Three Essays on Economics of Crime

by

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Abstract

This dissertation consists of three essays on economics of crime. The first chapter investigates the extent to which variations in temperature affect crime rates in the southeastern states within a typical empirical crime model framework, where crime rates are specified as a function of standard controls. County-level panel data for the period from 2010 to 2014 for the southeastern states are collected from the Federal Bureau of Investigation (FBI), the Centers for Disease Control and Prevention (CDC), and the Behavioral Risk Factor Surveillance System. This empirical analysis uses 2SLS because police presence is endogenous in the crime rate equations, and police presence is instrumented by the adjusted gross income level of each county. The results show that in the region, rise in average maximum and minimum daily temperature is associated with higher robbery, property, and grand larceny. Additionally, higher alcohol consumption has an impact on the increase of violence, robbery, assault, grand larceny, and motor vehicle theft.

Chapter 2 examines the relationship between mental health, opioid prescribing rate and the incidence of crime in the United States. The data from 2012 to 2015 for 3142 counties are employed to estimate the impacts of the mental health on the incidence of crime. An endogeneity issue of the number of law enforcement personnel and crime is observed. To break down the endogeneity problem between crime and the number of law enforcement personnel, an instrumental variable “annual average police wage” is employed. Results from the fixed-effect approach indicate that an increase in the number of law enforcement personnel decreases the probability of the number of robberies in urban counties. Additionally, an increase in the number of mental health providers lowers the number of burglaries in the urban counties.

Chapter 3 examines whether the supplemental nutrition assistance program (SNAP) implementations had an effect on criminal activities. To address this problem, the present study utilizes two main variations: (i) changes in waiver of the time limit for areas within the states, and (ii) increase in SNAP benefits. A county level panel data from 2009 to 2015 for 3134 counties is employed to investigate the relationship between SNAP benefits and crime. The findings show that SNAP benefits contribute a significant reduction in the criminal activities in both rural and urban counties. The estimation results indicate that changes in waivers to work-related time limit is one of the significant factors which has impact on the criminal activities. Additionally, Income motivated crimes such as property, robbery, and burglary are more likely to be affected by the changes in individuals' welfare and income level changes.

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"Science is the most reliable guide for civilization, for life, for success in the world. Searching a guide other than the science is meaning carelessness, ignorance and heresy". Mustafa Kemal Ataturk

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ESSAY 1: Climate Variability and Crime in the Southern States

Introduction

Criminal behaviors are significant economic obstacles to the development of nations (Soares, 2004). Anderson (1999) estimated that during the 1990s, the annual cost of crime in the United States exceeded 1 trillion dollars. Given the high cost of crime, research often focuses on the social and economic causes of crimes, in the hopes that such analyses could be used to decrease the cost of illegal behaviors (Fajnzylber, Lederman, and Loayz, 2002; Corman and Mocan, 2000).

According to FBI's Uniform Crime Reporting Program (UCR), more than 40% of the total violent and property crimes in the USA happens in the southern region of the US. As presented in Figure 1 and Figure 2, the southern region has the highest crime rate among all regions in the USA, for both violent and property crime. While the South has approximately 40% of the crime, the second highest region with crime, the Midwest, is around 20%. To understand the reasons for the high crime rates, the crime literature provides a number of studies that analyze what determines crime. These studies demonstrate that increased economic stress, excessive alcohol consumption, education level and unemployment are evidence of more offensive behaviors in the southern states (Lindquist, Cockerham, & Hwang, 1999; Lochner & Moretti, 2004).

Based on statistics from the Bureau of Justice (2007), around 37% of the violent crimes committed each year the offender was drinking at the time of his or her arrest (National Incident-Based Reporting System, 2007). Excessive alcohol consumption increases the risk of committing violent crime by increasing the risk of aggressive behavior, decreasing judgment and lowering inhibition (Alcohol Rehab Guide, 2016). As showed by Corman and Mocan (2013), alcohol consumption is positively correlated with increased rates of rape, grand larceny and assault. Accordingly, analyzing the impact of alcohol consumption on crime can be helpful in understanding how alcohol policies impact the occurrence of crimes. Another study indicates that alcohol misuse cost $223.5 billion dollars in 2006 (Sacks, Gonzales, Bouchery, Tomedi, & Brewer, 2015). Statistics from the National Institute on Alcohol Abuse and Alcoholism (NIAAA) illustrate that the cost of alcohol misuse in the USA was $249 billion dollars in 2010. Also, these studies indicate that excessive alcohol consumption has economic costs on four main fields. Approximately 72% of the total economic costs were related to workplace productivity, 11% were came from healthcare costs, 9% were in criminal justice costs and 6% comes from motor vehicle crashes (Centers for Disease Control and Prevention, 2014).

Previous studies have found a strong relationship between changes in climate, seasonality and crime (Linning, Andresen, & Brantingham, 2017;Linning, 2015; Ranson, 2014). The literature about crime suggests that higher temperature in the Southern states might have a positive impact on property and violent crime (Field, 1992; Ranson, 2014). In addition to the impact of climate change and excessive alcohol consumption on the higher crime statistics, much of the earlier literature discussed the seasonal variation in crime (Andresen & Malleson, 2013; Linning, Andresen, & Brantingham, 2017). While the crime theory suggest that seasonality is more related to violent crime, a research found that some other crime types are also more likely to be affected by the seasonal changes (Hipp, Bauer, Curran, & Bollen, 2004).

A better understanding of crime frequency is important to implement more efficient policies to decrease crime. So, this study investigates the extent to which variations in temperatures affect crime rates in the southeast states within a typical empirical crime model framework, where crime rates are specified as a function of standard controls. The remainder of this paper is organized as follows: Section 1 provides a review of literature on crime, alcohol consumption and changes in climate. Section 2 presents an econometric model, the empirical specifications and the econometric methodology. Section 3 explains the data, while including relevant literature. Finally, the results and conclusion are discussed in section 4 and section 5.

1) What determines crime?

After Becker's punishment theory, a large volume of economics literature has been developed to analyze the economic factors that influence crime. Around one decade after Becker's theory, the economic literature of crime focused on the success of punishment in decreasing crime (Ehrlich, 1975). While Ehrlich (1975) found there was a significant impact of capital punishment on crime rates, some recent studies found no association between crime and capital punishment (Katz, Levitt , & Shustorovich, 2003). Working with state-level panel data in the USA, Katz et al. found that good quality of life in prison is a more effective deterrent to crime than capital punishment.

The crime theory explains that property crime and violent crime might be correlated with climate change. Working with geographic regional, seasonal, monthly and daily variation of data, Anderson's study concluded that hot weather and crime go hand in hand (Anderson, 1989). Anderson's findings show that hotter regions are home to increased criminal activity. Working with county-level data, Ranson (2014), also found that temperature has a strong positive impact on criminal behaviors in the USA. Ranson's study also emphasize the influence of seasonality on crime variation. The crime literature shows that crime statistics peaks particularly in the summer months. Because of higher temperatures during the summer season, higher violent and property crime can be seen (Hipp, Bauer, Curran, & Bollen, 2004). Some crime categories for example murder shows variation by change in seasonality.

In addition to research on the weather and seasonality that impact crime, the effects of economic factors that contribute to crime have also been evaluated. In their work, Bouchery et al. (2011) analyzed the impact of excessive alcohol consumption on crime. Though their study ignored some intangible costs, they found that binge drinking is highly related to crime and the cost of alcohol-attributable crime was $73.3 billion (Boucheryr, Harwoodb, Sacks, Simon, & Brewer, 2011). Additionally, the economic cost of alcohol consumption and crime in New York City was analyzed by Corman and Mocan in 2000 and 2013. The 2013 study shows that alcohol consumption is not positively related to all crime types. According to their analysis, while alcohol consumption has a positive impact on rape, larceny, and assault, the other crime types are not positively related to the alcohol consumption. Their study in 2000 had different results. The results in the 2000 study indicate that drug use has a positive correlation with robbery and burglary but not other types of crime (Corman & Mocan, 2000; Corman & Mocan, 2013).

Another empirical study which examines the impact of alcohol consumption on crime was conducted by Zimmerman and Benson (2007). Their findings from the two-stage least squares model (2SLS) show that alcohol consumption has positive effect on rape (Zimmerman & Benson , 2007).

Most of the studies on the relationship between crime and alcohol accept that alcohol consumption is a function of other social-economic variables. The basic regression in the present study considers the number of law enforcement officers as a deterrence variable, then climate change variable, temperature and economic variable, unemployment rate, median household income level is considered as the factors that may have an impact the incidence of crime.

The studies on crime make known that an increase in the number of law enforcement personnel (police officers and civilian workers) results in a decrease in crime. One of the studies on police officer numbers and crime was conducted by Tella and Schargrodsky in 2004. The main purpose of their study was to analyze the deterrent effect of police on motor vehicle theft. The results suggest the negative impact of visible police officers on motor vehicle theft (Tella &

Schargrodsky, 2004). A second study highlights the importance of the number of police officers on the crime rate (Levitt, 2004). In the U.S., crime rate fell sharply for all crime types. According to Levitt's estimation, there are four primary reasons behind the decreasing crime rate: (1) increased number of police officers, (2) increased incarceration, (3) the decline of crack and (4) legalized abortion. Additionally, another study by Levitt (2002) addresses the same research question (Levitt, 2002). As stated in Levitt's paper, an increase in crime is likely to convince politicians to hire more police officers. Nevertheless, the results do not provide a clear explanation about what impact the number of police officer has on crime. Lastly, an important study by Anderson (1999) states that "If an outlay of $1,000,000 for additional law enforcement officers has no effect on the crime rate, but private expenditures on crime are able to decrease by $1,500,000, society is better off" (Anderson 1999: 613).

2) Empirical Methodology

In this section a simple crime supply model is used to explain the main logic behind the economics of crime. This study also follows the models stated below:

(1) $CR_i = f(Tmax_{imt}, Tmin_{imt}\ Prcpt_{imt}, A_{imt}, Pol_{imt}, Unemp_{imt},\ Inc_{imt}, S_{imt}, u_{imt})$

(2) $A_{itm} = \mathrm{g}\ (CR_{itm}, w/d_{itm}, e_{itm})$

(3) $Pol_{itm} = d(CR_{itm}, GInc_{itm}, \epsilon_{itm})$

So, equations (1)-(3) would be as follows:

(4) $CR_{itm} = f(Tmax_{itm}\ Tmin_{itm}, g(CR_{itm}, w/d_{itm}, e_{itm}), d(CR_{itm}, GInc_{itm}, \epsilon_{itm}), Unemp_{itm}, Inc_{itm}, u_{itm})$

(5) $CR_{itm} = f(\beta_0 + \beta_1 Tmax_{itm} + \beta_2 Tmin_{itm} + \beta_3 Prcpt_{itm} + \beta_4 A_{itm} + \beta_5 Pol_{itm} + \beta_6 Emp_{itm} + \beta_7 Inc_{itm} + \beta_8 S_{itm} + u_{itm})$

Equation (1) presents a crime supply equation where CR_{imt} is the crime rate in county i, year t, and month m, $Tmax$ is average annual maximum temperature, $Tmin$ is the average annual minimum temperature, $Prcpt$ is the precipitation, $\mathrm{A_i}$ is alcohol consumption, *Pol* is the number of law enforcement personnel, *Unemp* is the unemployment rate, Inc_i is the median household income, and S is the seasonality . The term of S were defined as dummy variables for annual seasons. The seasons are defined as winter (January-March), spring (April -June), summer (July – September), and fall (October – December). Winter has become an omitted variable and it is dropped. The error term u_i covers the unobserved individual attributes. This model assumes crime rate is a function of average temperatures, precipitation, seasonal variation, alcohol consumption, law enforcement size, unemployment rate and median household income. Equation (2) shows that alcohol consumption is the function of crime rate. Here the problem of endogeneity can be seen between the number of crimes and alcohol consumption. Thus, the instrumental variable method can be useful to deal with the endogeneity problem between crime rate and alcohol consumption. As seen on equation 2 and equation 4, being wet or dry county is included as an instrumental variable in the model. w/d refers to wet or dry county statues of each county. The validity of instruments variable,w/d, depends on the exogeneity and relevancy of the variable of w/d. According to the exogeneity assumption, the variable of w/d should not be correlated with the error term, u_i. Also, relevancy is another issue which expresses existence of a correlation between w/d and Alc_i. To sum up, two expectations from validation of w/d as an instrumental variable are:

(6) $cov\ (w/d_i, u_i) = 0$

(7) $cov\ (w/d_i, Alc_i) \neq 0$

Another variable which suffers from a problem of endogeneity in equation 1 is the number of law enforcement personnel. It is likely that the increasing crime rate in a county will result in hiring more law enforcement personnel. In other words, areas with higher crime rates need more law enforcement personnel. Conversely, it is likely to see higher crime rate as a result of lower number of law enforcement personnel.

Several studies discussed the endogeneity problem of crime and number of police officer personnel (Worrall & Kovandzic, 2010; Lin, 2009; Levitt, 1997; Levitt S. D., 1988; McCrary, 2002). To tackle down the endogeneity problem, an instrumental variable which is correlated with outcome variable but uncorrelated with the error term should be found. A leading paper written by Levitt (1997) used firefighters, mayoral and gubernatorial elections as two instrumental variables to eliminate the endogeneity of crime and police force. Levitt's study provides evidence on a negative correlation between police force and crime. On the other hand, McCrary (2002) stated that Levitt's analysis included some problems and the results are biased. In another study that discussed the endogeneity of police force and crime, Lin (2009) used the lagged state tax rates as an instrumental variable for local police numbers. In the present study, to eliminate the endogeneity problem, lagged county level gross tax income level in each county is employed.

So, instrumental variable, lagged county level gross income level $(GInc)$ is included in the model.

(8) $Pol_{ij} = \alpha + \beta_1 GInc_{t-1} + \beta_2 CR_{ij} + \varepsilon_{ij}$

(9) $cov\ (GInc_{t-1}, u_i) = 0$

(9) $cov\ (GInc_{t-1}, Pol_i) \neq 0$

As stated by Corman and Mocan (2013), the impact of excessive alcohol consumption on crime rates is tough to estimate. As demonstrated by u, some characteristics may have an impact on both offensive behaviors and alcohol consumption. To give an example, religion may be negatively related to both crime and alcohol consumption. Because of this endogeneity problem, a number of estimation results about crime and alcohol consumption are debatable. To eliminate this problem, researchers prefer to use a reduced form of an equation for crime. In the present study crime is calculated in log form to ensure spherical mean-zero errors assumption.

3) Data

To investigate the impact of climate variability on crime, a panel data approach is implemented. The estimation relies on panel data from a 5-year period of crime, and the explanatory variables. The states included in the presented study are Alabama, Georgia, Florida, Mississippi, North Carolina, South Carolina and Tennessee. The number of counties from each state are as follows: 67 counties from the state of Alabama, 67 counties from the state of Florida, 159 counties from the state of Georgia, 80 counties from the state of Mississippi, 102 counties from the state of North Carolina, 46 counties from the state of South Carolina, and 95 counties the from state of Tennessee. The sample of 616 counties from seven states is analyzed for each year between 2010 and 2014.

In this study, the number of crimes per year is used as an outcome variable. The explanatory variables are average maximum and minimum temperature, precipitation, unemployment rate, median household income, excessive alcohol consumption and the number of police enforcement personnel. In addition to these explanatory variables, a set of dummy variables are included. The dummy variables are defined as follow: (October to December) fall, (January to March) winter, (April to June) spring, and (July to September) summer. Data definitions and sources are presented on the Table 1.

For each county, statistics are collected from the public data sources and each variable is explained below:

The annual number of crimes by crime category is obtained from the Federal Bureau of Investigation (FBI)'s statistics department. The FBI's Uniform Crime Reporting Program divides violent crime into four offense categories: murder, forcible rape[1], robbery, and aggravated assault. For property crime, there are also four crime categories: burglary, larceny-theft, motor vehicle theft, and arson. All violent crime and property crime categories excluding arson are examined. Because of the limited data availability for arson, this crime type is not analyzed in our study. In this study, the outcome variable is the number of crimes which gives the number of violent and property crimes per 100,000 populations in each county.

3.1) Explanatory Variables

As mentioned in Section 2, the explanatory variables in the present study are annual average maximum and minimum temperature, precipitation, seasonality, excessive alcohol consumption, the number of law enforcement personnel, unemployment rate, and median household income.

The crime literature provides both empirical and theoretical framework to understand the impact of climate variation on crime and economic activities. It has been suggested that climate change maybe be positively related to both alcohol consumption and crime. One of the reasons can be higher social interaction in summertime, since people hesitate to be outside and continue their normal social activities during the winter season. Additionally, in a recent study conducted by Ranson (2014), warmer weather results in higher crime violence. To investigate the effects of

[1] The FBI Uniform Reporting System has changed the definition of "rape" in 2013. The definition of "rape" is revised and the term "forcible" was removed from the offense title. In the present study, the rape statistics are collected under the revised definition.

weather on increased crime, county level average maximum and minimum temperature data from the National Centers for Environmental Information is utilized.

Alcohol consumption is employed as an explanatory variable. The Behavioral Risk Factor Surveillance System (BRFSS) annual statistic data base provides the percent of population that binge drink, heavily drink, and engage in any form of alcohol consumption. BRFSS database covers the population over 18 years of age living in households with a land line telephone. Three alcohol consumption categories are stated: (1) Any drinking (2) Binge Drinking and, (3) Heavy Drinking. Any drinking refers to at least one drink in the last thirty days. Binge drinking is defined as any drinking which brings blood alcohol concentration level to 0.08 gr/dl. It generally happens after 5 drinks for men and 4 drinks for women. The last drinking type is heavy drinking. It is defined as at least 5 drinks in one occasion for at least 5 days of the week (Centers for Disease Control and Prevention, 2012). To examine the impact of alcohol consumption on crime, we choose excessive alcohol consumption. The excessive alcohol consumption reports the binge and heavy alcohol consumption during the last 30 days.

Also, it is important to note that adolescent alcohol use is a public health problem in the USA. The number of law enforcement personnel, especially number of police officers, has an impact on preventing underage drinking. So, an increase in the number of police officers has the potential to control underage drinking.

In our regression, the number of law enforcement personnel is another explanatory variable that is obtained from the FBI’s statistics department. The number of law enforcement personnel is measured as the number of people who carry a firearm and a badge, have full arrest powers, and are paid from governmental funds set aside specifically to pay sworn law enforcement personnel (U.S. Department of Justice, 2010- 2014). The FBI’s statistics department provides the total number of law enforcement personnel. In the present study, the number of police law enforcement personnel in each county is employed. The statistics show that Tunica county of Mississippi has the highest number of per capita law enforcement personnel in the Southeastern states with 1380 personnel on average in 2007 and 2010.

In addition to temperature variables, the number of law enforcement personnel, alcohol consumption, unemployment rate and median household income level are employed as the other right hand side variables. The variable of unemployment rate gives the percentage of population older than 16 years old and looking for a job. The Census Bureau provides county level annual estimates of unemployment rate. To combine regression predictions with direct estimates from the American Community Survey, Bayesian estimation techniques are applied to the Small Area Income and Poverty Estimates (SAIPE) program's models. (American Community Survey, 2016).

Lastly, the OLS estimation may have biased results due to a problem of endogeneity. To break down the endogeneity problem between crime and alcohol consumption we need to find an instrumental variable that will help to eliminate biased results. The present study needs the variable of "wet and dry counties" to solve an endogeneity problem between crime and alcohol consumption. A few studies indicate that alcohol consumption is positively related to crime (Brempong & Racine, 2006; Grönqvist & Niknami, 2014). So, being wet or dry county is used to instrument for alcohol consumption. This variable is obtained by the National Alcohol Beverage Control Association.

Another endogeneity problem is seen between crime and the number of law enforcement personnel. An increase in the number of law enforcement personnel may decrease the crime. Also, governments may decide to increase police level to deal with high crime rate. So, a potential endogeneity problem between crime and the number of police officer personnel presents a highly significant problem. To eliminate this problem, instrumental variable approach is employed. The residents' additional spending on the police protection has positive impact on the public safety. So, the availability of funds for public safety is a contributor of the public safety expenditures. In the present study, the lagged county level gross tax income data is used as an instrumental variable.

4) Results

Regression results are presented in Table 3 and Table 4. The results of specifications for each crime category are reported. The basic equation in the present study includes the following explanatory variables: average temperatures, precipitation, seasonality, excessive alcohol consumption (binge and heavy drinking), the number of law enforcement personnel, median household income and the unemployment rate. The two-stage least square (2SLS) model is employed as a main econometric methodology. The dependent variable is measured in the number of crimes per 100,000 people. Table 3 gives the 2SLS estimation results of violent crime categories.

Violent Crimes

The 2SLS estimates of the impact of weather and the alcohol consumption on violence, murder, rape, robbery, and assault are the first estimation results presented in Table 3. Economic Theory suggests that crime and alcohol consumption are positively related. However, problems of endogeneity between these variables have been discussed by researchers (Lin, 2009; Mocan and Corman, 2013). In the present study, wet or dry counties are employed as an instrumental variable to mitigate issues of endogeneity.

The 2SLS estimation results show that a 10%-point increase in *excessive alcohol consumption* leads to an increase in the probability of violence by 28 in 100,000. Also, a 10%-

point increase in *excessive alcohol consumption* leads to an increase in the probability of assault by 34 in 100,000. One can see a similar relationship for robbery. A 10%-point change in any level of alcohol consumption results in around 20 more robberies per 100,000. These results are similar to those obtained by Corman and Mocan (2000). While any alcohol consumption is highly significant positive impact on each of the violent crime categories, it does not have a significant impact on murder rates. It is important to note that 2SLS and OLS estimation results are significantly different from each other for violent crime (all violent categories are combined) and robbery. An OLS estimation assumes that there is a linear relationship between explanatory and dependent variables; therefore, an OLS estimation does not provide accurate results. While OLS shows that alcohol consumption has a nonsignificant impact on violence and robbery, 2SLS estimation results show alcohol consumption and those crime categories are statistically significant and positively correlated.

The average daily maximum and minimum temperature presented by crime nexus demonstrates a statistically significant relationship for robbery. A 1-degree Celsius increase in average daily maximum temperature results in 7 more robberies per 100,000 people. significantly positive effect on average daily minimum temperature can be seen for robbery. Within the seasonality variation, current crime literature is inconclusive. As stated in Table 3, the findings support that rape peaks during the summer season. According to a report released from the Department of Justice, one can see that rape and sexual assault rates are higher in summer months than in other seasons (Lauritsen & White, 2014).

The results for the impact of unemployment rate and income on the probability of violence show that while unemployment rate has positive impact on rape, robbery and assault, it does not have any statistically significant impact on other violent crimes. An increase in unemployment rate is likely to result in a higher number of rapes, robberies and assaults. Additionally, an increase in the median household income results in a lower number of murder and assault crimes in each county.

Property Crime

Continuing with the estimation results presented in Table 4, the findings show that excessive alcohol consumption leads to a higher level of burglary and motor theft. A 10%-point increase in excessive alcohol consumption levels results in 194 more burglaries per 100,000 and 55 more motor vehicle thefts in 100,000.

The second endogenous variable in the present study, the number of law enforcement personnel, is instrumented by county-level gross tax income. While a number of researchers have analyzed the potential endogeneity of policing in crime models, it is still an important problem to tackle (Lin, 2009; Levitt S. D., 1988; Kovandzic, Schaffer, Vieraitis, Orrick, & Piquero, 2016). Focusing on the violent crime results in Table 3, the findings show that the number of law enforcement personnel is significantly related to instances of violence, rape and assault. While the deterrence effect of the number of law enforcement on violent crime is limited, it is more efficient on property crimes.

The impact of the number of law enforcement on property crimes is presented in Table 4. The results from the 2SLS are closer to the estimates reported by Fafchamps and Moser (2003). Our estimation results show that the number of law enforcement personnel has an impact on property crimes, burglary, and grand larceny but not motor theft. Contrary to expectations, the right side variable of the number of law enforcement personnel appears to be unable to decrease crime through the deterrence effect. According to previous studies, some indirect impacts of the

the number of the law enforcement personnel on decreasing crime can be seen: (1) Law enforcement personnel can help to solve crime but are unable to stop it, (2) incarceration can decrease crime by sentencing offenders (Fafchamps & Moser, 2003; Kleck & Barnes, 2010).

Further, as argued in Ransom (2014), higher average temperatures may cause more crime in an area. In the present study, findings show that any change in the average daily minimum temperature is positively related to property crimes and grand larceny. More specifically, a 10 Celsius degree increase in average daily minimum temperature increases the occurrence of crime by 223 in property crimes and by 202 in grand larceny in a population of 100,000. The results for the impact of seasonality highlight that there is more property crime during the summer season while there is not a statistically significant impact during other seasons. Of the existing crime and seasonality literature discussing the association between crime and seasonality, the findings on Table 4 support that higher temperatures or warmer seasons are positively related to higher property crime rates.

Two other explanatory variables in the model are the median household income and unemployment rate. As one can see in Table 4, increases in the median household income have a negative association with motor vehicle theft and burglary. On the other hand, changes in the unemployment rate do not show an impact on the occurrence of crime except motor vehicle theft.

Summing up, in light of the above statement, one can see that climate variation and excessive alcohol consumption have significant impacts on crime. While spring and fall seasons do not show increases in the occurrence of crimes, more rape and property crimes can be seen during the summer season. Moreover, the impact of higher temperatures on the probability of crime is seen as another significant determinant of crime.

In addition to findings stated above, one can see that higher gross tax income can be an efficient way to decrease crime. As a government funding variable, county tax rates contribute to government revenues. Therefore, an increase in government revenue might be helpful to employ more police officers.

5) Conclusion

This paper has two main goals. The primary goal is to analyze the impact of climate variation on each crime type in the southeastern counties of the U.S. The second aim is to investigate the impacts of different level alcohol consumptions on crime rates.

The findings show that changes in average maximum or minimum temperatures is one of the most important determinants of crime. Additionally, the results show that endogeneity of alcohol consumption and endogeneity of the number of law enforcement personnel are two important problems which causes biased results. The endogeneity of alcohol consumption is tracked by an instrumental variable, wet and dry counties. The results indicate that increase of alcohol consumption rate of population is highly related with violent and property crimes. The second endogeneity problem of the number of law enforcement personnel is tracked by county gross tax income. The results show that increasing the number of law enforcement personnel is an effective deterrence to decrease all crime categories expect murder, robbery and motor vehicle theft.

Limitations

The present study has some limitations. Firstly, the outcome variables are gathered from the FBI UCR program. For a number of causes people do not choose to inform the law enforcement personnel. Of crime Thus, one can see that there are a number of crimes which are not reported.

Secondly, the data set is limited to the counties of seven Southeastern states of the USA. If the current study had access to all U.S. crime data, the results might be more accurate.

Tables and Figures

Table 1: Definitions and Data Sources

Variables	Definition	Data Source
Excessive Alcohol Consumption	Percentage	The University of Wisconsin Population Health Institute
Population	Total number of populations	U.S. Census Bureau
Number of Police Officer Personnel	Total Number of Police Officers	FBI The Uniform Crime Reporting (UCR) Program
Average Daily Maximum Air Temperature	Celsius Degree	Ag- Analytics at Cornell University
Average Daily Minimum Air Temperature	Celsius Degree	Ag- Analytics at Cornell University
Precipitation	Millimeters	Ag- Analytics at Cornell University
Seasonality	Winter (1-3), spring (4-6), summer (7-9), and fall (10-12)	Dummy Variable
Adjusted Gross Income Level	Thousands of Dollars	Internal Revenue Service (IRS)
Per Capita Violent Crime	Number of violent crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Per Capita Murder	Number of murder crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Per Capita Rape	Number of rape crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Per Capita Robbery	Number of robbery crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Per Capita Assault	Number of assault crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Per Capita Property Crime	Number of property crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Per Capita Burglary	Number of burglary crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Per Capita Grand Larceny	Number of grand larceny crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Per Capita Motor Theft	Number of motor theft crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Unemployment Rate	Number of employees	U.S. Census Bureau
Median Household Income	Thousands of Dollars	U.S. Census Bureau

Table 2: Summary Statistics

Variable	Mean	Median	Minimum	Maximum
Per Capita Violent Crime (per 100,000)	207.292	149.211	0	1604.01
Per Capita Rape (per 100,000)	13.5347	10.9	0	118.087
Per Capita Murder (per 100,000)	2.79412	1.83743	0	27.1771
Per Capita Robbery (per 100,000)	25.4507	14.5258	0	427.772
Per Capita Assault (per 100,000)	165.396	115.179	0	1447.57
Per Capita Property Crime (per 100,000)	1505.22	1391.13	0	8186.62
Per Capita Burglary (per 100,000)	505.466	452.566	0	2598.93
Per Capita Grand Larceny (per 100,000)	883.677	796.184	0	4900.23
Per Capita Motor Theft (per 100,000)	116.839	94.5933	0	996.238
Average Daily Maximum Air Temperature (Celsius Degree)	23.2	24.5	0	37.1
Average Daily Minimum Air Temperature (Celsius Degree)	10.7	10.8	-11.1	25.7
Precipitation (centimeters per year)	109	98.9	0.0216	572
Seasonality	2.52	3	1	4
Excessive Alcohol Consumption (% of population)	11.7	11.7	0	30
The Number of Police Officer Personnel (per 100,000)	95.5	41	1	1540
Population	120037	54467	10162	1752930
Median Income Level	39600	37900	20100	91700
Unemployment Rate	11.2	10.7	2.3	29
Adjusted Gross Income	2000000	505000	12000	58200000
Wet county	0.95132	1	0	1

Table 3: 2SLS Estimation Results for Violent Crime Categories (2010-2014)

Variable	All Violent Crime	Murder	Rape	Robbery	Assault
Constant	213.3	4.964	13.31	-1.983	195.3
	(-8.626)	(-0.273)	(0.849)	(-1.442)	(6.777)
Average Daily Max Air Temperature	0.224	0.007	0.017	-0.066*	0.223
	(-0.225)	(0.007)	(0.22)	(0.037)	(0.177)
Average Daily Min Air Temperature	-0.197	-0.008	-0.015	0.068*	-0.183
	(-0.219)	(0.006)	(0.021)	(0.036)	(0.172)
Precipitation	0.011**	0.000	0.000	-0.001	0.009**
	(-0.005)	(0.000)	(0.000)	(0.001)	(0.004)
Spring (Dummy)	151.1	-0.000	-0.071	0.040	0.131
	(2.335)	(0.764)	(0.223)	(0.402)	(1.921)
Summer (Dummy)	-0.133	0.000	(0.063)*	-0.035	-0.115
	(2.261)	(0.740)	(0.216)	(0.389)	(1.861)
Fall (Dummy)	0.000	0.000	0.000	0.000	0.000
	(2.296)	(0.752)	(0.219)	(0.395)	(1.889)
Excessive Alcohol Consumption	0.282**	0.011	-0.010)	0.204***	0.341*
	(0.553)	(0.042)	(0.031)	(0.034)	(0.184)
Number of Police Officer Personnel	-0.025***	-0.000	-0.007***	0.038	-0.049***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.005)
Unemployment Rate	2.805	0.013	0.132***	1.233***	1.566***
	(0.374)	(0.011)	(0.036)	(0.062)	(0.294)
Median Income Level	-1.654	-0.034***	-0.001	0.154	-1.773***
	(0.205)	(0.005)	(0.017)	(0.037)	(0.176)
R-squared	0.28	0.25	0.30	0.21	0.24

Note 1: Triple asterisks (***) shows the significant level at 1%. Double asterisks (**) shows the significant level at 5%. And single asterisks (*) shows the significant level at 10%.
Note 2: The numbers in parentheses show standard errors.

Table 4: 2SLS Estimation Results for Property Crime Categories (2010-2014)

Variable	All Property Crime	Burglary	Grand Larceny	Motor Vehicle Theft
Constant	1761.1	726.66	947.8	100.5
	-46.82	(17.63)	(29.39)	(4.641)
Average Daily Max Air Temperature	2.464**	-0.294	1.988***	-0.091
	(1.227)	(0.461)	(0.770)	(0.121)
Average Daily Min Air Temperature	2.534**	0.287	2.021***	0.125
	(1.191)	(0.448)	(0.747)	(0.117)
Precipitation	-0.019	-0.008	-0.010	-0.000
	(0.031)	(0.011)	-0.019	(0.003)
Spring (Dummy)	4.835	2.010	2.255	0.244
	(12.84)	(4.820)	(8.203)	(1.201)
Summer (Dummy)	-4.253*	-1.768	-1.985	-0.215
	(12.44)	(4.668)	(7.945)	(1.163)
Fall (Dummy)	0.000	0.000	0.000	0.000
	12.63	(4.740)	(8.067)	(1.181)
Excessive Alcohol Consumption	0.218	1.946***	-2.873	0.557***
	(0.943)	(0.431)	(0.593)	(0.1120
Number of Police Officer Personnel	-0.398***	-0.180***	-0.255***	0.039
	(0.034)	(0.013)	(0.021)	(0.034)
Unemployment Rate	4.225	3.180	-1.470	1.900***
	(2.032)	(0.765)	(1.275)	(0.201)
Median Income Level	-1.396	-4.765***	3.837	-0.249**
	(1.151)	(0.446)	(0.701)	(0.102)
R-squared	0.11	0.16	0.10	0.13

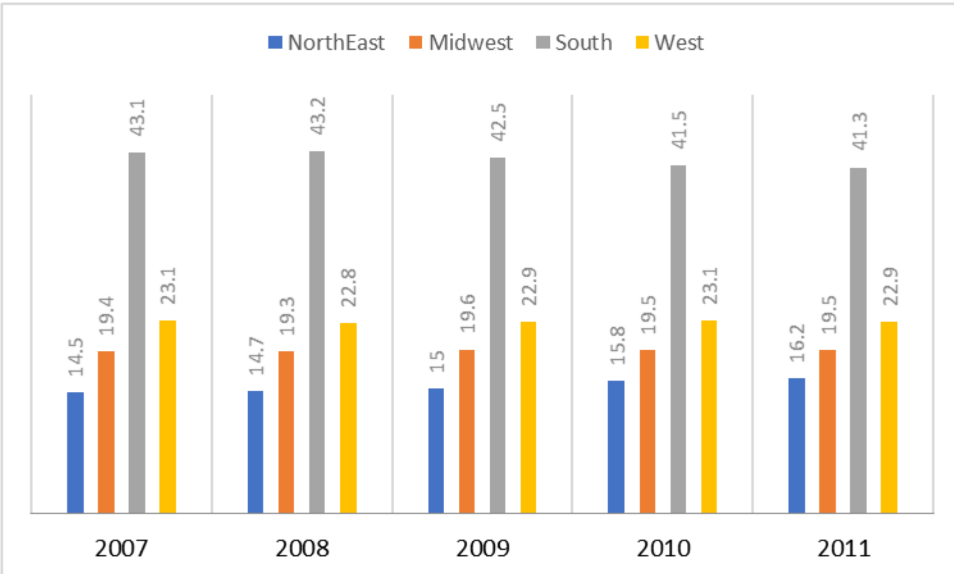
Note 1: Triple asterisks (***) shows the significant level at 1%. Double asterisks (**) shows the significant level at 5%. And single asterisks (*) shows the significant level at 10%.
Note 2: The numbers in parentheses show standard errors.

Table 5: Uniform Crime Reporting Offense Definitions

Offense	Definition
Murder	The willful (nonnegligent) killing of one human being by another.
Rape	The carnal knowledge of a female forcibly and against her will.
Assault	An unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury.
Robbery	The taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence or by putting the victim in fear.
Burglary	The unlawful entry of a structure to commit a felony or a theft
Larceny	The unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another.
Vehicle Theft	The theft or attempted theft of a motor vehicle

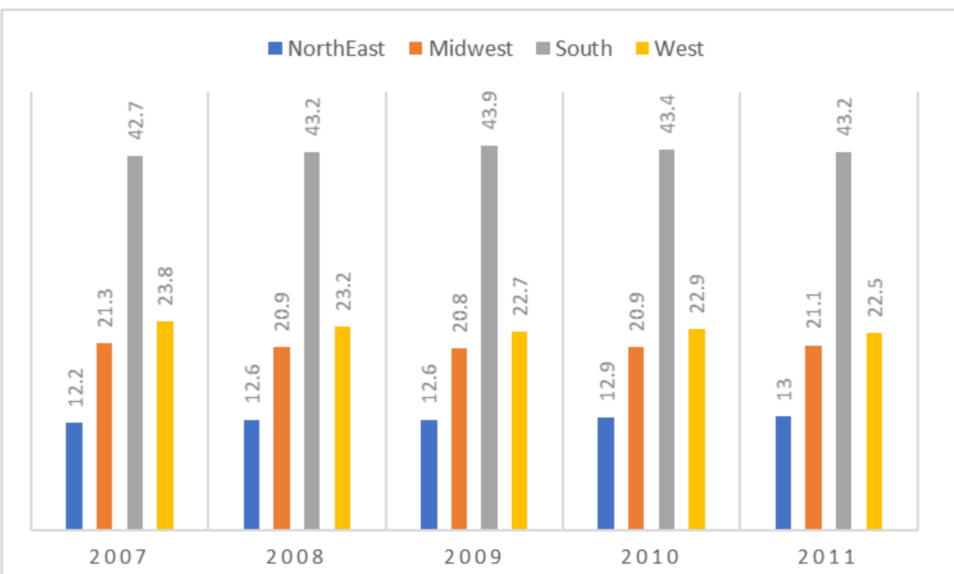
Source: FBI (2019)

Figure 1: **Violent Crime Percentage Distribution by Region 2010-2014**



Source: The federal bureau of investigation, The Uniform Crime Reporting (UCR) Program, 2017

Figure 2: **Property Crime Percentage Distribution by Region 2010-2014**



Source: The federal bureau of investigation, The Uniform Crime Reporting (UCR) Program, 2017

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Mental Health, Opioid Use and Crime: A County Level Study in the USA

Introduction

The Bureau of Justice Statistics' (BJS) National Crime Victimization Survey (NCVS) reported that U.S. residents aged 12 and older experienced more than five million violent victimizations in 2015 (Truman & Morgan, 2015). An analysis of the US National Epidemiologic Survey on Alcohol and Related Conditions data by Van Dorn, Volavka and Johnson (2012) found that people with serious mental illness were significantly more likely to commit a crime than people with no mental or substance use problems (Van Dorn, Volavka, & Johnson, 2012). This association between mental illness and violence is followed by researchers from many disciplines and the impact of mental wellness on crime is investigated by a number of researchers (Markowitz, 2005; Francesca, Feldman, & Leigh, 2014; Dobkin & Nicosia, 2009). A recent study including over 47,000 people reports that depressive symptoms and risk of violent crime are significantly associated with each other. 3.7% of men identified as clinically depressed committed violent crimes (Fazel, Wolf, Chang, & Larss, 2015). Similar results are found in other studies. Swanson et al.'s study based on more than 1,400 adult patients with mental disorders showed that nearly 19% commited violent crime during the last 6 months. (Swanson, Swartz, Van Dorn, Elbogen, Wagner, & Rosenheck, 2006).

Other research has brought to light that not only are criminals diagnosed with mental illness more likely to commit crimes, but that crime or fear of crime can have impact on wellbeing of both victims and non-victims (Cornaglia, Feldman, & Leigh, 2014). Dustmann and Fasani (2014) found that crime leads to a decrease in mental wellbeing for residents. Therefore, the incidence of crime has larger impact on mental wellness than an increase in unemployment rate (Dustmann & Fasani, 2014).

A second common thought is that there is link between crime and drug abuse. Since 2010, there has been a significant increase in the use of prescription opioids for nonmedical purposes. According to statistics from the Substance Abuse and Mental Health Services Administration, nearly 11.5 million people take pain relievers for non medical uses in the US (Substance Abuse and Mental Health Services Administration,2017). While current research studies focus on the impact of opioid abuse on violence, crime literature is inconclusive regarding the impact of drug abuse on incidence of crime. In cases of violent crime, Pacula and Kilmer (2003) found a statistically significant association between arrests and drug use. On the other hand, their findings show that marijuana use may have an influence on the likelihood of being apprehended after committing these crimes. The BJS (2008) reports that about 26% of victims of violence reported that the offender was under the influence of drugs or alcohol at the time the violence occurred. Additionally, the BJS statistics show that about 40% of all rape/sexual assaults and about 25% of all robberies against a college student were committed by an offender under the influence of drugs (Dorsey & Middleton, 2006).

Illegal drug distribution and consumption have resulted in an increased level of violent crime. Corman and Mocan (2000) examined drug-related crime in New York City, and their findings provide strong evidence on the positive relationship between drug use and robberies and burglaries. The authors found that a 10 percent decrease in drug use decreases robberies by 1.8-2.8 percent (Corman & Mocan, 2000).

Entorf and Winker (2008) provides an economic assessment of drug and incidence of violence in Germany within a Becker–Ehrlich model of crime supply. Their estimation with panel data from the German states indicates that drug offenses have a significant impact on property crimes such as robbery and theft (Entorf & Winker, 2008).

It is important to note that while criminological literature considers that drug use and criminal activities are related to each other; the economic theory of crime has limited literature on the drugs and crime nexus. On the other hand, a number of studies in economic literature supports that higher prices are negatively associated with consumption of alcohol and illegal drug use (Jacobi & Sovinsky, 2016; Williams, 2004; Galenianos & Gavazza, 2017). Jacobi and Sovinsky (2016) found that marijuana demand is much more elastic with respect to price.

The purpose of this study is to examine the impact of mental wellness and opioid abuse on the incidence of crime in U.S. counties. The remainder of this paper is organized as follows: Section 1 provides a review of literature on mental wellness, drug abuse and crime. Section 2 provides a simple model of crime and theoretical background. Section 3 presents econometric methodology and empirical specification. Section 4 explains the data. Finally, the results and conclusion are discussed under section 5 and section 6.

Background

Background on the Economics of Crime and Mental Wellness

After Becker's groundbreaking study (1968), a growing amount of literature focused on the cost of crime and determinants of crime (Corman & Mocan, 2000; Lochner & Moretti, 2004). While a number of studies estimate the determinants of crime, there are few studies to analyze the relationship between mental illness and crime in economics literature. According to the World Health Organization (WHO), nearly 4.5% of the world's population suffers from mental illness. Based on data from 2003, the cost of mental disorders makes up 6.2% of the United States' spending on health care (Mark et al, 2007). It is important to note that unlike the physical health problems, mental health disorders include more indirect costs than the direct costs. In addition to the direct costs of health care such as clinic visits, medications, psychotherapy sessions and inpatient stays, mental disorders have more indirect costs such as productivity loss and early retirement.

In 2011, the World Economic Forum (WEF) specified three approaches to estimate economic disease burden of mental health problems. One of the most commonly used approaches is the human capital approach, which estimates the economic cost of mental illness. Trautmann et al. (2016) indicate that indirect costs refer to the invisible costs which are related to disability, care seeking and loss of production due to work absence and early retirement. As reported by the WHO (2017), the cost of mental diseases on the world population is about $1 trillion in lost productivity each year.

The second commonly used approach is lost economic growth. The main idea behind this approach is that economic growth is related to labor and capital. An increase in healthcare expenditures and changes in saving rates and treatment costs can affect capital accumulation. Additionally, the impact of mental disorders on labor can be calculated only indirectly. In sum, it is possible to see that labor and capital are two factors of production that are likely to be negatively affected by mental health disorders. The final approach is related to Value of Statistical Life (VSL). The VSL method assumes that tradeoffs between money and risks may be used to estimate the risk of disability or death due to mental disorders (Trautmann, Rehm, & Wittchen, 2016).

A related question is whether mental diseases affect the economy by increasing incidence of crime. A total population study of 47,158 individuals conducted in Sweden explored the risks of violent crime in patients with mental disorders and aimed to estimate the association between mental disorders and violent crime in a cohort of twins (Fazel, Wolf, Chang, & Larss, 2015). Results show that after adjustment of familial, individual and sociodemographic factors, individuals with depression are more likely to commit violent crimes. In another study using a nationally representative online panel with 1,326 participants, McGinty et al. (2018) examine the link between serious mental illness and increased stigma. Data come from the March 2015 Current Population Survey and the 2012 American National Election Study. Results show that high crime rates and barriers to treatment have equal impact in increasing the public's willingness to pay higher or additional taxes to improve the mental health system (McGinty, Goldman, Pescosolido, & Barry, 2018).

Additionally, literature on mental health economics shows that mental health and physical activity are closely related to each other (Sturm & Cohen, 2014; Pretty, Peacock, Hine, Sellens, South, & Griffin, 2007). Existing literature supports that number of mental health providers, access to recreational facilities, and physical activity are significantly related to mental well-being. According to a cross-sectional study conducted by Sturm and Cohen (2014), access to recreational facilities is positively associated with mental wellness. Their study is based on secondary data analysis from Los Angeles. The findings indicate that distance to recreational facilities or parks have an impact on the frequency of park use and tome spent on physical activity (Sturm & Cohen, 2014).

Background on Opioid Abuse and Crime

There is some evidence that violence may increase with the excessive consumption of illicit drugs. Luca et al. (2015) examined the impact of alcohol prohibition on domestic violence against women in India. Using individual-level survey data, the authors found that alcohol prohibition can be an effective way to reduce both fatal and non-fatal crimes against women. The findings show that the prohibition of alcohol is associated with the reduction of 400 crimes against women per 10,000 people. This implies that nearly 25% of the total crime against women in India can be reduced by alcohol prohibition. Another study was conducted by Dobkin and Nicosia (2009) by using monthly, county-level dataset. The authors examined the relationship between methamphetamine prices, methamphetamine use and crime outcomes in an econometric framework. Using panel data from 1994 to 1998, the authors obtained two main findings. Firstly, the authors found that the price of methamphetamine and methamphetamine use among arrestees are negatively related. The results show that as the price of methamphetamine tripled, methamphetamine use declined about 55%. Secondly, the authors found a statistically significant relationship between increase of methamphetamine consumption and robbery (Dobkin & Nicosia, 2009).

In addition to the impact of methamphetamine use on incidence of crime, Darke et al. (2010) provides a comparative rate of violence among methamphetamine and opioid users. To estimate the comparative levels of violence among methamphetamine and opioid users, a cross-sectional analysis was conducted. In the Sydney region of Australia, 118 methamphetamine users, 161 heroin users and 121 regular users of both participated in face-to-face interviews. The findings indicated that across the whole sample, 82% had committed at least one violent crime and 74% had committed at least two crimes during the last 12 months. More particularly, the results show that methamphetamine users (51%) are more likely to commit a violent crime than opioid users (35%) (Darke , Torok , Kaye , Ross , & McKetin, 2010).

To the best of our knowledge, the present study is the first one to estimate the impact of mental health and opioid abuse in the incidence of crime for the United States in an economic framework. Previous crime and mental health studies (Darke at al.,2010; Fazel at al.,2015) are mostly conducted in the psychiatry framework. While the literature was not conclusive about the association of crime and mental health, the findings support that control variables such as education level, age, unemployment, and the number of law enforcement might be important factors which have an impact on incidence of crime.

Model

Criminal activities are resulting from the performance of deterrent factors and personal characteristics of criminals. After Becker's pioneered study (1968) in human capital and economics of crime, a growing literature focus on the economic aspects of the criminal activities. To examine the linkages between public health, drug addiction and crime, Dobkin and Nicosia (2009) estimated the impact of methamphetamine availability on crime. Their study emphasizes the correlation between supply of illicit drugs and crimes. The analytical framework used in the present study is developed from the economic models of crime developed by Becker (1968). Also this study utilizes Dobkin and Nicosia's empirical framework. Including opioid use, mental health indicators and criminals' characteristics provide us the following equation:

$$(1)\quad CR_{it} = \beta_0 + \beta_1 M_{it} + \beta_2 MU_{it} + \beta_3 P_{it} + \beta_4 Inact_{it} + \beta_5 L_{it} + \beta_6 Unemp_{it} + \beta_7 LF_{it} + \beta_8 MHH_{it} + \beta_9 HS_{it} + \beta_{10} Pvrt_{it} + \beta_{11} D_{it} + \varepsilon_{it}$$

Equation (1) presents a crime supply equation where *CR* is the crime rate in county i, year t.*M* is the number of mental health providers, *MU* is the number of average mentally unhealthy days per year, *P* the opioid prescription rate, *Inact* is the average physical inactivity rate per year, *L* is the number of law enforcement personnel, *Unemp* is the unemployment rate, *LF* is the labor force, *MHH* is the median household income, *HS* is the high school graduation rate, *Pvrt* is the poverty rate, and *D* is the demographic variables which show the shares of population in particular age group and race. The error term ε_{itm} covers the unobserved individual attributes. This model assumes crime rate is a function of opioid use, the number of mental health providers available in an area per 100,000, physical inactivity, the number of total law enforcement personnel, median household income, labor force, unemployment rate, high school graduation rate and demographic indicators.

Opioid consumption by the potential perpetrator (P_i) can be expressed by a similar demand function

$$(2) \quad P_{it} = p(MHH_{it}, Unemp_{it}, L_{it}, u_{it})$$

Equation (2) shows that opioid usage is the function of median household income, unemployment rate and the number of total law enforcement personnel. Several studies demonstrate that economic conditions may affect illicit drug use (MacDonald & Pudney, 2000; Carpenter, McClellan, & Rees, 2017). Therefore, opioid use is presented as a function of median household income and unemployment rate.

The number of total law enforcement and crime rate association can be explained by similar demand function:

$$(3) \; L_i = l(CR_{it}, MHH_{it}, W_{it}, v_{it})$$

Equation (3) is expressed as a function of crime rate, median household income and annual average wage of justice and safety personnel. Here the problem of endogeneity can be seen between the number of law enforcement personnel and crime rate.

The endogeneity problem of crime and number of police officer personnel is discussed by a number of researchers (Worrall & Kovandzic, 2010; Lin, 2009; Levitt, 1997; Levitt S. D., 1988; McCrary, 2002). As explained by Levitt (1997), in order to eliminate the endogeneity problem, an instrumental variable which is correlated with the outcome variable but that is uncorrelated with the error term should be found. An influential paper written by Levitt (1997) used firefighters, mayoral and gubernatorial elections as two instrumental variables to tackle endogeneity of crime and police force. Levitt found a negative correlation between police force and crime. On the other hand, McCrary (2002) found that Levitt's analysis included some mistakes and that the results were biased. In another study that discussed the endogeneity of police force and crime, Lin (2009) used the lagged state tax rates as an instrumental variable for local police numbers. In the present study, annual average wage of justice and safety personnel from local governments is used to eliminate the endogeneity problem between crime and the number of law enforcement personnel.

As seen in equation (2), an instrumental variable W_i, is included in the present study. W_i refers to the average annual wage of justice and safety personnel (NAICS 922). The validity of instruments variable, W_i, depends on the exogeneity and relevancy of the variable of W_i. According to the exogeneity assumption, the variable of W_i should not be correlated with the error term,u_i. Relevancy is another issue which expresses existence of a correlation between W_i and u_i. To sum up, two expectations from validation of W_i as an instrumental variable are:

(2) $cov(W_i, u_i) = 0$

(3) $cov(W_i, L) \neq 0$

So, substituting equations (2)-(3) into equation (1), gives a new form of crime supply equation as follows:

$$CR_{it} = f(p(MHH_{it}, Unemp_{it}, L_{it}, u_{it}), M_{it}, Inact_{it}, l(CR_{it}, MHH_{it}, W_{it}, v_{it} +)$$

$$MHH_{it}, LF_{it}, Unemp_{it}, HS_{it}, Pvrt_{it}, D_{it}, \varepsilon_{it})$$

A number of studies in the literature of economics of crime have used the fixed effect model to estimate the panel data (Raphael & Rudolf , 2001; Figlio, 2006; Jacob & Lefgren, 2003). In the present study, the fixed effect approach is employed to estimate the equation (6). An important advantage of the fixed effect model is that it accounts for any unobserved time-invariant characteristics that can be correlated with the sum of the explanatory variables (Markowitz, 2005).

Data

For the analysis of the potential impact of mental health problems on crime, a panel dataset in 3142 U.S. counties during the period from 2012 to 2015 is used. The crime statistics used in this study comes from the Federal Bureau of Investigation (FBI) Uniform Crime Reporting (UCR) Program. The FBI UCR program gathers crime statistics from regional law enforcement agencies in the United States. The dataset includes statistics on property crime including burglary, larceny-theft, motor vehicle theft and violent crime including murder, rape, robbery, and aggravated assault. In addition to crime and mental health indicators, the present study includes social and economic indicators.

Dependent variables

The FBI UCR program provides statistics on the number of crimes that occur in a calendar year. In this study, each crime category is calculated as a crime rate per 100,000 people by county. Additionally, the dataset is divided into two parts: urban counties and rural counties. We benefit from the FBI’s method to separate urban and rural counties.

Under violent crime, four crime categories are stated: murder, rape, robbery and assault. The definition of murder excludes suicides, deaths caused by negligence and accidental deaths. The definition of rape includes sexual assaults and rapes by force. Robbery is defined as attempting or taking of anything by violence, force, threat of force or putting the victim in danger. The last crime type, aggravated assault, is defined as an unlawful attack or threatened assault with a weapon.

Under property crime, three categories are stated: burglary, larceny-theft and motor vehicle theft. The definition of burglary includes any unlawful entry to commit a theft. Larceny theft is defined as any unlawful carrying, leading or riding away of properties. Motor-theft is defined as a theft or attempt to theft a motor vehicle (FBI, 2018).

Table 1 shows the means and standard deviations of all of the variables for both urban and rural counties. According to simple statistics, incidence of property crime (76.6) is nearly seven times more likely than incidence of violent crime (10.1) in urban counties. The statistics show that in both regions, murder has the lowest occurrence rate, and larceny theft has the highest possibility of occurrence.

Estimating the impact of mental wellness on the incidence of crime, the FBI's Uniform Crime Reports (UCR) are used to obtain county-level crime statistics. The FBI UCR program provides the number of crime statistics in each county. In the present study, the crime statistics from 3,142 counties are calculated as a number of crime occurrence per 100,000 in each county. The number of crimes in 100,000 people provides a better understanding about the density of criminal activities in each region.

A main limitation in constructing county-level crime data is unavailability of statistics from 786 counties. The FBI UCR program provides data from 18,000 regional agencies' submissions. The nationwide crime statistics includes 2,356 counties out of 3,142 counties.

Explanatory variables

Several studies provide evidence on the effectiveness of mental health treatments on reducing crime (Cuellar, McReynolds, & Wasserman, 2005; Bondurant, Lindo, & Swensen, 2018). A cross-sectional analysis conducted by Bondurant (2018) found that an increase in the number of substance abuse treatments availiable results in a statistically significant level decrease in violent and financially-motivated crime.

The second major component of our dataset is mental health indicators, specifically the number of mental health providers in an area. In the present study, the number of mental health providers per 100,000 is used to analyze the accessibility of help for mental disorders. The number of mental health provider statistics is obtained from the National Provider Identification (NPI) in accordance with the National Plan and Provider Enumeration System (NPPES). The variable of mental health providers includes licensed clinical social workers, psychiatrists, psychologists, counselors, and family therapists. The association between physical inactivity and mental disorders is also discussed in previous literature (Sturm and Cohen (2014). "Physical inactivity" data included in the present study show the percentage of the population who does not have time for physical activity. Physical activity includes activities such as running, walking, golf, and gardening. The data were obtained from the National Diabetes Surveillance System. County-level estimations are derived by using Bayesian multilevel modelling techniques. The variable of "mentally unhealthy days" reports the chronic diseases in a population. This variable is obtained by the Behavioral Risk Factor Surveillance System (BRFSS). A survey is conducted to population over 18 years of age.

A report released from the Bureau of Justice Statistics indicates that substance abuse is highly associated with increase in violence (BJS, 2008). In our study, the prescribing rate for opioids is included as another explanatory variable. The data come from the Centers for Disease

Control and Prevention (CDC). The CDC provides the opioid prescriptions dispensed per 100 persons per year at both state and county level. The data show the estimated rate of opioid prescriptions per 100 U.S. residents per year. Because of the prescription refills the statistics may be higher than 100 percent for some counties. Table 1 shows the opioid use statistics in both urban and rural territories. The statistics show that the mean value of opioid prescription rate in the rural counties (90.8) has surpassed the rate of urban counties (83.9). In 2017, the Centers for Disease Control and Prevention confirmed that the rates of drug overdose deaths have an increasing trend and have surpassed the rates of drug overdose deaths in urban counties. In addition, Keyes at al. (2014) found that increased sales of opioids in rural areas result in higher availability of opioids for nonmedical use. According to the authors' findings, there are three main reasons behind the increased use of opioids: (i) there is an increased availability of prescription opioids, (ii) opioid use has a lower perception of harm than other illicit drugs, and (iii) opioids are often used to self-medicate for pain.

The next explanatory variable in the present study is the number of law enforcement personnel in per 100,000. The FBI UCR program defines the number of law enforcement personnel as those who ordinarily carry a firearm, have full arrest power, and are paid from governmental funds. In our study, the number of law enforcement personnel data is obtained from the FBI Crime Uniform Program. It shows the number of law enforcement personnel per 100,000 people. Due to a problem of endogeneity between crime and the number of law enforcement personnel, it is likely to have biased results. To break down the endogeneity problem between crime and the number of law enforcement personnel, an instrumental variable "annual average police wage" from local governments is employed. The annual average police wage data comes from the Bureau of Labor Statistics.

The common thought supports that the presence and availability of police protection is an important contributor of public safety. It is likely to have lower crime rate if the county residences provide more funding for public services. Table 1 shows the median annual average police officer's wage is slightly higher in urban counties. While the mean police wage is $89,528 in the urban counties, it is $93,642 in the rural counties.

Median household income, educational attainment, unemployment rate, poverty rate, demographic indicators and labor force statistics come from the U.S. Census Bureau. Household income data includes the income level of householders who are 15 years and older. Median household income data are based on the average income distribution of all individuals. The data is calculated again by the changes in inflation rate with 2012 accepted as the base year. The Census Bureau Current Population Survey (CPS) provides information about county-level annual high school graduation rate. The ratio of the number of high school graduates to the population is calculated for each county. High school graduation rates are very similar for the urban and rural counties.

Unemployment rate and labor force data are also included in our model. The U.S. Census Bureau provides data that measure the counties of the nation's workforce, including labor force and unemployment rates. Table 1 shows that while labor force statistics are significantly different for urban and rural counties, unemployment rates are very slightly different for the urban and rural counties. The poverty rate in each county presents the percentage of the individuals those have income less than poverty line. The poverty rate comes from the U.S. Census Bureau. According to the poverty statistics, Sioux, North Dakota has the highest poverty rate (40.4%) among metropolitan counties. Crowley, Connecticut has the highest poverty rate (51.2%) among the metropolitan counties. Lastly, as stated by Fazel et. al (2015), social-demographic factors have a significant impact on the occurrence of crime. To estimate the impact of gender, age and race, nine demographic variables are included: percentage of population that identifies as African-American, American Indian, Asian, other Pacific Islander, Hispanic, non-Hispanic, female, rural and population aged between 18 -65.

Estimation and Results

Tables 3A,3B, 4A and 4B present the impact of mental health issues and opioid abuse on the probability of violent and property crimes in urban counties. Table 3A and table 3B present five models for violent crimes, and, Table 4A and 4B present the four models for property crimes. All the models are estimated by using fixed-effect approaches. The main advantage to the fixed-effect approach is that the fixed effect models can account for any unobserved time-invariant features that can estimate incidence of crime, and those may be correlated with some of the independent variables (Markowitz, 2005).

There are some issues with the estimations. As discussed in the previous sections, the number of law enforcement personnel can be endogenous in a crime regression. An instrumental variable: the annual average wages per employee by the local governments is employed in the fixed-effect estimations (NAICS 922 Justice, public order, and safety activities). The impact of the instrumental variable on the crime statistics is well-founded (Mas, 2006). Mas's analysis shows that as the officers receive their salary demand, arrest rate will increase. Additionally, if the officers lose arbitration cases, police performance will decrease (Mas, 2006). One of the other main issues to address in the present study is endogeneity. To detect the endogenous regressors, the Hausman specification test is performed.

Violence in urban counties

Table 3A, 3B, 4A, and table 4B show the estimation results for the probability of violence in the urban counties of the U.S. The most salient result is that the number of mentally unhealthy days is positively associated with the incidence of rape, assault and burglary. The number of mentally unhealthy days defines the burden of disabilities and chronic diseases in a population. The results show that a 1 unit increase in the number of mentally unhealthy days will increase the number of rapes by 8 per 100,000, assault by 66 per 100,000, and by burglary 131 burglary per 100,000 in urban counties. Additionally, the physical inactivity rate shows positive association with assault, burglary, grand larceny and motor vehicle theft. An increase in the physical inactivity rate increase the number of assaults by 10, burglary by 20, grand larceny by 37 per 100,000 population.

The estimation results provide evidence on the impact of the number of mental health providers on the urban area crimes. While an increase in the number of mental health providers helps to lower the property crimes and burglary in urban counties, it does not show the same impact on violent crimes.

The FBI's Preliminary Semiannual Uniform Crime Report, January - June 2017 reports that during the first six months of 2017, overall crime had a decreasing trend; though the number of murders increased by 1.5 percent (FBI, 2017). According to Rosenfeld's recent study (2017), the rise in use of opioid painkillers was one of the strongest factors of the rise in overdose deaths. (Rosenfeld, Gaston, Spivak, & Irazola, 2017). Our analysis also shows that there is a positive link between increased opioid use and property crimes but not violent crimes. The estimation results show that opioid use has a statistically significant impact on the all property crimes, burglary and grand larceny but not on any other crime statistics.

As discussed previously, the model employed in the present study consisted of issues with endogeneity in the number of law enforcement and crime. One of the most common principles of deterrence theory is that an increase in the number of law enforcement personnel results in a decrease in the crime statistics. Empirical studies in crime literature employ several approaches to deal with these biased estimations. In our study, instrumental variable approach (IV) is utilized to tackle the potential endogeneity issue. The Quarterly Census of Employment and Wage data from the Bureau of Labor Statistics provides annual average salary statistics for justice, public order, and safety activities employees (NAICS 922) by local governments. The annual average wage per employee data is employed as an instrumental variable.

The results highlight that the number of law enforcement has a statistically significant impact on the robbery rates. In urban counties, each additional law enforcement employee decreases the robbery rates by 8 per 100,000 population, respectively. While one can see that any change in the number of law enforcement personnel has an impact on the robbery rates, it does not have an impact on the other crime categories. Previous crime literature provides similar findings (Corman & Mocan, 2000; Tella & Schargrodsky, 2004).

Unemployment has the potential to motivate people to earn income through illegal activities. The estimates in the tables support this common assumption. The strongest results are found for property crimes. A significant relationship between unemployment rate and property crimes of burglary, grand larceny, and motor vehicle theft was identified. A one percent point increase in the unemployment rate increases the burglary rate by 106 per 100,000. Similarly, an additional one percent point increase in the unemployment rate causes about 122 more grand larceny rate per 100,000. These estimated coefficients indicate that any change in the unemployment rate creates a stronger impact for crime motivation for property crimes in urban counties. Also, the unemployment rate has impact on the incidence of murder and robberies.

Additionally, high school graduation is one of the strongest variables in our model. As stated by Lochner (2003), schooling is one of the most significant factors which lowers the incarceration rate. Tables 3B and 4B show that with the exception of grand larceny and assault, an increase the high school graduation rate decreases the occurrence of crime in urban counties. The present study also provides evidence on the impact of demographic characteristics on the urban area crimes. The share of native Hawaiian and Hispanic population has a positive association with the number of rape, and female population density has a negative impact on the occurrence of rape in urban counties. On the other hand, the results do not provide any evidence on the impact of demographic indicators impact on increasing crime.

Violence in the rural counties

Based on federal crime data, the rural area violent crime rate has been higher than the national average for the last decade. According to the crime researchers' analysis, increased drug abuse and limited number of police officers are some of the explanations for increasing violence in rural counties. Additionally, farmers' mental health issues related to financial problems could contribute. The United States Department of Agriculture (USDA) estimated that the net income of farmers has decreased by 50% since 2013. As a results of farmers' financial problems, suicide rates among "farming, fishing, and forestry" occupational groups are significantly higher than in any other occupation (CDC, 2018).

Tables 5A, 5B, 6A and 6B display results using rural counties as units of analysis. One of the most salient factors which increase the incidence of rural area crimes is the number of mentally unhealthy days. As presented in Table 5A, an increase in the number of mentally unhealthy days has positive impact on murder. A 1-unit increase results in about 1.3 more murder in 100,000 population. Additionally, one can see that a 1-unit increase in the mentally unhealthy days increases the all violent crime by 11 in 100,000 population. Unlike what is seen in urban area, the opioid prescription rate has no impact on the incidence of crimes within rural populations.

Additionally, as stated on Table 6, unemployment rate is one of the most powerful factors which has an impact on rural area robberies but not the other crime categories. Based on the findings, an increase in the unemployment rate increases the number of robberies, but it does not have an impact on the rural crime rate as a whole. The estimates for rural counties show that unlike urban area crime results, the number of mental health providers have limited impact on the violent or property crime rates. According to a new study, psychiatrists, psychologists, and psychiatric nurse practitioners are not distributed equally in every part of the U.S. Moreover, 65% of the rural counties do not have a psychiatrist (Andrilla, Patterson, Garberson, Coulthard, & Larson, 2018). Similarly, the number of law enforcement personnel does not show a statistically significant impact on rural area crime rates.

Lastly, our results provide evidence that attainment of high school diplomas has a significant impact on lowering motor vehicle theft. A one percentage point increase in the high school graduation rate leads to decrease in total motor vehicle theft by about 16 in 100,000 population. The influence of education on crime prevention is discussed by Machin et al. (2011). Improving education supports better social benefits, and through better social and economic outcomes, a reduction in crime can be observed (Machin, Marie, & Vujic, 2011). Additionally, in the present study, the importance of poverty rate of the population is analyzed. Based on the outcomes, poverty rate is positively related to number of rapes and robberies by coefficient of 0.021 and 0.071.

In light of what is stated above, results support the explanatory variables have limited explanation power on the occurance of crime in rural counties.

Conclusion

Mental health disorders have commonly been associated with incidence of violence. Based on this association, the main objective this study is to determine whether better mental health outcomes can be used as a tool to reduce violence. The econometric framework in this study provides the means to answer this question. The present study provides empirical evidence about mental health disorders in urban areas related to the occurrence of crimes. It is interesting to note that while the number of mental health providers per 100,000 people is about 70% higher in rural counties, the number of providers shows limited impact on the reducing of crime in rural communities.

Estimations of the impact of opioid prescription rates on crime prove that opioid abuse is positively associated with all property crime categories in urban counties expect motor vehicle theft. Additionally, the findings from the fixed-effect model support that the physical inactivity rate does not have an impact on rural county crime rates. On the other hand, it is positively associated with instances of assault, burglary and grand larceny in urban counties.

The results of this study can be used to provide empirical analyses to help policymakers reduce crime via mental health treatment. Our findings show that an increase in the number of mental health providers may be an effective way to decrease crime in urban areas. Future works may contribute to the literature about the reasons why rural area mental health providers have very limited impact on reducing crime. Lastly, opioid abuse and its impact has become a growing interest of the researchers. Investigating the relationship between crime and opioid use may motivate policy makers to reduce crimes in urban counties.

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Tables and Figures

Table 1: Summary Statistics

	Rural				Urban			
Variables	Mean	Median	Min	Max	Mean	Median	Min	Max
Demographics								
African American	8.3	1.3	0	86.3	10.5	5.4	0	74.7
American Indian/ Alaskan Native	2.51	0.524	0	87.4	1.09	0.498	0	83.7
Asian	0.894	0.467	0	43.9	2.06	1.07	0	34.1
Native Hawaiian/ Other Pacific Isl.	0.0876	0.0324	0	12.7	0.107	0.0616	0	2.42
Hispanic	8.04	2.93	0	97.2	9.51	4.68	0.3	95.6
Non-Hispanic	79.4	88	-0.3	99.6	75.8	80.4	3.5	98.9
Female	49.8	50.4	25.1	56	50.4	50.6	34.1	58
Rural	66.7	67.4	0	100	41	32.9	0	100
Population aged 18-65 (percentage)	59.9	59.7	45.7	84.7	61.9	61.9	40.7	75.4
Opioid Prescribing Rates	90.8	85.5	0	578	83.9	81	0	335
Physical Inactivity Rate (percentage)	28.5	29	9.2	44	25.4	26	0	43.5
Mental Health Providers (per 100,000)	60.8	9	0	10800	160	30	0	24600
High School Education (percentage)	0.827	0.84	0	1	0.811	0.83	0	1
Mentally Unhealthy Days per year	3.51	3.4	0.4	10.1	3.31	3.4	0	7.2
Median Household Income	46.00	43.20	22.8	122.4	52.8	50.7	28.5	126
Labor Force (Thousands)	23	8.23	0.067	2020	111	46.8	0.381	5010
Unemployment Rate	6.8	6.5	1.1	20.7	6.62	6.3	2.2	27.4
Poverty Rate	18.1	17.4	3	47.3	14.99	14.60	3.30	40.40
Total Law Enforcement (per 100,000)	20.6	16.5	0.393	1520	135	115	0	3290
Annual Average Police Wage	83224	89528	0	30752	87389	93642	0	403624
Violent Crime (per 100,000)	10.1	6.46	0	323	94	55.5	0	2190
Murder (per 100,000)	0.164	0	0	13.9	1.34	0	0	64.4
Rape (per 100,000)	1.31	0.646	0	69.1	8.9	3.89	0	392
Robbery (per 100,000)	0.557	0	0	117	10.2	3.71	0	259
Assault (per 100,000)	8.11	4.69	0	316	72.5	39.1	0	1890
Property Crime (per 100,000)	76.6	59.5	0	5130	735	538	0	12700
Burglary (per 100,000)	25.2	18.7	0	1100	217	158	0	4320
Grand Larceny (per 100,000)	46.5	35.3	0	3850	475	320	0	8270
Motor Vehicle Theft (per 100,000)	5.04	3.52	0	202	48.4	30.8	0	1020

Table 2: Definitions and Data Sources

Variables	Definition	Data Source
Opioid Prescribing Rates	Retail opioid prescriptions dispensed per 100 persons	U.S. Centers for Disease Control and Prevention
Number of mentally unhealthy days	Number of self-reported days of poor mental health per year	The University of Wisconsin Population Health Institute
Physical Inactivity Rate	Percentage	The University of Wisconsin Population Health Institute
Mental Health Providers	Number of mental health treatment facilities per capita	National Plan and Provider Enumeration System (NPPES)
High School Education	High school completion rate	U.S. Census Bureau
Total Law Enforcement	Number of law enforcement personnel per 100,000	FBI The Uniform Crime Reporting (UCR) Program
Annual Average Police Wage	Annual wage rates for Justice and safety personnel	U.S. Bureau of Labor Statistics
Median Household Income	Median household income level	U.S. Census Bureau
Demographics	Percentage of population	U.S. Census Bureau
Labor Force (Thousand)	Number of people employed and looking for work	U.S. Census Bureau
Unemployment Rate	Percentage of people not employed	U.S. Census Bureau
Poverty Rate	Percentage of people under poverty line	U.S. Census Bureau
Violent Crime	Number of violent crime per 100,000 people	U.S. Census Bureau
Murder	Number of murder crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Rape	Number of rape crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Robbery	Number of robbery crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Assault	Number of assault crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Property	Number of property crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Burglary	Number of burglary crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Larceny	Number of grand larceny crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Motor Theft	Number of motor theft crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program

Table 3A: The impact of mental health on violent crime in the US urban counties: Fixed effect regressions

Variables	All Violent Crime	Murder	Rape	Robbery	Assault
Const	48.92	0.205**	2.621***	2.383*	13.80***
	(56.12)	(0.087)	(0.522)	(1.865)	(3.281)
Demographics					
African American	-0.778	0.409*	0.416	0.116	0.137
	(4.301)	(0.159)	(0.809)	(1.017)	(5.003)
American Indian/ Alaskan Native	4.453	-0.656	3.133	-0.561	1.940
	(14.83)	(0.790)	(2.805)	(4.1003)	(15.17)
Asian	7.921	-0.004	4.518	0.852	5.957
	(16.45)	(0.003)	(2.742)	(3.717)	(13.09)
Native Hawaiian/ Other Pacific Isl.	-22.13	-0.178	17.81*	3.445	-39.81
	(69.15)	(1.990)	(11.12)	(13.87)	(60.12)
Hispanic	17.94	-0.107	4.702*	0.133	10.31
	(11.45)	(0.943)	(1.205)	(3.624)	(14.78)
Non-Hispanic	1.215	-0.436	-0.174	-0.107	1.687
	(5.666)	(0.199)	(0.821)	(1.557)	(6.931)
Female	8.148	0.117	-3.001*	-1.508	-1.671
	(8.751)	(0.297)	(1.158)	(1.996)	(8.880)
Rural	-0.650	-0.005	0.143	0.121	-0.345
	(0.902)	(0.002)	(0.991)	(0.141)	(0.275)
Population aged 18-65	-9.931	0.351	-5.113	-1.113	-6.102
	(10.44)	(0.475)	(3.651)	(3.867)	(13.96)
Opioid Prescribing Rates	0.044	-0.000	-0.002	-0.002	0.005
	(0.091)	(0.000)	(0.002)	(0.001)	(0.007)
Mentally Unhealthy Days	-3.715	0.008	0.084**	0.033	0.661**
	(8.244)	(0.007)	(0.042)	(0.069)	(0.265)
Physical Inactivity Rate	0.522	0.001	-0.004	0.009	0.101***
	(0.774)	(0.001)	(0.006)	(0.009)	(0.036)

Notes: Robust standard errors are reported in parentheses.
(*) Statistical level of significance: $p < 0.1$, (**) Statistical level of significance: $p < 0.5$, (***) Statistical level of significance: $p < 0.01$.

Table 3B: The impact of mental health on violent crime in the US urban counties: Fixed effect regressions (Continued)

Variables	All Violent Crime	Murder	Rape	Robbery	Assault
Mental Health Providers	-0.002	-0.000	-0.000	-0.000	-0.0004
	(0.002)	(0.000)	(0.000)	(0.000)	(0.0002)
High School Education	-50.94	-29.2***	-1.624***	-4.686***	-5.998
	(52.01)	(0.055)	(0.330)	(0.547)	(2.075)
Total Law Enforcement	-2.791	0.027	0.039	-0.008*	-0.008
	(5.068)	(0.038)	(0.148)	(0.006)	(0.290)
Median Household Income	0.241	0.0005	-0.004	0.02	-0.015
	(0.444)	(0.0007)	(0.004)	(0.03)	(0.027)
Labor Force	0.000	0.000	-0.000	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Rate	0.738	0.005**	-0.019	0.056**	0.111
	(1.151)	(0.002)	(0.015)	(0.025)	(0.097)
Poverty Rate	0.770	0.003	-0.014	0.031	0.058
	(1.271)	(0.001)	(0.010)	(0.018)	(0.068)
R-squared	0.25	0.16	0.18	0.14	0.22
Observations	923	923	923	923	923

Notes: Robust standard errors are reported in parentheses.
(*) Statistical level of significance: $p < 0.1$, (**) Statistical level of significance: $p < 0.5$, (***) Statistical level of significance: $p < 0.01$.

Table 4A: The impact of mental health on property crime in the US urban counties: Fixed effect regressions

Variables	All Property Crime	Burglary	Grand Larceny	Motor Theft
Const	15.2	26.71	80.06***	8.894***
	(26.59)	(27.52)	(17.97)	(2.370)
Demographics				
African American	9.001	1.489	9.754	1.761
	(35.98)	(13.88)	(26.71)	(1.954)
American Indian/ Alaskan Native	-5.551	-14.10	-8.905	4.078
	(123.9)	(48.44)	(60.90)	(6.771)
Asian	109.1	25.09	56.89	7.442
	(118.1)	(37.09)	(61.95)	(7.961)
Native Hawaiian/ Other Pacific Islander	172.8	16.96	59.83	25.89
	(444.9)	(168.0)	(245.4)	(33.34)
Hispanic	47.89	9.807	40.96	6.219
	(109.8)	(41.08)	(79.02)	(8.007)
Non-Hispanic	31.48	11.325	17.67	1.997
	(38.49)	(17.19)	(24.42)	(2.707)
Female	40.61	0.791	-31.80	-8.859
	(69.23)	(29.88)	(44.89)	(4.612)
Rural	5.569	0.501	3.326	0.201
	(5.980)	(1.859)	(4.561)	(0.298)
Population aged 18-65	-37.88	-0.903	-20.22	-2.987
	(118.9)	(31.66)	(44.32)	(8.711)
Opioid Prescribing Rates	0.149***	0.055***	0.097**	0.002
	(0.057)	(0.016)	(0.638)	(0.005)
Mentally Unhealthy Days	2.416	1.315**	0.675	0.228
	(2.148)	(0.608)	(1.451)	(0.191)
Physical Inactivity Rate	0.595	0.203**	0.370*	0.057**
	(0.294	(0.083)	(0.119)	(0.026)

Notes: Robust standard errors are reported in parentheses.
(*) Statistical level of significance: p < 0.1, (**) Statistical level of significance: p < 0.5, (***) Statistical level of significance: p < 0.01.

Table 4B: The impact of mental health on property crime in the US urban counties: Fixed effect regressions (Continued)

Variables	All Property Crime	Burglary	Grand Larceny	Motor Theft
Mental Health Providers	-0.005***	-0.001	-0.004	-0.0002
	(0.002)	(0.000)	(0.001)	(0.0001)
High School Education	-145.68***	-37.55***	-97.59	-13.20**
	(16.81)	(4,785)	(91.35)	(1,498)
Total Law Enforcement	-12.97	-2.762	-10.52	0.353
	(25.18)	(5.810)	(19.51)	(0.747)
Median Household Income	0.322	-0.001	0.302	0.029
	(0.219)	(0.062)	(0.408)	(0.019)
Labor Force	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Rate	2.388***	1.068***	1.227	0.126*
	(0.791)	(0.224)	(0.534)	(0.070)
Poverty Rate	0.069	0.112	-0.092	0.084*
	(0.556)	(0.157)	(0.375)	(0.049)
R-squared	0.24	0.21	0.24	0.21
Observations	923	923	923	923

Notes: Robust standard errors are reported in parentheses.
(*) Statistical level of significance: $p < 0.1$, (**) Statistical level of significance: $p < 0.5$, (***) Statistical level of significance: $p < 0.01$.

Table 5A: The impact of mental health on violent crime in the US rural counties: Fixed effect regressions

Variables	All Violent Crime	Murder	Rape	Robbery	Assault
Const	-18.34	1.141	101.4	1.899	101.4
	(16.10)	(1.156)	(737.4)	(3.125)	(737.4)
Demographics					
African American	0.711	0.001	-0.109	0.088	0.277
	(0.707)	(0.005)	(0.607)	(0.096)	(0.563)
American Indian/ Alaskan Native	0.661	0.007	-0.405	-0.006	0.566
	(0.704)	(0.028)	(0.655)	(0.007)	(0.876)
Asian	0.609	0.003	-0.308	-0.177*	1.139
	(0.893)	(0.007)	(0.311)	(0.059)	(0.287)
Native Hawaiian/ Other Pacific Isl.	6.778	-0.888	0.144	-0.291	6.897
	(18.91)	(0.967)	(7.567)	(1.122)	(19.76)
Hispanic	0.399	0.145	-0.033	-0.073	0.798
	(0.877)	(0.312)	(0.121)	(0.091)	(0.345)
Non-Hispanic	0.654	0.013	-0.192	-0.000	0.378
	(0.745)	(0.035)	(0.112)	(0.033)	(0.745)
Female	-0.099	0.111	-0.127	0.121	-0.677
	(0.718)	(0.034)	(0.299)	(0.909)	(0.821)
Rural	0.000	0.002	0.019	-0.005	0.000
	(0.002)	(0.004)	(0.022)	(0.006)	(0.000)
Population aged 18-65	-0.609	-0.011	0.009	0.029	-0.331
	(0.885)	(0.027)	(0.091)	(0.041)	(0.492)
Opioid Prescribing Rates	0.004	0.000	0.019	0.004	0.019
	(0.016)	(0.001)	(0.014)	(0.002)	(0.140)
Mentally Unhealthy Days	1.153**	0.129**	-5.435	-0.321	-5.435
	(0.678)	(0.063)	(41.72)	(0.226)	(41.72)
Physical Inactivity Rate	0.203	0.008	-0.655	-0.006	-0.655
	(0.139)	(0.013)	(4.867)	(0.025)	(4.867)

Notes: Robust standard errors are reported in parentheses.
(*) Statistical level of significance: $p < 0.1$, (**) Statistical level of significance: $p < 0.5$, (***) Statistical level of significance: $p < 0.01$.

Table 5B: The impact of mental health on violent crime in the US rural counties: Fixed effect regressions (Continued)

Variables	All Violent Crime	Murder	Rape	Robbery	Assault
Mental Health Providers	0.006	0.000	-0.015	-0.001	-0.015
	(0.005)	(0.005)	(0.116)	(0.000)	(0.011)
High School Education	5.652	0.225	-20.95	-1.315	-20.94
	(6.788)	(0.648)	(147.1)	(1.157)	(147.16)
Total Law Enforcement	-1.098	-0.007	-4.73	-0.155	-4.739
	(0.135)	(0.013)	(35.49)	(0.097)	(35.49)
Median Household Income	0.193	-0.005	0.243	0.031	0.243
	(0.512)	(0.009)	(1.96)	(0.013)	(1.959)
Labor Force	0.000	0.000	0.000	0.000	0.000
	(0.00)	(0.000)	(0.00)	(0.000)	0.000
Unemployment Rate	-0.002	-0.01	1.035	0.098*	1.035
	(0.001)	(0.029)	(7.789)	(0.056)	(7.780)
Poverty Rate	0.131	-0.008	0.021**	0.071**	0.246
	(0.141)	(0.012)	(1.94)	(0.033)	(1.990)
R-squared	0.13	0.11	0.11	0.13	0.16
Observations	552	559	502	559	557

Notes: Robust standard errors are reported in parentheses.
(*) Statistical level of significance: $p < 0.1$, (**) Statistical level of significance: $p < 0.5$, (***) Statistical level of significance: $p < 0.01$.

Table 6A: The impact of mental health on property crime in the US rural counties: Fixed effect regressions

Variables	All Property Crime	Burglary	Grand Larceny	Motor Theft
Const	485.25	175.37	309.1	38.28
	(361.5)	(132.8)	(231.4)	(39.74
Demographics				
African American	7.912	1.891	4.319	0.604
	(9.821)	(2.871)	(5.781)	(0.741)
American Indian/ Alaskan Native	7.673	0.532	5.225	0.876
	(7.771)	(1.333)	(3.491)	(0.933)
Asian	1.998	-1.328	2.578	0.007
	(4.887)	(1.777)	(4.771)	(0.323)
Native Hawaiian/ Other Pacific Islander	187.1	45.78	166.9	11.81
	(178.6)	(53.41)	(109.7)	(23.52)
Hispanic	2.247	0.517	4.006	0.141
	(3.335)	(1.001)	(3.971)	(0.189)
Non-Hispanic	6.998	0.846	6.241	0.456
	(4.154)	(1.891)	(3.322)	(0.971)
Female	1.998	0.754	1.629	0.003
	(4.786)	(0.991)	(2.998)	(0.117)
Rural	0.986	-0.181	-0.771	-0.008
	(0.991)	(0.193)	(0.361)	(0.009)
Population aged 18-65	-1.211	0.418	-1.441	-0.067
	(2.912)	(0.944)	(1.580)	(0.188)
Opioid Prescribing Rates	0.367	0.150	0.181	0.020
	(0.276)	(0.100)	(0.173)	(0.002)
Mentally Unhealthy Days	-30.45	-11.723	-18.62	-2.904
	(27.20)	(9.995)	(17.33)	(2.222)
Physical Inactivity Rate	-2.415	-0.947	-1.129	-0.024
	(2.753)	(0.999)	(1.726)	(0.222)

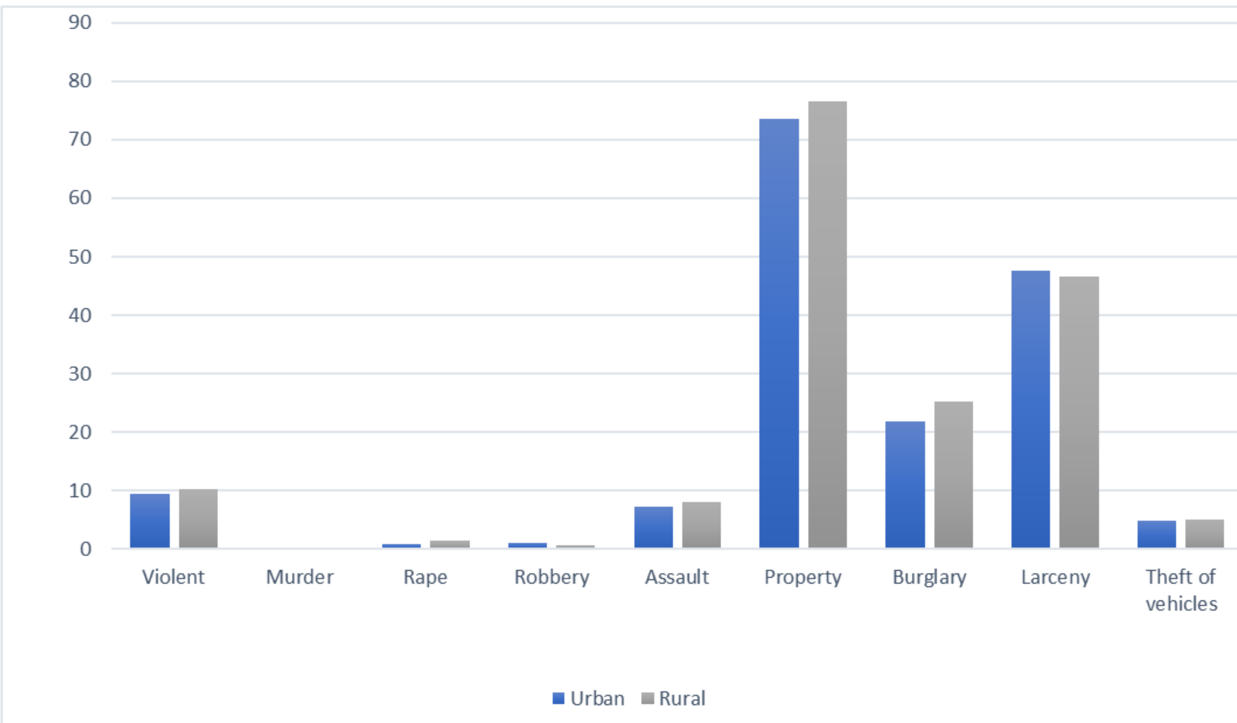
Notes: Robust standard errors are reported in parentheses.
(*) Statistical level of significance: $p < 0.1$, (**) Statistical level of significance: $p < 0.5$, (***) Statistical level of significance: $p < 0.01$.

Table 6B: The impact of mental health on property crime in the US rural counties: Fixed effect regressions (Continued)

Variables	All Property Crime	Burglary	Grand Larceny	Motor Theft
Mental Health Providers	-0.087	0.030	-0.054	0.006
	(0.068)	(0.024)	(0.043)	(0.005)
High School Education	-148.6	49.48	-99.9	-16.52*
	(112.6)	(41.40)	(71.18)	(9.115)
Total Law Enforcement	-15.60	-6.087	-9.133	-1.296
	(12.61)	(4.624)	(8.082)	(1.097)
Median Household Income	-0.484	0.100	0.207	0.096
	(1.421)	(0.519)	(0.888)	(0.114)
Labor Force	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Rate	5.763	2.854	2.804	0.282
	(3.970)	(1.452)	(2.504)	(0.321)
Poverty Rate	1.373	0.517**	0.588	0.155
	(2.373)	(0.866)	(1.480)	(0.196)
R-squared	0.13	0.13	0.13	0.22
Observations	558	559	559	558

Notes: Robust standard errors are reported in parentheses.
(*) Statistical level of significance: $p < 0.1$, (**) Statistical level of significance: $p < 0.5$, (***) Statistical level of significance: $p < 0.01$.

Figure 1: Crime trends in urban and rural counties in the US - during 2012-2015
(Recorded offences per 100,000of population)



Welfare payments, food stamps, and crime: Evidence from US county-level data

Introduction

An extensive crime literature documents that criminal activities are motivated by labor market conditions and the acquisition of cash (Carr & Packham, 2017; Wright et al., 2014; Armey, Lipow, & Webb, 2014; Lovett, 2018). Over the past few years, a number of studies have investigated the impact of social assistance programs such as the Supplemental Nutrition Assistance Program (SNAP, formerly the Food Stamp Program) on criminal activities in the United States.

SNAP is the largest government funded nutrition assistance program. It provides benefits to low income families and individuals. According to a recent statistic released by the United States Department of Agriculture, as of January 2019, about 20 million households and 40.5 million Americans receive SNAP benefits. Survey data shows that approximately one sixth of all children in the United States receive SNAP benefits (USDA, 2019). In addition to reducing food insecurity and inequality, SNAP benefits may contribute to a large reduction in criminal activities. The link between timing of welfare payments and crime is discussed by a number of researchers (Carr & Packham, 2017; Foley F., 2008; Lovett, 2018). As stated by Carr and Packham (2017), most SNAP recipients spend benefits from SNAP during the second or third week following receipt. Using day-level administrative data, the authors found that during the second- and third-weeks following SNAP receipt, there is a decrease in theft. Then, there is an increase in theft during the last week of the benefit cycle (Carr & Packham, 2017). Similarly, Foley (2008) examined the timing effect of welfare payments on crime. Foley's analysis, based on daily reported incidents of major crimes in twelve U.S. cities, shows that monthly welfare payments are more likely to have a negative impact on financially motivated crimes such as burglary, larceny-theft, motor vehicle theft, and robbery.

The main objective of this paper is investigating the impact of social assistance programs on crime. As one of the most prominent and largest federal food assistance programs, SNAP is covered in the present study. While previous work has looked at the effect of the timing of SNAP benefits on criminal activities, this paper is the first to investigate the impact of changes in the SNAP program on criminal activities in rural and urban counties in the United States. In doing so, this paper contributes to the literature in two ways: (1) estimating the effect of the SNAP program on criminal activities, and (2) comparing the results for urban and rural counties. Our study proceeds as follows: The next section provides a presentation of the econometric approach and empirical specification. This section is followed by .a discussion of the data used in the study. Finally, the results and conclusion are discussed.

Empirical Methodology

We are interested in examining the causal relationship between crime and changes in SNAP benefits in rural and urban counties in the United States. Therefore, we employ a simple crime model to explain the association between our dependent and independent variables. The analytical framework used in this study is developed from the economic models of crime by Becker (1968). According to Becker's study, criminal activities result from the performance of the deterrent factors and personal characteristics of the criminals.

This study also follows the models stated below:

$$CR_{it} = \beta_0 + \beta_1 W_{it} + \beta_2 SNAP_{it} + \beta_3 HHSnap_{it} + \beta_4 Unemp_{it} + \beta_5 LF_{it} + \beta_6 Inc_{it} + \beta_7 D_{it} + \gamma_{it} + \varepsilon_{it} \tag{1}$$

Equation (1) presents a crime supply equation where CR_{it} is the crime rate in county i and year t. We utilize an annual dataset. $SNAP_{it}$is the first dummy variable in the model. It presents the increase in SNAP benefits during the recession years of 2009 to 2013. The second dummy variable is presented by W . It captures whether or not the county had in place a waiver so that unemployed adults without children could receive benefits (waiver). $HHSNAP_{it}$ represents the percentage of household receiving the food stamps, $Unemp$ presents the unemployment rate, *LF* presents the labor force, *Inc* is the median household income, *D* presents the share of several demographic groups: (1) male, (2) female, (3) white, (4) African- American, (5) American- Indian, (6) Asian, (7) Native Hawaiian, and (8) Hispanic. $\gamma_{it}$is the county fixed effect variable. Lastly, the error term ε_{it} covers the unobserved individual attributes.

We employ fixed effects regression approach to estimate equation (1). An important advantage of the fixed effects model is that it accounts for any unobserved time-invariant characteristics that can be correlated with the some of the explanatory variables (Markowitz, 2005).

Data

Based on federal crime data, the rural violent crime rate was above the national average during the last decade (FBI, 2019). To investigate the impact of SNAP benefits on crime a panel data approach is implemented. A county level annual dataset for the years 2009 and 2015 was obtained. Our SNAP data comes from the American Community Survey from the Census Bureau. These survey data provide information on the number of households receiving SNAP benefits. The annual crime statistics used in the present study come from Federal Bureau of Investigation (FBI) Uniform Crime Reporting (UCR) Program. The number of crimes per 100,000 people in each year is used as an outcome variable. The crime dataset covers statistics on property crime including burglary, larceny-theft, and motor vehicle theft and also on violent crime including murder, rape, robbery, and aggravated assault.

Table 1 shows the definition of variables and provides a description of the main data sources. The sample of 3134 counties in this study includes 1166 urban counties and 1968 rural counties. To assess the impact of changes in the SNAP program, two dummy variables are used, one to capture whether or not the county had in place a waiver so that unemployed adults without children could receive benefits (waiver) and another to capture the temporary increase in SNAP benefits during the recession years of 2009 to 2013.

Dependent Variables

The number of crimes by violent and property categories is obtained from the Federal Bureau of Investigation (FBI)'s statistics department. The FBI Uniform Crime Reporting program (UCR) provides data from 18,000 regional agencies. The UCR separates violent crime into four offense categories: murder, forcible rape, robbery, and aggravated assault. For property crime, there are four crime categories: burglary, larceny-theft, motor vehicle theft, and arson. Because of limited data availability for arson, this crime type is not included in our study.

The outcome variables are the number of crimes per 100,000 population in each county. Table 2 shows the means and standard deviations of all the variables for both urban and rural counties. According to the simple statistics, the incidence of property crime is about 76% more likely in urban counties and the incidence of violent crime is about 50% more likely in urban counties. The statistics show that in both regions, murder has the lowest occurrence rate and larceny theft has the highest.

Explanatory Variables

The data on households receiving food stamps/SNAP are obtained from the U.S. Census Bureau. This variable gives the percentage of households participating in the program. The statistics show that among rural counties, Owsley County, Kentucky, has the highest SNAP participation rate, 48%. In urban counties Sioux County, North Dakota, has the highest SNAP participation, 39%. Median household income, unemployment rate and labor force participation are also included as right-hand side variables. The variable for the unemployment rate gives the percentage of population older than 16 years old who are not employed and looking for a job. The Census Bureau provides county level annual estimates of the unemployment rate.

Two dummy variables capture changes in the SNAP program that affected both benefits level and who could receive benefits. The first dummy variable, "waiver" presents the SNAP certification policy waiver statues of each counties. According to the law, each state may request to waive their time limit particularly for the higher-unemployment areas. If a county waived the three-month time limit, it is given 1. If a county has its time limit to provide SNAP benefit, it is given 0. As part of the1996 Personal Responsibility and Work Opportunity Act, the general rules of the SNAP program prevent unemployed adults aged 18 to 50 without dependent children from receiving SNAP benefits for more than three months in any 36-month period. States may seek waivers to temporarily suspend this three-month limit for individuals in areas of high unemployment. Seeking the waiver is optional for states, and thus areas with similar unemployment levels may have different rules for unemployed adults without dependent children. Further, USDA has firm guidelines on which states are eligible for these waivers. During the recession, Congress passed the 2009 American Recovery and Reinvestment Act (ARRA), which allowed USDA to grant waivers for a larger portion of the country because of the generally high level of unemployment (Bolen & Dean, 2018). Information on which areas had waivers that allowed for unemployed adults without dependent children to collect benefits for more than a three-month period was obtained from the U.S. Department of Agriculture, Food and Nutrition Service.

In addition to allowing states to more easily receive waivers for unemployed adults without dependent children, the 2009 ARRA temporarily expanded the amount of SNAP benefits. SNAP is a supplement to a household's nutritional needs for every month. The income of families and expenses are two indicators of the size of SNAP benefits. According to the federal rule, there are three things to determining the eligibility of families for SNAP: (i) generally the gross monthly income must be 130 percent of the poverty line, (ii) households' income after deduction must be below poverty line, and (iii) assests must be below some certain limits. (U.S. Department of Agriculture, Food and Nutrition Service, 2019). From April 2009 through October 2013, the maximum monthly benefit was increased by 13.6% and benefits for households who received less than the maximum but more than the minimum increased by the same dollar amount as for households of the same size receiving the maximum benefit, meaning the average percentage increase for these households would be somewhat larger. Households receiving the minimum benefit received a $2 per month increase in benefits in 2009 (Jennings & Rosenbaum, 2015). As a second dummy variable, "SNAP" is used to show the peak year in SNAP benefit payments. One can see that from 2009 to 2013 there is a significant increase in SNAP benefit payments. So, the time period between 2009 and 2013 are given "1", the other are given "0".

To combine regression predictions with direct estimates from the American Community Survey, we utilize the Small Area Income and Poverty Estimates (SAIPE) program's models. (American Community Survey, 2016). Median household income data are based on the average income distribution of all individuals. The data is adjusted for inflation with 2009 as the base year.

Also, the data set includes the share of different demographic groups as another explanatory variable. The percentage of men is one category. The shares of six different races in rural and urban counties are also included: (i) white, (ii) African-American, (iii) American-Indian, (iv) Asian, (v) Native Hawaiian, and (vi) Hispanic. To deal with multicollinearity issue, The category with at least two races are omitted. The race and gender statistics are obtained from the United States Census Bureau database.

Results

Table 3 presents the main results regarding SNAP's impact on violent crime in rural counties. Column 1 examines the responses for all violent crime, column 2 examines the responses for murder, column 3 examines the responses for rape, column 4 examines the responses for robbery and column 5 responses for assault. The results show that there is a negative association between the number of robberies per 100,000 people and the percentage of households receiving benefits from SNAP. This result is consistent with the literature (Carr & Packham, 2017; Wright , et al., 2014). On the other hand, one cannot see the impact of SNAP participation of households in the other crime categories. One likely reason might be that robbery is an income motivated crime. A decrease in the individuals' income or welfare level can encourage them to commit robbery. Secondly, states may request to waive the Able- Bodied Adults Without Dependents ABAWD time limit. According to the results presented in Table 3, there is a negative association between waivers and all violent crime categories except murder in rural counties.

Table 4 shows the fixed effect estimation results in rural counties for property crime rates. Column 1 examines all property crime, column 2 examines burglary, column 3 examines grand larceny and column 4 examines motor vehicle theft. The findings indicate that increases in median household income negatively affect burglary but do not affect motor vehicle theft or grand larceny in rural counties. One of the reasons might be that burglary is more likely to be motivated by a need for cash. The percentage of households receiving food stamps decreases the property, burglary and motor vehicle theft but not grand larceny. Additionally, findings support that waivers have a negative and statistically significant impact on property crimes. So, one can see that waivers can lead to decreases in property crime in rural counties. Lastly, the share of male population in each rural county is another variable which has a positive association with grand larceny.

Table 5 and Table 6 display results using urban counties as units of analysis. Table 5 presents the main findings regarding SNAP's effects on violent crime in urban counties. Column 1 examines all violent crime in urban areas. Column 2 examines murder. Column 3 examines rape, column 4 examines robbery, and column 5 assault. The findings show that the unemployment rate is positively related to violent crime. A one-percent increase in the unemployment rate causes 66 percent more violent crime per capita. The results show that percentage in households receiving food stamp via SNAP participation has a negative association with robbery. A one percent increase in the households' SNAP participation leads to a decrease in the number of robberies by 13 less robbery per 100,000. This result is similar to findings for rural counties. Additionally, as shown in Table 5, demographic variables have statistically significant impacts. For example, the share of population that is Hispanic is negatively related to all violent crime, robbery and assault but not to rape and robbery. Additionally, the native Hawaiian population is negatively related to rape and the Asian population is negatively related to robbery. These findings are match a report released by FBI. According to FBI's recent statistics, native Hawaiian and Asian populations are the two groups which have the lowest crime rates (FBI, 2019).

Lastly, table 6 presents the fixed effect estimation results for property crimes in urban counties. The findings provide evidence that a one percent increase in household income level decreases per capita property crime by 41 percent, burglary by 11 percent, and larceny by 5 percent. Additionally, the percentage of households receiving SNAP has negative impact on burglary and motor vehicle theft.

Summing up, one can see that the percentage of household receiving food stamp and median household income have significant impacts on crime, particularly, income motivated crimes such as property, robbery, and burglary are more likely to be affected by the changes in individuals' welfare and income level changes.

Conclusion

SNAP is a widely used and large federal food assistance program, serving more than 40 million people in the United States. In the present study we investigate the impact of SNAP participation on criminal activities in rural and urban counties. This paper has two main goals. The primary goal is to analyze the impact of SNAP participation on each crime type in the counties of the U.S. The second aim is to compare and examine the findings for urban and rural counties.

The findings show that households' SNAP participations are one of the most important determinants of crime, any decrease in individual's income and welfare level encourages them to commit income motivated crime. So, one can see that the results are consistent with perspective that income related crimes are more likely to be affected by the changes in economic conditions.

TABLES AND FIGURES

Table 1: Definitions and Data sources

Variable	Definition	Data Source
Violent Crime (per 100,000)	Number of violent crime per 100,000 people	U.S. Census Bureau
Property Crime (per 100,000)	Number of murder crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Murder (per 100,000)	Number of rape crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Rape (100,000)	Number of robbery crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Robbery (per 100,000)	Number of assault crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Assault (per 100,000)	Number of property crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Burglary (per 100,000)	Number of burglary crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Grand Larceny (per 100,000)	Number of grand larceny crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Motor (per 100,000)	Number of motor theft crime per 100,000 people	FBI The Uniform Crime Reporting (UCR) Program
Households receiving food stamps	Percentage of households receiving food stamps	U.S. Census Bureau
Snap		Dummy Variable
Waiver		Dummy Variable
Median Household Income	Median household income level	U.S. Census Bureau
Labor Force	Number of people employed plus those unemployed but looking for work	U.S. Census Bureau
Unemployment Rate	Number of people not employed	U.S. Census Bureau
Population	Number of people in each county	U.S. Census Bureau
Demographics	Percentage of population	U.S. Census Bureau

Table 2: Summary Statistics

	RURAL				URBAN			
Variable	**Mean**	**Median**	**Min**	**Max**	**Mean**	**Median**	**Min**	**Max**
Waiver	0.233	0	0	1	0.138	0	0	1
Snap Dummy	0.285	1	0	1	0.714	1	0	1
Population	23400	16600	41	191000	226000	95100	57	10000000
Male	48	49.6	0	3140	47.8	49.2	0	4090
Female	586	50.2	0	980000	233	50.8	0	700000
White	85.4	92.9	9.04	100	81.3	85.8	12.6	99.8
African American	7.82	1.1	0	86.8	10.9	5.4	0	79.5
American Indian/ Alaskan Native	2.39	0.4	0	89.4	0.777	0.3	0	83.6
Asian	0.613	0.4	0	52.2	2.14	1.1	0	44.8
Native Hawaiian/ Other Pacific Islander	0.0644	0	0	12.9	0.105	0	0	35.3
Hispanic	7.89	2.7	0	98.7	8.87	4.4	0	95.6
Median Household Income	41.4	40.8	18.9	107	52.2	49.9	22.1	124
Households receiving food stamps	13.4	12.5	0	47.8	11.4	10.8	0	39
Labor Force	58.6	59	18.5	96.8	63.3	64	24.3	96.2
Unemployment Rate	8	7.6	0	36.1	8.22	7.9	0	27.5
Violent Crime (per 100,000)	205	159	0	3450	295	238	0	2090
Property Crime (per 100,000)	1660	1510	0	13600	2390	2220	0	8760
Murder (per 100,000)	2.7	0	0	217	3.59	2.24	0	62.2
Rape (100,000)	25.2	18.2	0	893	28.5	24.7	0	181
Robbery (per 100,000)	17.6	7.54	0	645	59.5	34.8	0	844
Assault (per 100,000)	159	115	0	3450	203	164	0	1600
Burglary (per 100,000)	456	379	0	5680	566	498	0	3380
Grand Larceny (per 100,000)	1120	1010	0	12300	1670	1570	0	6190
Motor (per 100,000)	85.6	70.2	0	2050	151	112	0	1410

Table 3: The impact of SNAP participation on violent crime in the US rural counties: Fixed effect regressions

Variables	All Violent Crime	Murder	Rape	Robbery	Assault
Const	511.9	21.54*	55.75	12.06	417.6
	(119.4)	(11.71)	(39.77)	(13.41)	(61.91)
Waivers (Dummy)	-10.71**	-0.151	-1.963**	-0.941**	6.917
	(3.497)	(0.203)	(0.981)	(0.415)	(6.127)
SNAP benefits (Dummy)	-4.114	0.449**	-0.881	0.049	-3.911
	(4.992)	(0.167)	(0.564)	(0.449)	(2.521)
Households receiving food stamps	-0.722	-0.063	0.534	-0.496**	-0.418
	(0.848)	(0.045)	(0.544)	(0.151)	(0.449)
Median household Income	0.890	-0.041	0.619	0.003	0.331
	(0.762)	(0.052)	(0.654)	(0.079)	(0.414)
Labor Force	-0.132	-0.004	0.621	0.231	0.081
	(0.731)	(0.004)	(0.667)	(0.113)	(0.482)
Unemployment	-1.248	0.032	-0.307	-0.094	-0.919
	(1.165)	(0.054)	(0.137)	(0.140)	(0.692)
Demographics					
Female	0.000	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
White	-2.065	-0.192	-0.311*	-0.049	-2.521
	(1.185)	(0.135)	(0.170)	(0.101)	(0.561)
African American	-2.265	0.012	-0.256	0.667	-3.085
	(2.294)	(0.103)	(0.318)	(0.539)	(1.383)
American Indian/ Alaskan Native	-4.940	-0.069	0.173	0.187	-5.274***
	(5.601)	(0.108)	(0.431)	(0.305)	(1.401)
Asian	1.520	-0.471	1.143	-0.202	1.204
	(4.174)	(0.446)	(0.777)	(0.349)	(2.342)
Native Hawaiian/ Other Pac.	-6.577	-0.285	-2.364	0.568	-4.578
	(10.37)	(0.497)	(2.478)	(1.221)	(7.336)
Hispanic	-1.068	0.103	0.794	-0.223	-1.948
	(2.480)	(0.176)	(0.667)	(0.255)	(0.867)
R-squared	0.76	0.27	0.61	0.76	0.51
Number of counties	1968	1968	1968	1968	1968
Observations	13,776	13,776	13,776	13,776	13,776

Notes: Robust standard errors are reported in parentheses.

(*) Statistical level of significance: $p < 0.1$, (**) Statistical level of significance: $p < 0.5$, (***) Statistical level of significance: $p < 0.01$.

Table 4: The impact of SNAP participation on property crime in the US rural counties: Fixed effect regressions

Variables	All Property Crime	Burglary	Grand Larceny	Motor Theft
Const	2394	598.6***	1803	123.4**
	(1648.4)	(238.1)	(5784)	(58.72)
Waiver (Dummy)	-57.81**	-7.753	25.60	8.591
	(17.28)	(6.712)	(47.14)	(9.201)
SNAP benefits (Dummy)	14.71	3.972	-239.6***	-1.449
	(22.29)	(6.503)	(38.47)	(4.439)
Households receiving food stamps	-26.88***	-13.65***	2.441	-1.402***
	(4.321)	(1.760)	(4.213)	(0.375)
Median household Income	-6.178*	-3.833*	8.219	1.019
	(3.810)	(3.911)	(9.619)	(3.995)
Labor Force	13.19	5.183	-4.901	-0.852
	(4.001)	(5.109)	(3.309)	(1.612)
Unemployment	16.76***	4.917***	5.809	0.611
	(6.002)	(1.681)	(4.702)	(0.694)
Demographics				
Female	0.000	-0.000	-0.000	-0.000*
	(0.00)	(0.00)	(0.00)	(0.00)
White	-10.76*	-1.798	-9.044	-0.247
	(7.285)	(1.939)	(5.609)	(0.501)
African American	-4.932	-800	-5.204	0.487
	(10.34)	(3.895)	(7.065)	(0.879)
American Indian/ Alaskan Na.	10.68	1.070	-10.48	0.644
	(20.57)	(4.209)	(16.52)	(1.003)
Asian	-28.32	4.018	-19.55	-1.207
	(20.91)	(8.737)	(15.00)	(1.509)
Native Hawaiian/ Other Pac.	-29.22	-5.614	2.409	-1.156
	(51.94)	(18.22)	(34.52)	(5.571)
Hispanic	-6.001	-6.143	(13.86)	0.251
	(11.57)	(3.915)	(9.262)	(1.175)
R-squared	0.58	0.67	0.59	0.52
Number of counties	1968	1968	1968	1968
Observations	13,776	13,776	13,776	13,776

Notes: Robust standard errors are reported in parentheses.

(*) Statistical level of significance: $p < 0.1$, (**) Statistical level of significance: $p < 0.5$, (***) Statistical level of significance: $p < 0.01$.

Table 5: The impact of SNAP participation on violent crime in the US urban counties: Fixed effect regressions

Variables	All Violent Crime	Murder	Rape	Robbery	Assault
Const	199.3	7.291	0.348	131.6	86.71
	(170.9)	(6.691)	(20.41)	(391.5)	(197.4)
Waiver (Dummy)	8.591	-0.391*	-2.648***	1.703	0.287
	(4.924)	(0.158)	(0.731)	(2.087)	(4.821)
SNAP benefits (Dummy	-7.299**	0.135	-1.028*	-1.179	-5.226*
	(3.271)	(0.169)	(0.574)	(0.809)	(2.883)
Households receiving food stamps	0.635	0.096	1.081	-1.308***	-104.5
	(1.261)	-0.093	(0.139)	(0.028)	(1.009)
Median household Income	-0.991	-0.041	0.556	-0.261	-1.512
	(0.988)	(0.039)	(0.681)	(0.224)	(0.907)
Labor Force	-2.071	-0.095	-0.709	-0.379*	-0.830
	(1.393)	(0.051)	(0.142)	(0.261)	(1.219)
Unemployment	6.641***	0.183	-2.001	-0.394	-3.974
	(1.483)	(0.070)	(1.691)	(0.385)	(5.935)
Demographics					
Female	0.000	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
White	4.466	-0.012	0.218	0.410	3.857*
	(5.936)	(0.056)	(0.165)	(0.322)	(1.976)
African American	3.372	0.281**	0.294	-0.699	3.552
	(2.522)	(0.122)	(0.315)	(0.831)	(2.242)
American Indian/ Alaskan	-0.813	-0.192	0.702	0.377	-1.635
	(6.260)	(0.207)	(0.860)	(1.046)	(5.623)
Asian	-0.085	-0.119	1.494	-3.632**	2.178
	(4.072)	(0.157)	(0.603)	(1.376)	(3.556)
Native Hawaiian/ Other Pac.	0.657	0.018	-0.970*	1.262	0.344
	(1.608)	(0.060)	(0.583)	(3.457)	(1.462)
Hispanic	-7.441**	-0.026	1.200	-3.212**	-5.394*
	(3.493)	(0.089)	(3.042)	(0.808)	(2.961)
R-squared	0.38	0.61	0.68	0.58	0.67
Number of counties	1166	1166	1166	1166	1166
Observations	8162	8162	8162	8162	8162

Notes: Robust standard errors are reported in parentheses.
(*) Statistical level of significance: $p < 0.1$, (**) Statistical level of significance: $p < 0.5$, (***) Statistical level of significance: $p < 0.01$.

Table 6: The impact of SNAP participation on property crime in the US urban counties: Fixed effect regressions

Variables	All Property Crime	Burglary	Grand Larceny	Motor Theft
Const	1453	983.2	2534***	267.3
	(1988)	(159.1)	(387.6)	(381.2)
Waiver (Dummy)	-146.9**	-11.15	-86.80***	1.325
	(63.64)	(11.68)	(15.97)	(4.596)
SNAP benefits (Dummy)	119.1	-75.66***	12.81	-5.804**
	(32.98)	(8.250)	(12.41)	(2.812)
Households receiving food stamps	3.219	-3.179***	-31.61	-2.341***
	(8.215)	(1.717)	-51.64	(0.711)
Median household Income	-41.01***	-11.33*	-5.236**	0.791
	(3.189)	(1.033)	(2.831)	(0.661)
Labor Force	61.14	10.431	7.996	-1.197
	(52.02)	(0.692)	(9.878)	(2.871)
Unemployment	21.32	18.94***	21.02	-2.681
	(15.31)	(1.751)	(33.91)	(2.187)
Demographics				
Female	0.001	0.000	0.000	0.000
	(0.011)	(0.00)	(0.00)	(0.00)
White	-16.19	-6.431	-3.716	0.306
	(14.79)	(7.331)	(3.437)	(1.163)
African American	11.02	1.685	-24.50**	-1.274
	(23.69)	(1.350)	(6.576)	(2.177)
American Indian/ Alaskan Native	-23.17	-10.12	9.322	8.251
	(23.69)	(18.83)	(17.91)	(9.452)
Asian	52.23	0.241	-63.34*	-5.491*
	(22.43)	(2.125)	(12.57)	(3.072)
Native Hawaiian/ Other Pacific Islander	-130.6*	-21.64	27.22	0.553
	(83.15)	(25.23)	(41.12)	(1.183)
Hispanic	12.49	2.141	-33.18	3.410
	(3.895)	(4.418)	(36.55)	(3.278)
R-squared	0.32	0.34	0.38	0.33
Number of counties	1166	1166	1166	1166
Observations	8162	8162	8162	8162

Notes: Robust standard errors are reported in parentheses.

(*) Statistical level of significance: $p < 0.1$, (**) Statistical level of significance: $p < 0.5$, (***) Statistical level of significance: $p < 0.01$.

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