

FROM PAIN RELIEF TO PAINFUL REALITY: THE IMPACT OF OPIOID ABUSE AND MENTAL HEALTH ON CRIME*

Suzan ODABAŞI** 

Abstract

This research analyzes the relationship between opioid prescription rates, mental health, and crime incidence in the United States. Utilizing data from 2012 to 2015 from 3142 counties, this study seeks to unravel the multifaceted impact of opioid prescription rate and mental health on crime rates in urban counties. A notable endogeneity issue surfaces in the relationship between law enforcement personnel and crime. To mitigate this challenge, we introduce an instrumental variable, the “annual average police wage.” Employing a fixed-effect approach, our findings reveal a compelling association—increasing the number of law enforcement personnel correlates with a reduction in the likelihood of robberies in urban counties. Estimations of the impact of opioid prescription rates on crime prove that opioid prescription rate is positively associated with all property crime categories in urban counties except motor vehicle theft. Furthermore, an upswing in the count of mental health providers is linked to a decrease in burglaries in urban areas. This analysis sheds light on the nuanced dynamics involving mental health, opioid abuse, and criminal activity, offering valuable insights for policymakers and practitioners alike.

Keywords: Opioid, Mental Health, Access to Health Services, Violence, Urban Crime, Panel Data

JEL Codes: D91, I12, I15, I31, O1

1. Introduction

According to the CDC’s definition, “mental health is the component of behavioral health that includes our emotional, psychological, and social well-being”. Therefore, mental health is a key part to overall health and is tightly associated to individuals’ physical health (CDC, 2025). 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. 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 (Skeem and Mulvey, 2020; Cornaglia et al., 2014; Kury and Hebe, 2021; Odabasi,

* This paper is based on a chapter from the author’s doctoral dissertation.

** Usak University, Department of Economics, Email: suzan.gurgil@usak.edu.tr ORCID ID: 0000-0002-4646-8640.

2023a) 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 et al, 2015). Similarly, Swanson et al.'s study based on more than 1,400 adult patients with mental disorders showed that nearly 19% committed violent crime during the last 6 months (Swanson et al., 2006).

A common thought is that there is a 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 (SAMSHA, 2019). 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, a statistically significant association between arrests and drug use is found (Donnelly 2021; Proctor and Kopak, 2022). On the other hand, their findings show that marijuana use may have an influence on the likelihood of being apprehended after committing these crimes. Similarly, 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.

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, the studies in economic literature support the idea that higher prices are negatively associated with consumption of alcohol and illegal drug use (Scherbaum et al., 2021; Galenianos and Gavazza, 2017; Jacobi and Sovinsky, 2016).

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. Opioids are a class of drugs that relieve pain, but they also carry a high risk of misuse, dependence, and addiction. This study addresses a research gap by examining how mental health and opioid prescription rate might influence the crime in urban counties, thereby contributing original insights into the intersection of crime literature and mental health economics. 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 data. Finally, the results and conclusion are discussed under section 4 and section 5.

2. Literature Review

2.1. Background on the Economics of Crime and Mental Well-being

Following Becker's ground-breaking study (1968) on the economic aspects of crime, an increasing body of literature has centered on both the expenses associated with criminal activity and the factors that drive criminal behavior. (Gibbs et al., 2023; Bell et al., 2022; Kirchmaier et al., 2020).

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 to 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 et al., 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 et al., 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.

2.2. Background on Opioid Abuse and Crime

The economics of crime literature provides empirical evidences on violence may increase with the excessive consumption of illicit drugs (Odabasi, 2023b). 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 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.

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%).

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. 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.

3. Model

The analytical framework used in the present study is developed to seeks to examine the relationship between menal health related indicators and criminal activities Also, this study utilizes Dobkin and Nicosia's empirical framework (2009). Including opioid use, mental health indicators and criminals' characteristics provide us the following equation:

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

Equation (1) presents a crime supply equation where is the crime rate in county i, year t. is the number of mental health providers, is the number of average mentally unhealthy days per year, the opioid prescription rate, is the average physical inactivity rate per year, is the number of law enforcement personnel, is the unemployment rate, is the median household income, is the high school graduation rate, is the poverty rate, and is the demographic variables which show the shares of population in particular age group and race. The error term 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, unemployment rate, high school graduation rate, and demographic indicators such as race, age, and gender (Table 1).

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

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

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 (Glei and Weinstein, 2019; Naghizadeh et al., 2023; Wu and Evangelist, 2022; Azagba et al., 2021). 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:

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

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 the crime rate.

The endogeneity problem of crime and number of police officer personnel is discussed by a number of researchers (Mello 2019; Lin 2009).

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).¹ 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 u_i and W_i . To sum up, two expectations from validation of as an instrumental variable are:

$$(2) \text{ cov } (W_i, u_i) = 0$$

$$(3) \text{ cov } (W_{it}, L) \neq 0 \quad (4)$$

A number of studies in literature in economics of crime have used the fixed effect model to estimate the panel data (Burkhardt et al., 2019; Leslie and Wilson, 2020; Bondy et al., 2020). In the present

¹ The NAICS code is an industrial classification system commonly used in the United States of America.

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).

For the data cleaning and merging phase RStudio programing is used, while regression analyses were performed with GRETTL.

3.1 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 (Table 2). The study period was determined by data availability. The CDC provides opioid prescription data up to 2016, in addition to the other variables data availability, the upper limit of the time frame used in our analysis. The crime statistics used in this study come from the Federal Bureau of Investigation (FBI) Uniform Crime Reporting (UCR) Program (FBI, 2018). The FBI UCR gathers crime statistics from regional law enforcement agencies in the US. 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.

3.2 Dependent Variables

The FBI UCR program provides statistics on the number of crimes that occur in a calendar year in urban counties. In this study, each crime category is calculated as a crime rate per 100,000 people by county. We benefit from the FBI's method of separating 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 property. 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 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 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.

3.3 Explanatory Variables

The second major component of our dataset is mental health related indicators: (1) Opioid prescribing rate, (2) physical inactivity rate, (3) mental health providers, and (4) mentally unhealthy days. 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). NPPES provider statistics may not fully provide actual provider availability, as the registry may include inactive providers or geographic misclassification. On the other hand, the NPPES system remains one of the most comprehensive national sources for provider data. 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 Kohen, 2019). “Physical inactivity” data included in the present study show the percentage of the population who does not have time for physical activity. Physical activity statistics covers activities such as running, walking, golf, and gardening. 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. BRFSS mental health statistics rely on self-reported “mentally unhealthy days,” which can be subjective and personal perception. (BRFSS, 2018).

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 opioid prescription rate is included as another explanatory variable. The data come from the Centers for Disease Control and Prevention (CDC) (CDC, 2018). The CDC provides 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. In 2017, the CDC 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 et 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 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 (FBI, 2018). 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, 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 (BLS, 2018).

The common thought supports that the presence and availability of police protection is an important contributor to public safety. It is likely to have lower crime rate if the county residences provide more funding for public services.

Median household income, educational attainment, unemployment rate, poverty rate, and demographic indicators statistics come from the U.S. Census Bureau (The Census Bureau, 2018). 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 rates. The ratio of the number of high school graduates to the population is calculated for each county.

The unemployment rate data are provided by The U.S. Census Bureau that measure the counties of the nation’s workforce, including labor force and unemployment rates. The poverty rate in each county presents the percentage of the individuals who have income less than poverty line. The poverty rate comes from the U.S. Census Bureau (The Census Bureau, 2016). According to the poverty statistics, Sioux, North Dakota has the highest poverty rate (40.4%) among nonmetropolitan 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, and population aged between 18 – 65 (see Table 2).

4. Estimation and Results

Tables 3 and 4 present the impact of mental health related factors and opioid prescribing rate on the incidence of violent and property crimes in urban counties. Table 3 presents five models for each violent crime, and Table 4 presents the four models for each property crimes. All the models are estimated by using fixed-effect approaches. The main advantage of 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).

According to the results obtained from the fixed effect estimation, opioid prescribing rate is somehow surprisingly showing no statically significant impact on violent crime. On the other hand, the findings state that opioid prescribing rate is statistically significant and negative impact on the incidence of “all property crime”, “burglary”, and “grand larceny”. The coefficient of 0.055 for burglary shows that a one-unit increase in the opioid prescribing rate is associated with a 0.055-unit increase

in the burglary in urban counties, holding other factors constant. Similarly, the coefficient of 0.097 for grand larceny indicates that a one-unit increase in the opioid prescribing rate is associated with a 0.097-unit increase in the burglary in urban counties, holding other factors constant.

It is important to note that there are some endogeneity issues with the estimations. To tackle down the endogeneity problem between the number of law enforcement personnel and crime, an instrumental variable: the annual average wages per employee by the local governments, is employed in the fixed-effect estimations. The impact of the instrumental variable on the crime statistics is well-founded. Mas's analysis shows that as the officers receive their salary demand, the arrest rate will increase. Additionally, if the officers lose arbitration cases, police performance will decrease (Mas, 2006). One of the main methodological concerns in this study is endogeneity. To address this, we first applied a Hausman specification test to detect the presence of endogenous regressors. In addition, a separate Hausman test was conducted to determine the appropriate econometric approach for the panel model. The significant result ($p \leq 0.001$) indicated that the fixed-effects estimator was the most appropriate for our analysis.

Homoskedasticity is one of the key assumptions in panel data estimations. By performing a White test, it is expected to see if the squared residuals are related to the regressors or not. The null hypothesis states that the errors are homoskedastic. The White test did not reject the null hypothesis, states that no evidence of heteroskedasticity in the model residuals ($\chi^2 = 12.4$, $p = 0.18$).

Table 3 and 4 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 burglary by 131 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 increases 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 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, 2018). 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 (Fondevila, 2023). 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 all property crimes, burglary and grand larceny but not on any other crime.

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 (Fondevila, 2023).

Unemployment has the potential to motivate people to earn an 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 an 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 and Moretti (2004), 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 (Lochner and Moretti, 2004). The present study also provides evidence on the impact of demographic characteristics on urban area crimes. The share of native Hawaiian and Hispanic population has a positive association with the number of rapes, 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.

5. Conclusion

Mental health disorders have commonly been associated with incidence of violence. In addition to mental health problems, the opioid crisis in the United States has increased attention on the social and economic impacts of opioid misuse, in addition to its medical outcomes. Based on

this association between opioid prescribing rate, mental health, and crime, the main objective of this study is to determine whether better mental health outcomes can be used as a tool to reduce violence. This study aims to provide evidence on how mental health and opioid prescription rate are associated with crime in urban counties.

Following the rural–urban classification defined by the FBI, about 923 counties are included in the present study. A fixed-effects approach is employed to examine the extent to which the opioid prescribing rate and mental health–related factors affect the incidence of crime. The results emphasize the role of opioid prescribing rate, mentally unhealthy days, and high school graduation rate in crime prevention.

The results confirm that “number of mentally unhealthy days” and “number of mental health providers per 100,000 people” are two mental health related indicators linked to occurrence of crime during the 2012–2015 in urban counties. These findings point out the importance of mental health problems in the occurrence of crimes.

In addition to mental health related variables, 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 except motor vehicle theft. This association may be explained by the economic and social stressors associated with opioid misuse, such as unemployment, poverty, and cultural norms, which can increase the likelihood of property crime. While several economic and social factors might be relating to the increase crime and opioid prescription rates, strong financial and behavioral pressures make property crimes more likely. Similarly, Giles and Malcolm (2021) report a strong positive association between property crime and the use of pain relievers, whereas the association with violent crime is relatively weak.

Another important finding points out the importance of education in reducing the incidence of violent and property crime in urban counties. The estimation results show that “high school graduation rate” is one of most significant socio-economic indicators included in the model. According to the results, counties with lower high school graduation rates tend to experience significantly higher levels of both violent and property crime. This suggests that educational attainment can serve as effective crime prevention strategies. Therefore it is expected to exhibit higher productivity in workforce and social coherence.

The results of this study can be used to provide empirical analyses to help policymakers reduce crime via mental health treatment. Policy makers should particularly focus on prescription monitoring, expanding access to addiction treatment services, and improving the availability of mental health care. It is important to note that an individual-level data and longer time period might provide better insights and more reliable results regarding the impact of mental health and opioid abuse on crime. Future studies should use individual-level data and longer time spans to yield more reliable evidence on the impact of mental health and opioid abuse on crime. An additional important point is about the potential overlap between opioid prescribing rate and

mental health related variables. However, the potential issue of multicollinearity may warrant further investigation in future research.

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.

References

- Azagba, S., Shan, L., Wolfson, M., Hall, M., & Chaloupka, F. (2021). Problem drinking as intentional risky behavior: Examining the association between state health insurance coverage and excessive alcohol consumption. *Preventive Medicine Reports*, 24, 101556. <https://doi.org/10.1016/j.pmedr.2021.101556>
- Becker, G. S. (1968). Crime and punishment: An economic approach. *Journal of Political Economy*, 76(2), 169–217.
- Bell, B., Costa, R., & Machin, S. (2022). Why does education reduce crime? *Journal of Political Economy*, 130(3), 732–765. <https://doi.org/10.1086/717104>
- Bondy, M., Roth, S., & Sager, L. (2020). Crime is in the air: The contemporaneous relationship between air pollution and crime. *Journal of the Association of Environmental and Resource Economists*, 7(3), 555–585. <https://doi.org/10.1086/707795>
- Burkhardt, J., Bayham, J., Wilson, A., Carter, E., Berman, J. D., O'Dell, K., & Pierce, J. R. (2019). The effect of pollution on crime: Evidence from data on particulate matter and ozone. *Journal of Environmental Economics and Management*, 98, 102267. <https://doi.org/10.1016/j.jeem.2019.102267>
- Centers for Disease Control and Prevention. (2025, June 9). About mental health. <https://www.cdc.gov/mental-health/about/index.html>
- Centers for Disease Control and Prevention. (2018). U.S. opioid dispensing rate maps. <https://www.cdc.gov/drugoverdose/maps/rxrate-maps.html>
- Cornaglia, F., Feldman, N. E., & Leigh, A. (2014). Crime and mental well-being. *The Journal of Human Resources*, 49(1), 110–140. <https://doi.org/10.3368/jhr.49.1.110>
- Darke, S., Torok, M., Kaye, S., Ross, J., & McKetin, R. (2010). Comparative rates of violent crime among regular methamphetamine and opioid users: Offending and victimization. *Addiction*, 105(5), 916–919. <https://doi.org/10.1111/j.1360-0443.2009.02872.x>
- Dobkin, C., & Nicosia, N. (2009). The war on drugs: Methamphetamine, public health, and crime. *American Economic Review*, 99(1), 324–349. <https://doi.org/10.1257/aer.99.1.324>
- Donnelly, E. A., Wagner, J., Stenger, M., Cortina, H. G., O'Connell, D. J., & Anderson, T. L. (2021). Opioids, race, and drug enforcement: Exploring local relationships between neighborhood context and Black–White opioid-related possession arrests. *Criminal Justice Policy Review*, 32(3), 219–244. <https://doi.org/10.1177/088.740.3420979984>
- Bureau of Justice Statistics. (2008). Drugs and crime facts. <https://bjs.ojp.gov/content/pub/pdf/dcf.pdf>
- Entorf, H., & Winker, P. (2008). Investigating the drugs–crime channel in economics of crime models: Empirical evidence from panel data of the German states. *International Review of Law and Economics*, 28(1), 8–22. <https://doi.org/10.1016/j.irle.2007.01.005>
- Fazel, S., Wolf, A., Chang, Z., & Larsson, H. (2015). Depression and violence: A Swedish population study. *The Lancet Psychiatry*, 2(3), 224–232. [https://doi.org/10.1016/S2215-0366\(15\)00100-X](https://doi.org/10.1016/S2215-0366(15)00100-X)
- FBI Uniform Crime Reporting Program. (2018). Crime data explorer. United States Department of Justice. <https://crime-data-explorer.fr.cloud.gov/>

- Federal Bureau of Investigation. (2018). Crime in the United States. https://www2.fbi.gov/ucr/cius2009/about/offense_definitions.html
- Fondevila, G., Vilalta-Perdomo, C., Galindo Pérez, M. C., & Cafferata, F. G. (2023). The deterrence effect of police stations on crime in Buenos Aires and Mexico City. *Papers in Applied Geography*, 9(1), 1–2.
- Galenianos, M., & Gavazza, A. (2017). A structural model of the retail market for illicit drugs. *American Economic Review*, 107(3), 858–896. <https://doi.org/10.1257/aer.20151507>
- Gibbs, C., De Biasi, A., Cobbina-Dungy, J. E., Speers, M., Costantino, M., & Rivers, L. (2023). COVID-19 and youth violence: Views from the frontline. *Journal of Crime and Justice*, 46(1), 44–64. <https://doi.org/10.1080/0735648X.2022.214.3930>
- Glei, D. A., & Weinstein, M. (2019). Drug and alcohol abuse: The role of economic insecurity. *American Journal of Health Behavior*, 43(4), 838–853. <https://doi.org/10.5993/AJHB.43.4.19>
- Jacobi, L., & Sovinsky, M. (2016). Marijuana on Main Street? Estimating demand in markets with limited access. *American Economic Review*, 106(8), 2009–2045. <https://doi.org/10.1257/aer.20130484>
- Keyes, K. M., Cerdá, M., Brady, J. E., Havens, J. R., & Galea, S. (2014). Understanding the rural–urban differences in nonmedical prescription opioid use and abuse in the United States. *American Journal of Public Health*, 104(2), e52–e59. <https://doi.org/10.2105/AJPH.2013.301709>
- Kirchmaier, T., Machin, S., Sandi, M., & Witt, R. (2020). Prices, policing and policy: The dynamics of crime booms and busts. *Journal of the European Economic Association*, 18(2), 1040–1077. <https://doi.org/10.1093/jea/jvz032>
- Kury, H., & Heße, R. (2021). Dealing with mental illness and violence in the (youth-) prison. In *Crime Prevention and Justice in 2030: The UN and the Universal Declaration of Human Rights* (pp. 155–176). Springer. https://doi.org/10.1007/978-3-030-79509-8_7
- Leslie, E., & Wilson, R. (2020). Sheltering in place and domestic violence: Evidence from calls for service during COVID-19. *Journal of Public Economics*, 189, 104241. <https://doi.org/10.1016/j.jpubeco.2020.104241>
- Levitt, S. D. (1997). Using electoral cycles in police hiring to estimate the effect of police on crime. *American Economic Review*, 87(3), 270–290.
- Lin, M. J. (2009). More police, less crime: Evidence from US state data. *International Review of Law and Economics*, 29(2), 73–80. <https://doi.org/10.1016/j.irle.2008.07.002>
- Lochner, L., & Moretti, E. (2004). The effect of education on crime: Evidence from prison inmates, arrests, and self-reports. *American Economic Review*, 94(1), 155–189. <https://doi.org/10.1257/000.282.804322970751>
- Luca, D. L., Owens, E., & Sharma, G. (2015). Can alcohol prohibition reduce violence against women? *American Economic Review*, 105(5), 625–629. <https://doi.org/10.1257/aer.p20151081>
- Markowitz, S. (2005). Alcohol, drugs and violent crime. *International Review of Law and Economics*, 25(1), 20–44. <https://doi.org/10.1016/j.irle.2004.06.003>
- Mas, A. (2006). Pay, reference points, and police performance. *The Quarterly Journal of Economics*, 121(3), 783–821.
- McCrary, J. (2002). Using electoral cycles in police hiring to estimate the effects of police on crime: Comment. *American Economic Review*, 92(4), 1236–1243. <https://doi.org/10.1257/000.282.80260344666>
- McGinty, E. E., Goldman, H. H., Pescosolido, B. A., & Barry, C. L. (2018). Communicating about mental illness and violence: Balancing stigma and increased support for services. *Journal of Health Politics, Policy and Law*, 43(2), 185–228. <https://doi.org/10.1215/03616.878.4316123>

- Mello, S. (2019). More COPS, less crime. *Journal of Public Economics*, 172, 174–200. <https://doi.org/10.1016/j.jpubeco.2019.01.003>
- Naghizadeh, S., Faramarzi, E., Akbari, H., Jafari, N., Sarbakhsh, P., & Mohammadpoorasl, A. (2023). Prevalence of smoking, alcohol consumption, and drug abuse in Iranian adults: Results of Azar cohort study. *Health Promotion Perspectives*, 13(2), 99–107. <https://doi.org/10.34172/hpp.2023.12>
- Odabaşı, S. (2023a). Drug overdose deaths and economic factors: an empirical analysis of US counties, 2008–2018. *International Journal of Economics and Business Research*, 25(3), 366–378.
- Odabaşı, S. (2023b). The relationship between the Supplemental Nutrition Assistance Program (SNAP) and suicide rates: evidence from panel data. *International Journal of Happiness and Development*, 8(1), 1–16.
- Proctor, S. L., & Kopak, A. M. (2022). Mental health correlates of substance use behaviors among a nationally representative sample of juvenile offenders. *Journal of Criminological Research, Policy and Practice*, 8(1), 45–52. <https://doi.org/10.1108/JCRPP-09-2021-0053>
- Rosenfeld, R., Gaston, S., Spivak, H., & Irazola, S. (2017). Assessing and responding to the recent homicide rise in the United States. National Institute of Justice. <https://nij.ojp.gov/library/publications/assessing-and-responding-recent-homicide-rise-united-states>
- SAMSHA. (2019). Substance Abuse and Mental Health Services Administration. <https://www.samhsa.gov/>
- Scherbaum, N., Bonnet, U., Hafermann, H., Schifano, F., Bender, S., Grigoleit, T., & Specka, M. (2021). Availability of illegal drugs during the COVID-19 pandemic in Western Germany. *Frontiers in Psychiatry*, 12, 648273. <https://doi.org/10.3389/fpsy.2021.648273>
- Skeem, J., & Mulvey, E. (2020). What role does serious mental illness play in mass shootings, and how should we address it? *Criminology & Public Policy*, 19(1), 85–108. <https://doi.org/10.1111/1745-9133.12459>
- Sturm, R., & Cohen, D. (2014). Proximity to urban parks and mental health. *The Journal of Mental Health Policy and Economics*, 17(1), 19–24.
- Swanson, J. W., Swartz, M. S., Van Dorn, R. A., Elbogen, E. B., Wagner, H. R., & Rosenheck, R. A. (2006). National study of violent behavior in persons with schizophrenia. *Archives of General Psychiatry*, 63(5), 490–499. <https://doi.org/10.1001/archpsyc.63.5.490>
- The Behavioral Risk Factor Surveillance System (BRFSS). (2018). Centers for Disease Control and Prevention. <https://www.cdc.gov/brfss/index.html>
- The Bureau of Labor Statistics (BLS). (2018). United States Department of Labor. <https://www.bls.gov/data/#wages>
- Trautmann, S., Rehm, J., & Wittchen, H.-U. (2016). The economic costs of mental disorders: Do our societies react appropriately to the burden of mental disorders? US National Library of Medicine National Institutes of Health. <https://doi.org/10.1007/s00127.015.1016-y>
- U.S. Census Bureau. (2018). American Community Survey 5-year estimates. <https://www.census.gov/programs-surveys/acs/>
- Van Dorn, R., Volavka, J., & Johnson, N. (2012). Mental disorder and violence: Is there a relationship beyond substance use? *Social Psychiatry and Psychiatric Epidemiology*, 47(3), 487–503. <https://doi.org/10.1007/s00127.011.0356-x>
- Wu, P., & Evangelist, M. (2022). Unemployment insurance and opioid overdose mortality in the United States. *Demography*, 59(2), 485–509. <https://doi.org/10.1215/00703.370.9621850>
- World Health Organization. (2017). Depression and other common mental disorders: Global health estimates. Geneva: WHO.

Appendix

Table 1: Summary Statistics

Variables	Mean	Median	Min	Max
Demographics				
African American	10.5	5.4	0	74.7
American Indian/ Alaskan Native	1.09	0.498	0	83.7
Asian	2.06	1.07	0	34.1
Native Hawaiian/ Other Pacific Islander	0.107	0.0616	0	2.42
Hispanic	9.51	4.68	0.3	95.6
Non-Hispanic	75.8	80.4	3.5	98.9
Female	50.4	50.6	34.1	58
Rural	41	32.9	0	100
Population aged 18-65 (percentage)	61.9	61.9	40.7	75.4
Opioid Prescribing Rates (per)	83.9	81	0	335
Physical Inactivity Rate (percentage)	25.4	26	0	43.5
Mental Health Providers (per 100,000)	160	30	0	24600
High School Education (percentage)	0.811	0.83	0	1
Mentally Unhealthy Days per year	3.31	3.4	0	7.2
Median Household Income	52.8	50.7	28.5	126
Unemployment Rate	6.62	6.3	2.2	27.4
Poverty Rate	14.99	14.60	3.30	40.40
Total Law Enforcement (per 100,000)	135	115	0	3290
Annual Average Police Wage	87389	93642	0	403624
Violent Crime (per 100,000)	94	55.5	0	2190
Murder (per 100,000)	1.34	0	0	64.4
Rape (per 100,000)	8.9	3.89	0	392
Robbery (per 100,000)	10.2	3.71	0	259
Assault (per 100,000)	72.5	39.1	0	1890
Property Crime (per 100,000)	735	538	0	12700
Burglary (per 100,000)	217	158	0	4320
Grand Larceny (per 100,000)	475	320	0	8270
Motor Vehicle Theft (per 100,000)	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 (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
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 crimes per 100,000 people	U.S. Census Bureau
Murder	Number of murder crime per 100,000 people	FBI (UCR) Program
Rape	Number of rape crime per 100,000 people	FBI (UCR) Program
Robbery	Number of robbery crime per 100,000 people	FBI (UCR) Program
Assault	Number of assault crime per 100,000 people	FBI (UCR) Program
Property Burglary	Number of property crime per 100,000 people	FBI (UCR) Program
Burglary	Number of burglary crime per 100,000 people	FBI (UCR) Program
Larceny	Number of grand larceny crime per 100,000 people	FBI (UCR) Program
Motor Theft	Number of motor theft crime per 100,000 people	FBI (UCR) Program

Table 3: The Impact of Mental Health on Violent Crime in the US Urban Counties: Fixed Effect Regressions

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

Notes: Robust standard errors are reported in parentheses.

(*) $p < 0.1$; (**) $p < 0.05$; (***) $p < 0.01$.

Table 3: 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 (0.002)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.0004 (0.0002)
High School Education	-50.94 (52.01)	-29.2*** (0.055)	-1.624*** (0.330)	-4.686*** (0.547)	-5.998 (2.075)
Total Law Enforcement	-2.791 (5.068)	0.027 (0.038)	0.039 (0.148)	-0.008* (0.006)	-0.008 (0.290)
Median Household Income	0.241 (0.444)	0.0005 (0.0007)	-0.004 (0.004)	0.02 (0.03)	-0.015 (0.027)
Unemployment Rate	0.738 (1.151)	0.005** (0.002)	-0.019 (0.015)	0.056** (0.025)	0.111 (0.097)
Poverty Rate	0.770 (1.271)	0.003 (0.001)	-0.014 (0.010)	0.031 (0.018)	0.058 (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.

(*) p < 0.1; (**) p < 0.05; (***) p < 0.01.

Table 4: The Impact of Mental Health in Property Crime in the US Urban Counties: Fixed Effect Regressions

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

Notes: Robust standard errors are reported in parentheses.

(*) p < 0.1; (**) p < 0.05; (***) p < 0.01.

Table 4: 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*** (0.002)	-0.001 (0.000)	-0.004 (0.001)	-0.0002 (0.0001)
High School Education	-145.68*** (16.81)	-37.55*** (4,785)	-97.59 (91.35)	-13.20** (1,498)
Total Law Enforcement	-12.97 (25.18)	-2.762 (5.810)	-10.52 (19.51)	0.353 (0.747)
Median Household Income	0.322 (0.219)	-0.001 (0.062)	0.302 (0.408)	0.029 (0.019)
Unemployment Rate	2.388*** (0.791)	1.068*** (0.224)	1.227 (0.534)	0.126* (0.070)
Poverty Rate	0.069 (0.556)	0.112 (0.157)	-0.092 (0.375)	0.084* (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.

(*) $p < 0.1$; (**) $p < 0.05$; (***) $p < 0.01$.