age dummy from 41 to 45	-18.42* (9.4010)	-12.89** (5.4535)	-0.375 (8.5152)	-7.724* (4.1731)	-9.820 (7.5109)	-10.48*** (3.7348)
Age dummy from 46 to 50	-22.40** (8.9498)	-19.23*** (5.7076)	-20.22** (9.6585)	-15.52*** (4.1470)	-20.95** (7.9594)	-17.69*** (4.2325)
Age dummy from 51 to 55	-23.81*** (7.7028)	-22.67*** (5.3892)	-25.82*** (8.6605)	-29.62*** (3.8698)	-24.07*** (6.5836)	-25.96*** (3.2341)
High school	-5.852 (9.1193)	12.29*** (3.1462)	-4.352 (9.0815)	12.30*** (2.5244)	-3.780 (6.3918)	12.22*** (2.1625)
College degree	0.835 (11.4695)	19.45*** (3.6619)	5.220 (14.1327)	23.51*** (3.2231)	2.547 (8.5480)	20.90*** (2.2623)
Graduate school	26.68*** (7.8415)	-2.183* (12.3776)	-19.25* (7.2552)	7.712 (13.9288)	27.07*** (6.0194)	0.253 (8.2870)
State Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
State-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Age&Edu Interaction Term	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,142	28,981	13,390	34,207	30,532	63,188
Average LFP	54.16	58.60	60.48	58.58	59.96	58.59

Note:$*p < 0.10$, $**p < 0.05$, $***p < 0.01$. The omitted groups are Male, Age dummy from 20 to 25 and Less than high school. Data from 2011-2015 Current Population Survey. Estimates report the regression results for black only. Sample is limited to childless adults between ages 20-55 with family incomes were below 150% of the FPL (Federal Poverty level). Regressions are adjusted using indicators for state, year, state-specific time trend, sex, age dummy, education and age-education interaction term. All standard errors are clustered on state.

Figure 3.1: Budget Set for Childless Adults before and after Medicaid Expansion



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