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IZA DP No. 17086

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ABSTRACT

Homelessness and Crime: An Examination of California*

We employ a unique 10-year panel dataset from California to examine both the effect crime has on homelessness as well as the effect homelessness has on crime. Our main estimator accounts for endogeneity by incorporating dynamics, controlling for time invariant unobserved heterogeneity, and relaxing the strict exogeneity assumption for our key variables of interest. We find strong evidence that regions experiencing increases in property crime, but not violent crime, should expect a practically significant increase in homelessness, whereas increases in homelessness increases the number of violent crimes, but not property crimes. Robustness and falsification checks confirm the results.

JEL Classification: K14, R20, C23

Keywords: homeless, crime, instrumental variables

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1. Introduction and background

One of the most persistent and unresolved social mysteries in a wealthy and prosperous United States (US) is homelessness. While homelessness itself is an important social problem to resolve, it is often also directly linked to crime in the public consciousness. Indeed, more than 200,000 Google Scholar articles address both "homelessness" and "crime", and more than 7 million stories in the "News" filter of Google Search referenced "homelessness" and "crime" in just the year 2023. Many existing studies explore the relationship between homelessness and crime by measuring the impact of local or community policy changes or by presenting simple summary measures that routinely demonstrate how crime and homelessness statistics move in the same direction. However, there is more nuance to this relationship that deserves attention. The same ingredients that typically generate homelessness can also influence crime. Moreover, examinations reflecting the causal direction of the relationship between homelessness and crime are relatively sparse. In this study we attempt to investigate both causal directions for nearly the entire state of California over multiple years and across different types of crime after adjusting (as much as we can) for those common ingredients that intuitively and theoretically affect both homelessness and crime. Our approach attempts to find causal (or at least semi-structural) relationships through panel data techniques that leverage instrumental variable techniques.

1.1 Homelessness

The homeless are individuals or families who lack fixed, regular, and adequate nighttime residence.[1] According to national point-in-time (PIT) estimates, on a given night in 2022 more

[1] This is the primary definition used by the US Department of Housing and Urban Development, taken from U.S. Code Title 42 Chapter 119 Subchapter 1. Additionally, homeless are defined as those with nighttime residences that are typically not designed for sleeping, those living in supervised shelters designated as temporary living

than 580,000 people were experiencing homelessness in the United States, or approximately 18 people per 10,000. Children under 18 make up roughly 17% of all homeless individuals. Additionally, 60% are men, 50% are White, and 37% are African American. Fully 40% of the overall homeless population lack shelters and instead reside overnight in public or private locations not typically designed as sleeping accommodations, such as the street or in abandoned buildings. Among these unsheltered homeless, 60% reside in urban areas and 72% are individual adults without children present. Nearly one-third demonstrate chronic patterns of homelessness, and less than 1% of the homeless are unaccompanied youth, children under 18 without a parent or guardian present.

National PIT estimates suggest homelessness decreased from a peak of nearly 650,000 in 2007 by approximately 100,000 through 2016. Figure 1 portrays a homelessness time series of this study's California data. Though somewhat increasing back to more than 580,000 in 2022, perhaps most concerning is how the unsheltered homeless numbers also increased by 35% during this time, from roughly 173,000 to nearly 234,000. Fortunately, families with children comprise only 3% of the unsheltered homeless, but increasing numbers of unsheltered adults are nevertheless worrisome. Moreover, much of this rise in homelessness since 2016 is fueled by chronic homelessness, those who experience extended or repeated homelessness while struggling with a disability. Numbers of chronically homeless individuals, 60% of them unsheltered, increased by 65% from approximately 77,500 to 127,800[2].

The causes of homelessness are many, but all are linked to low income. First and perhaps foremost is a lack of affordable rental housing for low-income individuals and families. Only

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arrangements, and those who will imminently lose their housing, have no subsequent residence identified, and do not have the resources to obtain housing.

[2] All descriptive statistics in the previous paragraphs come from de Sousa et al. (2022).

33% of low-income households living below the federal poverty line can find an available and affordable rental home (Aurand et al., 2023). Low-income individuals are also typically less healthy (Benzeval and Judge, 2001) and face greater obstacles to access health care services (Lazar and Davenport, 2018). The combined effect leads to households choosing between paying expensive medical bills or housing.

Researching homelessness is warranted as its costs to individuals and communities are numerous. Homeless people are more likely to struggle with chronic health conditions such as anemia, asthma, diabetes, heart disease, tuberculosis, HIV, viral hepatitis, and lung and kidney disease, as well as suffer from other health conditions such as dementia, head injuries, epilepsy, and even amputations (Sutherland et al., 2021; Beijer et al., 2012; Stubbs et al., 2019). Tragically, mental illness, drug abuse, and drug overdose is also linked to homelessness, leading to overdose-caused mortality at rates 12 times higher than the general population (Fine et al., 2022; Ayano et al., 2020; Ayano et al., 2021). Consequently, homeless individuals face a 60% higher risk of mortality than housed individuals living in poverty (Meyer et al., 2023).

Homelessness costs families and communities as well. Prenatal development is more challenging among the homeless; infants demonstrate lower birth weights, more respiratory problems, and fevers (Clark et al., 2019). Health deficiencies tend to continue past birth for homeless children, leading to more hospitalizations, stunted growth, and iron deficiencies (Weinreb et al., 1998; Fierman et al., 1991; Fierman et al, 1993). Homeless children are also more likely to experience traumatic events typically linked to negative health and social outcomes such as developmental delays (Hart-Shegos, 1999), psychiatric problems (Grant et al., 2007), child separations from their parents (Shinn et al., 2008), and substantial disruption to educational outcomes like attendance and degree-completion (Canfield, et al., 2016; Chassman et al., 2020). Further costs of homelessness to communities include higher rates of visits at hospital Emergency Departments, more often using ambulances, experiencing longer hospital stays, and having higher hospital readmission rates (Coe et al., 2015). Moreover though, the tendency to criminalize homelessness and close/clean homeless encampments also carry high costs for municipalities in terms of sanitation expenses and connecting encampment residents with relevant resources (Dunton et al., 2021), as well as enforcing anti-homeless ordinances (Rankin, 2019).

1.2 Crime

The literature and public consciousness clearly demonstrate that crime and homelessness are linked, but prior to examining the causal links, it is important to first explore different types of crime and their related causes and costs to society. Law enforcement databases such as that of the State of California separate crimes into two large categories according to the Federal Bureau of Investigation's Uniform Crime Report: violent and property crimes. Violent crimes include homicide, rape, robbery, assault, and human trafficking whereas property crimes include burglary, larceny-theft, motor vehicle theft and arson[3]. Both violent and property crime in California generally decreased in recent history. Violent crime peaked in the early 1990s at more than 1,000 violent crimes per 100,000 residents, but substantially declined to less than 400 in 2014 before increasing again to approximately 500 violent crimes per 100,000 residents in 2022. Property crime peaked in the early 1980s at nearly 7,000 per 100,000 residents but fell

[3] The theft crimes are closely related but distinct. "Robbery" constitutes the violent theft of property or money by force, "burglary" is the unlawful entry of a structure with an intent to commit a crime, and "larceny-theft" is the unlawful removal of property. Distinctions taken from the Office for Victims of Crime 2018 National Crime Victims' Rights Week Resource Guide: Crime and Victimization Fact Sheets (https://ovc.ojp.gov).

dramatically to approximately 2,000 in 2022[4]. Figure 1 demonstrates a similar and largely downward trend in both property and violent crime in California throughout the years of data used in this study, 2007 – 2016.

The costs of crime to society are large. A reputable report from the US Department of Justice (Miller et al., 1996) estimates the typical discounted present value of a crime's cost is approximately $20,000 per victim or $900 billion annually in 2023 inflation-adjusted dollars. Notably this estimate includes both tangible costs (medical costs, property loss, lost productivity, etc.) as well as intangible costs (fear, pain, lost quality of life, etc.), with most of the costs typically falling on victims of violent crime more so than property crime. Indeed, Cohen and Piquero (2009) further document the large cost imbalance born by victims of violent crime vs. property crime; costs of murder, rape, armed robbery, and aggravated assault are estimated to be no less than $29,000 whereas property crimes' estimated costs are typically less than $5,000. The costs of crime further accumulate by including legal system costs and incarceration costs. For instance, the inflation-adjusted average incarceration cost per inmate is approximately $42,000 (Mai and Subramanian, 2017). Victims of crime also experience substantial labor market disruptions. These "scars" inflict both short- and long-run costs on victims. One year after a criminal incident, victims suffer earnings decreases by 8.4% - 12.9% that persist even after 4 years post-incident (Bindler and Ketel, 2022; Bindler et al., 2020).

Property and violent crimes share both similar and distinct causes. First, rational-choice theory implies individuals commit crimes in general if the anticipated gains exceed the costs (Becker, 1968; Chamlin and Cochran, 2000). Potential criminals thus balance the probability of achieving a crime coupled with the magnitude of that crime's benefit against the probability of

[4] Data taken from the Public Policy Institute of California October 2023 Fact Sheet (https://ppic.org/publication/crime-trends-in-california/).

arrest for committing a crime and the magnitude of a criminal conviction's associated penalty. Many prevailing sociological theories of crime inform how the benefits and costs of any crime can fluctuate in a number of dimensions and for a wide variety of reasons.[5] Yet, biological factors can also influence the rationality, or seeming lack thereof, of criminal choices. Such factors include specific genes, neurological characteristics, or physiological traits, such as hormone or blood lead levels, that correlate with antisocial or criminal behaviors (Larregue, 2024). Further environmental and physiological factors such as air pollution (Bondy et al., 2020) and substance abuse (Fazel et al., 2009) are linked to criminal behavior.

There are also noteworthy causal differences between property and violent crime. Mental health disorders such as schizophrenia are more commonly linked to violence and violent crimes than property crimes (Joyal et al., 2007; Walsh et al., 2002). Chester (1976) posits that poverty is a root cause of property crime while Hannon (2002) specifies this relationship seems strongest when potential criminals have more opportunities to commit property crime, namely when nearby neighborhoods are relatively wealthy. Inequality also plays a role in determining criminal behavior, though differently for property and violent crime. In general, crimes are typically committed by the most disadvantaged in society, and this is aggravated in areas of high inequality. Kelly (2000) finds that poverty impacts property crime, but inequality does not. However, Kelly (2000) suggests that inequality does have a strong positive impact on violent crime. This is perhaps explained by the literature's strain and social disorganization theories. The strain theory first introduced by Merton (1938) posits that individuals in the low end of the societal ladder are increasingly frustrated as inequality worsens, perhaps giving them cause to commit violent crimes in acts of protest. Increasing inequality may also signify worsening or

[5] In the literature these commonly include, but are not limited to, Criminal Opportunity Theory, Routine Activities Theory, Social Learning Theory, and Strain Theory.

weakening mechanisms that maintain social order and control. Thus, Shaw and McKay's (1942) social disorganization theory offers support for Kelly's (2000) finding that inequality may lead to violent crime in areas with greater social disorganization.

1.3 Linking homelessness and crime

The link between homelessness and crime is at least partially location based. The homeless tend to disproportionately suffer from poor health and often have mental health challenges or other visible chronic health conditions that contribute to the social stigma attached to homelessness, thus shunning and dismissing them from suburban, tourist and commercial centers. Consequently, unsheltered homeless tend to inhabit sections of cities that are prone to crime (Fischer, 1992). This alone will generate correlations between homelessness and crime. Moreover though, and perhaps partially as a result, homeless individuals are far more likely than the general population to be victims of violent crime and attacks (Meinbresse et al., 2014). Homeless women are 44 times more likely than women in the general population to be victims of sexual violence (Riley et al., 2020). Children are far more likely to be exposed to gun-violence when homeless, with 45% reporting they had witnessed or experienced gun victimization (Hsu et al., 2020).

Regardless of the type of crime, homelessness is theoretically and intuitively linked, but causality and its direction remain unsettled. Moreover, the theoretical predictions and the literature's results are mixed when disaggregating crime into the two main types; property and violent. First, increased homelessness may theoretically cause increased property crime. Since the homeless typically live in poverty, the expected benefit of committing a crime likely exceeds the expected cost of being punished for the crime, thus making crime attractive (Becker, 1968).

This theoretical approach suggests that homelessness may cause property crimes aimed at subsistence and survival, such as breaking into buildings for shelter, or non-violent acts of theft (Fischer et al., 2008). Yet whereas Kelly (2000) finds that poverty increases property crime, Hannon (2002) suggests the link may be weak in large areas of poverty where there is little opportunity to gain from theft.

Second, homeless individuals have little economic incentive to commit violent crimes. However, Kelly (2000) suggests that certain areas of high-income inequality may lead homeless individuals to commit violent crimes due to strain or social disorganization. Homeless individuals are also more likely to suffer from mental illnesses that have been linked to higher rates of violent crime (Mulvey, 1994). Indeed, Fischer et al. (2008) find that increased severity of mental illness symptoms among the homeless correspond with increased likelihood of committing a violent crime. Yet, the literature also finds evidence of no causality that homelessness causes violent crime (Snow et al., 1989).

The reverse causal relationship is also possible; an increase in crime may cause increases in homelessness. For instance, one driver of homelessness includes individuals (and families) fleeing instances of domestic violence and abuse (Riley et al., 2020). Regions with higher instances of domestic violence may therefore also result in higher rates of homelessness. Additionally, and although not explored in the empirical literature, intuition suggests that repeated robberies may reduce people's ability to pay rent, or vehicle theft may make employment difficult to maintain and therefore and lead to homelessness. Moreover, criminally convicted individuals are far less likely to find employment after serving their sentences and consequently be less able to afford housing (Visher et al., 2011). Thus, regions with more criminal activity may also have increased rates of ex-convict homelessness.

There are likely other characteristics that regionally vary but are correlated with both criminal activity and homelessness. If these characteristics are uncontrolled in studies, then homelessness may be incorrectly identified as a causal mechanism for crime, or vice versa. One approach in the literature to detect causal relationships between homelessness and crime more clearly relies on policy or practice changes in local areas. For instance, Berk and MacDonald (2010) assess the impact of the Safer Cities Initiative in Los Angeles County, CA that began in 2005. Police were instructed to clear out homeless encampments in the downtown Los Angeles area and issue citations and fines following a "broken-windows" framework for policing; reducing the social disorder indicative in homeless encampments can reduce crime more generally. The authors found only modest reductions in property and violent crime in the treatment area, suggesting that removing homeless encampments has only a partial effect on crime reduction. Faraji et al. (2018) explore how varying openings of emergency winter homeless shelters in Vancouver, CA affect local property crime. The authors find mixed results; increases in thefts but decreases in breaking and entering near the opened shelters. These approaches are certainly valuable, but their external validity may be limited by the local region's idiosyncrasies.

This study instead leverages state-wide California crime and homelessness panel data to disentangle the causal effects. We highlight California since it contains the most homeless individuals (171,521) of any state, as well as the highest per capita homeless population at 43.7 homeless people per 10,000 (de Sousa et al, 2022).[6] Our econometric model controls for factors intuitively linked with homelessness and crime such as unemployment rates, weather, income

[6] In addition, California's crime data is more reliable than the national Uniform Crime Report (UCR). Maltz and Targonski (2002) argue that because of a myriad of flaws, the UCR data should not be used in empirical studies such as this.

levels, and the race, education, age, and sex composition of the population. We recognize the dynamic nature of the data by incorporating lags and acknowledge the variables' inherent endogenous relationships by controlling for fixed effects and leveraging instrumental variables. Finally, we explore the relationships between homelessness and separate crime measures in both causal directions. The model results suggest that homelessness has a significant positive effect on only violent crime, while only property crime has a significant and positive effect on homelessness.

2. Data

Our dataset contains 10 years of data from California for the years 2007-2016, but our statistical methodology's inclusion of lagged values limits the estimation sample to only 8 years.[7] We are primarily interested in investigating the relationship between homelessness and crime. First, homeless data come from the U.S. Department of Housing and Urban Development (HUD). The unit of observation is approximately the Continuum of Care (CoC), defined by HUD as a regional planning organization that works to coordinate housing and other services for homeless populations. Second, crime data come from the State of California's Department of Justice database, examining violent and property crime separately as well as aggregating them. Violent crimes include homicide, rape, robbery, and aggravated assault whereas property crimes include burglaries, motor vehicle theft and a multitude of larceny and theft offenses. While some property crimes in these data may be considered violent, they are largely not categorized as such and are closer to the non-violent crime designation in the literature.[8]

[7] The dataset begins in 2007 as it is the first year of homeless data availability.
[8] An important comment regarding drug crimes is warranted. Homeless individuals are unfortunately and disproportionately burdened by drug addiction and abuse. However, for the purposes of this study we focus only on crimes that directly afflict bystanders. Possession of illegal drugs, for instance, is indeed a crime, but not one that

Crime data are collected at the county level but the homeless CoC data do not perfectly align with counties in California. In some instances, a CoC might contain multiple counties while in other instances several CoCs exist within a single county. Since our crime and homelessness units of observations are not geographically matched, we transform the dataset in two different ways. First, when more than one CoC exist in a county, we sum the homeless and population data across the multiple CoCs to form a combined CoC for that county. Second, we treat multiple counties within one CoC as a single multi-county observation by weighing each county's data according to the population in each county within the CoC. In all, the dataset contains 41 geographic unit observations, but for simplicity we refer to each geographic unit in the dataset as a CoC. The dataset covers nearly the entirety of California's population centers, and the 8-year panel is reasonably balanced with only 3 CoCs appearing in two of the eight years and one CoC appearing in three years.

Table 1 contains crime and homelessness summary statistics of CoC/year observations. The average number of homeless individuals per year across CoCs is approximately 3,200. In per capita terms that sums to roughly 4 homeless for every thousand people. Table 1 also presents measures of total crime alongside violent and property crime separately. More than 31,000 total crimes are committed annually on average across California's CoCs, with property crimes making up more than 85% of the total. There are roughly 3 crimes per 100 people committed per year on average across the CoCs, but only 4 violent crimes per 1,000 people. Based on the substantial standard deviations of each measure, we see a large amount of variation in each measure between the CoCs. We also observe changes in each measure over time. Figure 1 presents time series of per capita measures of property crime, violent crime and homelessness.

necessarily negatively impacts another person. We do count, though, any crime involving theft or violence with the intent of procuring additional drugs.

While the three measures largely decrease over the sample period, they also exhibit some periods of growth at varying years throughout.

While level and per capita measures of crime and homelessness are easily interpretable, we also include the log per capita summary statistics of each variable in Table 1 as these are featured in our model estimations for two primary reasons. First, it is common in the crime literature to measure crime in log per capita terms (Levitt, 2001; Lochner and Moretti, 2004). Second, our log per capita measures of crime and homelessness have more appropriate distributional properties for model estimation. The level and per-capita forms of crime and homelessness are asymmetrically distributed, but the log per capita forms are reasonably symmetrical. Figure 2 demonstrates the relative symmetry of the log per capita measures of homelessness and total crime in the data[9].

We also include independent variables in each model that control for factors that theoretically and intuitively correlate with homelessness and crime. All are measured at the county level and suitably transformed to the CoC level when necessary. First, weather is intuitively correlated with both homelessness and crime. Temperature determines the extent of homelessness, particularly the unsheltered, with warm climates having higher rates of homelessness than cold climates (Corinth and Lucas, 2018). Regarding the relationship between weather and crime, Trujillo and Howley (2021) offers a concise overview of results in the literature as well as the relationship's theoretical underpinnings. Felson (2000) posits that crime is more likely the more pleasant is the climate. Heilmann et al. (2021) found that crime increases as temperatures climb but Ranson (2014) showed that crime can indeed increase in warm temperatures but decrease in cold temperatures. Precipitation can also play a role. For instance,

[9] We note the density of log per capita of property and violent crime looks very similar to their aggregate.

Jacob et al. (2007) found that precipitation and crime are inversely related. We obtain precipitation as measured in inches and temperature data from the National Oceanic and Atmospheric Administration: National Centers for Environmental Information. Following the literature's guidance that extreme weather conditions can influence criminal behavior, we measure the number of days below 32° Fahrenheit (0° Celsius) and above 90° Fahrenheit (32° Celsius), respectively.

We also include the CoC unemployment rates and income levels as controls for regional economic strength, which intuitively and theoretically play large roles in explaining both homelessness and crime (Calvo-Armengol et al., 2007; Mustard, 2010). Unemployment rates are gathered from the US Bureau of Labor Statistics' Local Area Unemployment Statistics and incomes are obtained from the US Census Bureau's Small Area Income and Poverty Estimates Program. Demographic heterogeneity is also typically controlled for in crime and homelessness studies. As such, we collect from the UW Census Bureau the CoC population proportions of Black, Hispanic and women as controls in our estimations, as well as proportions reflecting age ranges of the CoC populations. Finally, educational attainment tends to be negatively correlated with both crime (Lochner and Moretti, 2004) and homelessness (Nilsson et al., 2019). We therefore control for regional educational attainment using data from the US Census Bureau's Small Area Income and Poverty Estimates Program. Finally, we include the log of police per capita as a control since police presence is typically related to both crime (Lin, 2009; Di Tella & Schargrodsky, 2004) and homelessness (Berk and MacDonald, 2010). However, police presence may also correlate over time with regional sociological factors that themselves correlate with homelessness and crime. As described in section 3.2, we include a lagged measure of police presence as an instrument in our primary model to address the inherent endogeneity. These police data are collected from the State of California's Department of Justice database.[10]

Table 2 outlines the summary statistics for the study's independent variables. Again, except for the "log of police per capita" and "percentage female", the standard deviations indicate a substantial amount of inter-CoC variation. On average in these data there are approximately 1.5 police officers per 1,000 people.[11] The average 9.91% unemployment rate was typical for this period during and after the Great Recession. As California is known as a warm climate state, a surprising average number of annual sub-freezing days (32) occurred during the sample period. The percentage of the population in these California data that are Black (5.1%) is much lower than the national average of 13.6%, whereas the percentage of the population that is Hispanic (32.7%) is much higher than the national percentage (19.1%).[12] California's average income per-capita of more than $59,000 across the CoCs is much larger than the national average of roughly $43,500 during the sample period.[13]

3. Models

Estimating the relationship between crime and homelessness is fraught with several complications. Arguably the largest concerns the observable and unobservable factors that affect both crime and homelessness. Some factors might impact crime and homelessness similarly

[10] The police variable incorporates a broad range of law enforcement employees. For instance, law enforcement officers stationed within school districts, community colleges, universities, hospitals, developmental centers, airports, and the California State Fair are all included. In addition to local police departments, the variable also accounts for officers within county Sheriff's Departments, Departments of Parks and Recreation, Ports and Harbor Police, the US Marshal's Office, and the California Highway Patrol.

[11] The FBI's Crime in the US 2017 Table 77 places this rate at approximately 2.3 officers per 1,000 people. The discrepancy is likely due to the CoC data transformations and some missing lower population California counties.

[12] The national rates come from the US Census Bureau Quick Facts tables.

[13] US Bureau of Economic Analysis, Personal income per capita, retrieved from FRED, Federal Reserve Bank of St. Louis, series A792RC0A052NBEA.

whereas other factors might impact them differently. Including a robust quantity of control variables in the models can begin to account for these effects, but there are likely unobservable effects that we cannot directly control. Moreover, there likely exist factors that correlate with both homelessness and crime either directly or indirectly. We attempt to correct for this endogeneity using two approaches.

First, we control for unobservable characteristics fixed over time that likely vary between the CoCs. For instance, there may be certain cultural differences between CoCs that likely do not fluctuate much over time but also correlate with crime and homelessness. Second, we attempt to control for those effects that likely include feedback loops in the models' relationships. Namely, there may exist social or other factors that affect crime and homelessness over time, but that crime and homelessness may also affect in turn. For instance, there may be regional and temporal variation in the number of individuals with mental health conditions, and professionals and clinics serving such individuals, that might correlate with the quantity of crime and homelessness. The feedback effect might be how criminal activity and homelessness can then, in turn, cause strain in individuals' mental health and affect the number of suffering individuals seeking help from professionals and clinics. Another unobservable factor with potential feedback effects might include differences in regional or municipal traditions in how crimes and homelessness are publicly treated and recorded. The degree of tolerance towards crime and homelessness in those regional traditions might vary. Some regions might ignore minor instances like jaywalking (or even more serious offenses) or sleeping on the street whereas others might not. This tolerance may invite or allow crime and homelessness to increase, which might in turn reduce the region's tolerance for crime or homelessness. Some of these feedback effects might be time-constant and therefore captured in the CoC fixed effects, but others might change over time due to exogenous shocks. These effects require an additional approach.

3.1 Baseline Model (Naïve Model that does not account for unobservable factors)

We start with a "Naïve" model that utilizes a simple OLS estimator and includes the controls outlined in Table 2. It is naïve in the sense that the model does not control for the unobservable factors mentioned above. In this baseline model we also add a lagged dependent variable to address the dynamic nature of crime and homelessness and, in part, because the literature has modeled crime with these dynamics. Levitt (2004) and Bender and Theodossiou (2016) document that crime tends to be persistent, where high levels in one period are associated with high levels in the next period, and analogously low levels in one period tend to persist into the next period. Thus, it is important to include these persistence effects in the crime and homelessness equations.

Our two main variables of interest will be $h_{i,t}$ and $c_{i,t}$ where $h_{i,t}$ is the log of homelessness per capita in CoC *i* in year *t* and $c_{i,t}$ is the log of crime per capita in CoC *i* in year *t*. We examine overall crime as well as property crime and violent crime separately. Our two equations of interest are:

$$h_{i,t} = \alpha_0 + \alpha_1 h_{i,t-1} + \rho_1 c_{i,t} + \rho_2 p_{i,t} + \boldsymbol{x'}_{i,t}\boldsymbol{\theta} + \tau_{u,t} + \varepsilon_{h,i,t} \quad (1)$$

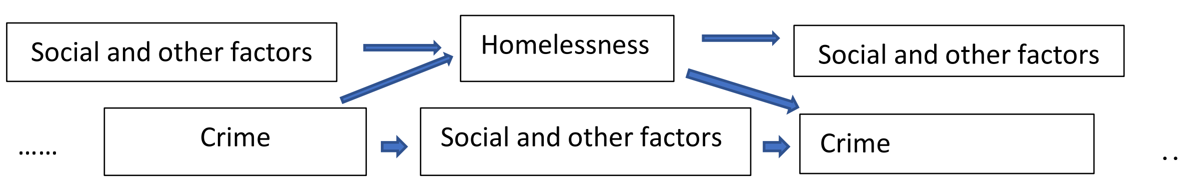
$$c_{i,t} = \beta_0 + \beta_1 c_{i,t-1} + \varphi_1 h_{i,t} + \varphi_2 p_{i,t} + \boldsymbol{x'}_{i,t}\boldsymbol{\delta} + \tau_{c,t} + \varepsilon_{c,i,t} \quad (2)$$

where $\boldsymbol{x}_{i,t}$ is a vector of time variant controls found in Table 2 and $p_{i,t}$ is the log of the number of police per capita. We divide the police measure out from $\boldsymbol{x}_{i,t}$ due to its importance and potential endogeneity we address in section 3.2. The τ terms represent year dummies; the α , β , ρ , φ , $\boldsymbol{\delta}$, $\boldsymbol{\theta}$ terms and vectors are estimable coefficients. The two equations are dynamic because of the inclusion of the lagged value of $h_{i,t-1}$ in equation (1) and the lagged value of $c_{i,t-1}$ in equation (2). Inclusion of the lagged left-hand side variables is appropriate if past values affect current values or if, following a change in homelessness or crime, they tend to revert partially but not fully to their previous levels in future years. We also estimate a version of equation (1) where we include property and violent crimes as separate variables.

3.2 Main Econometric Model

If we consider the ideal experiments a policy maker might consider, they might comprise treatments devoting resources to (randomly) changing the homeless population and measure the effect on crime, or similarly treatments devoting resources to (randomly) changing crime and measure the effect on homeless individuals. If, for example, reducing homelessness also reduces crime, but it is not true that reducing crime reduces homelessness, then policy makers may accrue more value by spending resources on reducing homelessness; they gain the added effect of reducing crime. Random control trials are best suited to measuring these relationships but are not implementable. In modern econometrics there are two alternative approaches when random control trial experiments cannot be conducted. First, sources of "natural" random variation may provide a suitable proxy for a random control trial. These random variation, or natural experiment, studies are highly valuable. However, it is quite difficult to find these situations. Moreover, they have the added disadvantage of often being limited to a small geographic region or a specific period of time. Second, we could instead try to control for as many factors as possible and use a modeling structure that creates quasi-random variation through empirical techniques such as instrumental variables. Since we cannot find a circumstance featuring natural random variation in crime or homelessness, and we are interested in the magnitude that a policy of reducing homelessness or crime may have on the other, we focus on the latter approach.

As previously noted, there are multiple complications in estimating the relationship between crime and homelessness. Aside from reasonably exogenous and time variant independent variables that we control for in standard OLS estimates, there are unobservable time invariant independent variables that risk substantial omitted variable bias if left unchecked. We control for these by including CoC fixed effects in the model. Moreover, there is likely endogeneity in models measuring the relationship between crime and homelessness; they are interrelated with each other and with omitted and unobservable time variant factors. These complications are perhaps best illustrated in the following flow diagram:



The flow diagram shows how crime and social and other factors may affect homelessness, but in turn homelessness and social and other factors may affect crime. One might consider these effects as "feedback", or inter-relationships, that bias simple OLS estimates. Our first OLS model does account for the diagram's arrows to some extent through the controls listed in Table 2 but fails to account for both time invariant unobservable factors in the horizonal arrows and the "feedback" or inter-relationships illustrated by the diagonal arrows. Our main model is superior to the first OLS model (equations 1 and 2) in two ways. First, it accounts for time invariant heterogeneity among CoCs using fixed effects. Second, it accounts for, to some extent, the "feedback" endogeneity by incorporating an instrumental variable technique to better account for the inter-relationships between social and other factors, crime, and homelessness.

Our main model begins with the following two augmentations of equations 1 and 2:

$$h_{i,t} = \alpha_0 + \sum_{j=1}^{z} \alpha_j\, h_{i,t-j} + \rho_1 c_{i,t} + \rho_2 p_{i,t} + \boldsymbol{x'}_{it}\boldsymbol{\theta} + \tau_{u,t} + a_i + \varepsilon_{h,i,t} \qquad (1')$$

$$c_{i,t} = \beta_0 + \sum_{j=1}^{z} \beta_j\, c_{i,t-j} + \varphi_1 h_{i,t} + \varphi_2 p_{i,t} + \boldsymbol{x'}_{it}\boldsymbol{\delta} + \tau_{c,t} + a_i + \varepsilon_{c,i,t} \qquad (2').$$

Equations (1') and (2') are similar to (1) and (2) but allow for multiple lags of the dependent variable when $z > 1$. We will see that including more than one-period lags in these functional forms is not necessary, but we will use this more general form to investigate the length of the persistence of our variables of interest.

Equations (1’) and (2’) introduce the a_i term that represents the CoC fixed effect, thereby accounting for time invariant unobserved heterogeneity. However, since we also include lagged dependent variable(s) to permit the respective dependent variable(s) to behave dynamically, we introduce bias that Nickell (1981) demonstrates produces inconsistent estimates. If we consider equation (1), the common way to control for the fixed effect is to demean the equation using the “within estimator” by regressing $h_{it} - \bar{h}_i$ on $h_{it-1} - \bar{h}_i$ (a bar over a variable indicates averaging over time). Alongside other demeaned independent variables, the demeaned error term would then be $\varepsilon_{h,i,t} - \bar{\varepsilon}_{h,i}$. Since h_{it} is correlated with $\varepsilon_{h,i,t}$, and h_{it-1} is correlated with $\varepsilon_{h,i,t-1}$, this implies $h_{it-1} - \bar{h}_i$ is correlated with $\varepsilon_{h,i,t} - \bar{\varepsilon}_{h,i}$, thus generating a correlation between the lagged dependent variable regressor and the error term, and biasing the coefficient on the lagged dependent variable. This would, in turn, likely bias the other coefficients through so-called “smearing”. Implementing the “within estimator” process in this dynamic panel data model can only be consistent if $\bar{\varepsilon}_{i,h}$ is small relative to $\varepsilon_{h,i,t}$, but this is only true if the number of time periods goes to infinity. That is, of course, not the case in these data, so our estimation procedure corrects for this bias.

There remains the endogeneity concerns we previously raised. Our primary model and estimation procedure will help account for the endogeneity of crime in equation (1') by allowing current crime and policing to be correlated with current and past time-variant unobservable factors that affect homelessness. Similarly, our approach allows current homelessness and policing to be correlated with current and past time-variant unobservable factors that affect crime in equation (2').

To correct for the "Nickell bias" and to account for the endogeneity of the key right-hand side variables we use the approach pioneered by Arellano and Bond (1991) but later extended by Arellano and Bover (1995) and Blundell and Bond (1998). It begins by first differencing (1') and (2'):

$$\Delta h_{i,t} = \sum_{j=1}^{z} \alpha_j \, \Delta h_{i,t-j} + \rho_1 \Delta c_{i,t} + \rho_2 \Delta p_{i,t} + \Delta \boldsymbol{x'}_{it} \boldsymbol{\theta} + \tau_{u,t} + \Delta \varepsilon_{h,i,t} \quad (1'')$$

$$\Delta c_{i,t} = \sum_{j=1}^{z} \beta_j \Delta \, c_{i,t-j} + \varphi_1 \Delta h_{i,t} + \varphi_2 \Delta p_{i,t} + \Delta \boldsymbol{x'}_{it} \boldsymbol{\delta} + \tau_{c,t} + \Delta \varepsilon_{c,i,t} \quad (2'')$$

where $\Delta h_{i,t} = \left(h_{i,t} - h_{i.t-1}\right)$, for instance. This method is often referred to as the Arellano-Bover or Blundell-Bond estimator (henceforth we abbreviate this as AB/BB). The AB/BB estimates allow us to "endogenize" variables in these equations by including lagged values as (excluded) instruments. We "endogenize" crime and police in the homeless equations and homeless and police in the crime equations.

Examining this in terms of homelessness equations, in equation (1") we incorporate $c_{i,t-2}$ and $p_{i,t-2}$ as excluded instruments and $\Delta c_{i,t-1}$ and $\Delta p_{i,t-1}$ in the level equation (1'). While police is not a main concern in our study, we choose police for its clear endogeneity issues with crime and homelessness and the resulting "smearing"; the fear that one endogenous variable can smear bias across the other estimated coefficients. This approach permits us to relax the strict exogeneity assumption, allowing $E[c_{i,s}\ \varepsilon_{h,i,t}] \neq 0$ and $E[p_{i,s-1}\ \varepsilon_{h,i,t}] \neq 0$ for $s \geq t$, and allowing for the current number of crimes and police to be correlated with current and past time-variant unobservable factors that affect homelessness. This both accounts for their current endogeneity as well as correcting for the "feedback" problem. It is possible to include further lags of the variables as additional instruments, and we do so in section 4.4 robustness checks, however we opt against this in the primary model to prevent including too many instruments that can lead to finite sample bias.

It is also necessary to correct for the Nickell bias we create when including both lagged dependent variables and fixed effects. Again considering the homeless equation, under this model the parameter estimates will be inconsistent if estimated with OLS because, even if the error term is serially uncorrelated, $(h_{i,t-1} - h_{i.t-2})$ is correlated with$(\varepsilon_{h,i,t} - \varepsilon_{h,i,t-1})$ since h_{it-1} is by definition correlated with $\varepsilon_{h,i,t-1}$. In the homelessness equation, we make the assumption that $E[h_{is}\ \Delta\varepsilon_{h,i,t}] = 0$ for $s \leq t-2$ in equation (1') so that $h_{i,t-2}$, h_{it-3}, and h_{it-4} are used as additional (excluded) instruments in equation (1'') (Arellano and Bond, 1991). We add the additional assumption that $E[\Delta h_{it-1}\ \varepsilon_{it}] = 0$ so that Δh_{it-1} can be used as an instrument in equation (1'). Blundell and Bond (1998) showed that incorporating this second instrument in the level equation produces large efficiency gains, and these level restrictions remain informative in the cases where the first-differenced instruments may become weak (Baltagi, 2013, pp. 167-168).[14]

[14] It is possible to use many lags of the dependent variable as instruments. However, we limit the lags of the dependent variable to, at most when available, three periods. For example, for 2010 the fourth year of our panel, in our level equation we would have $h_{i,2010}$ as our dependent variable, $h_{i,2009}$ would be a right-hand side variable and would be instrumented with $\Delta crime_{i,2009}$ and $\Delta crime_{i,2008}$. For the differenced equation we would have $\Delta crime_{i,2010}$ as our dependent variable, $\Delta crime_{i,2009}$ as a right-hand side variable and it would be instrumented

To summarize our excluded instruments again considering the homeless equation, we use $h_{i,t-2}$, $h_{i,t-3}$, and $h_{i,t-4}$, $c_{i,t-2}$ and $p_{i,t-2}$ as additional excluded instruments in equation 1" while using Δh_{it-1}, $\Delta c_{i,t-1}$ and $\Delta p_{i,t-1}$ in equation 1'. When two lags of the dependent variable are used as independent variables, all instruments that are versions of the dependent variable are lagged an additional period. As mentioned above "excludability" is satisfied if the errors are not serially correlated. We discuss a test for this in subsection 4.1. "Validity" is satisfied because one variable is always "part" of another. For example, in equation 1' $(h_{i,t-1} - h_{i,t-2})$ would need to be correlated with $h_{i,t-1}$. This is clearly satisfied because $h_{i,t-1}$ is part of $(h_{i,t-1} - h_{i,t-2})$. Similarly, in equation 1" $h_{i,t-2}$ needs to be correlated with $(h_{i,t-1} - h_{i,t-2})$. This too is satisfied because $h_{i,t-2}$ is part of $(h_{i,t-1} - h_{i,t-2})$. A similar argument can be made for both the crime and police variables and their instruments. Since our approach uses panel data techniques that include instrumental variables, it might be termed a quasi-experimental design.

We use a one-step estimator. While there exists a GMM two-step estimator that may be more efficient, the one step estimator is consistent, and both estimators are asymptotically equivalent if the errors are $IID(0, \sigma_{\varepsilon}^2)$. Figure 2 shows that our left-hand-side variables are somewhat normally distributed. To account for the small-sample downward bias in the standard errors found in a Monte Carlo study by Arellano and Bond (1991) we use the correction based on a Taylor series expansion create by WindMeijer (2005). There is additional technical detail behind this estimator but omit it for brevity's sake. We direct the interested reader to Baltagi (2013, pp. 157-168).

with $crime_{i,2008}$ and $crime_{i,2007}$. For 2009 we would only have one homeless instrument for each equation and for 2011 and later we would have three instruments for each equation.

4. Results

The main estimates appear in Tables 3 and 4. We include five sets of results; first, an OLS model with no controls (column 1) and an OLS model with controls and including a lagged dependent variable (column 2). The column 2 estimate might be referred to as a LDV (lagged dependent variable model). Column 3 estimates are from an OLS model with controls and including CoC fixed effects, column 4 presents results from an AB/BB estimation with a single lagged dependent variable, and finally column 5 shows results from an AB/BB estimation with two lagged dependent variables. Estimates in column 4 reflect our primary results while the estimates in column 5 merely demonstrate that in all specifications only one lag of the dependent variable is necessary. In table 3 we include four sets of all of these estimations, one with total crime (property crime and violent crime summed together) as the independent variable, one with only violent crime, one with only property crime, and finally one with both property and violent crime included as separate independent variables.

The importance of including dynamics is illustrated by the statistically significant coefficient on the (once) lagged dependent variables in estimates (2), (4) and (5) in both the homelessness estimation (Table 3) and the crime estimation (Table 4). The coefficient on the one period lagged crime is larger in Table 4 than the lagged value of homelessness in Table 3. This demonstrates there is more persistence in crime than homelessness. When included in column 5 estimates, the coefficient on the second lag of crime or homelessness is small in magnitude and never statistically significant. This indicates that there is only short-term persistence in crime and homelessness across time. Also, in both equations the coefficients on these (once) lagged variables shrink in magnitude once we employ the AB/BB modeling strategy in column 4 relative to column 2, demonstrating the importance of controlling for the effect of unobserved heterogeneity and accounting for endogeneity.

4.1 Model Evaluation

In order for our AB/BB model to provide consistent estimates and to be able to relax the strict exogeneity assumption mentioned above, the order-one first differenced errors must be statistically correlated, and the correlations of higher order errors (two, three, etc.) must be statistically zero. It is common practice to examine the first three orders of the differenced errors with the Arellano-Bond (AB) test (Arellano and Bond, 1991; Baltagi, 2013, p. 158). We therefore test the following three hypotheses for both equations:

$H_o\colon E[\Delta\varepsilon_{i,t}\Delta\varepsilon_{i,t-s}] = 0$ for $s = 1, 2, 3$.

In order for our AB/BB estimates to be consistent we need to reject H_o at order one (s = 1) but fail to reject the H_o at orders two and three (s = 2, 3). The p-value results for each of these hypothesis tests and for each estimation can be found in columns 4 and 5 of Tables 3 and 4. We analyze these tests at the 5% level to remain consistent with our evaluation criteria throughout. Tables 3 and 4 show that all the AB/BB estimates pass these tests. All order one p-values are less than 0.05 and all order two and order three p-values are greater than 0.05.

4.2 Effect of Crime on Homelessness

We start by examining the results from the relationship exploring the effect crime has on homelessness found in Table 3. The first estimation, a simple OLS estimation with no controls, indicates that for overall crime and property crime there is no association between crime and homelessness, but for violent crime there is a positive association. After including the controls listed in Table 2 along with once lagged homelessness, the column 2 results suggest there is no evidence that crime impacts homelessness in any of the models. In column 3, controlling for CoC time-invariant fixed effects but not lagged homelessness shows a positive and significant relationship between only violent crime and homelessness. However, we then estimate homelessness using our primary AB/BB model with one lagged dependent variable in column 4. This model accounts for the endogeneity issues discussed above as well as CoC time-invariant fixed effects. While we find no evidence in column 4 that overall crime or violent crime impact homelessness, we see that property crime is significantly and positively related to homelessness. Specifically, a one percent increase in property crime per capita increases homelessness per capita by approximately 1.2 percent. This result persists when including both violent and property crime as predictors in the same estimation as demonstrated in panel D of Table 3; the coefficient on property crime is still positive, and in fact increases in magnitude, while the coefficient on violent crime is still statistically insignificant and interestingly even turns negative in value.

A key finding is that the homeless population only seems to change as a result of changing property crime; the coefficient for violent crime is not only statistically insignificant, but it is also small in magnitude (and even negative in the model with both crimes included). It is important to note that, when we examine the models with one type of crime as a predictor, the results from the simple correlation and the preferred model are the complete opposite. In a simple correlation it appears that violent crime leads to homelessness (this is also true in a fixed effects model with controls) and that there is no evidence that property crime affects homelessness. However, in the preferred model the opposite is true: there is no evidence that violent crime affects homelessness, but there is strong evidence that more property crime leads to homelessness. Based on these results it appears that the previously discussed endogeneity issues play a large role in how crime affects homelessness.

It is noteworthy to mention that property crime's statistically insignificant coefficient in column 5 of the property crime estimation (panel C in Table 3) should be interpreted with caution. First, the additional lagged homelessness variable introduces a different and smaller dataset with fewer observations. Second, the two-period lagged dependent variable coefficient is statistically insignificant and small in magnitude. Thus, we only present these results in column 5 for completeness purposes and to demonstrate that only a one-period lag of the dependent variable is necessary. Additionally, in the panel D estimation that includes both types of crime, the coefficient on property crime is statistically significant even in column 5.

The effect size of the property crime coefficient invites further examination. If we examine the more conservative model with only property crime (panel C), a one percent increase in property crime increases homelessness by 1.209 percent (in column 4).[15] An elasticity of approximately 1.2 suggests homelessness is relatively sensitive to changes in the quantity of property crimes in a region. If we examine this effect at the mean values of the homelessness and crime variables, we find that an increase of approximately 267.34 previous property crimes (a 1% increase of the mean number of 26,775.93) increases the number of homeless individuals by approximately 39.16 individuals (a 1.209% increase from the mean value of 3,238.979). This means that approximately every 6-7 additional property crimes are associated with one additional homeless person. The size of this result must be interpreted with some caution because the coefficient estimate's 95% confidence interval is fairly wide; the bottom is 0.154. If we instead

[15] The results for per capita crime and homelessness and total crime and homelessness will have the identical value because when taking the partial derivatives of crime and homelessness per capita and solving for the coefficient, the population variable will cancel out.

use the bottom of the 95% confidence interval but still examine the outcomes at mean values, we find that approximately every 54 additional property crimes will result in one more individual becoming homeless. This is arguably still a substantial effect, but obviously not nearly as large. These numbers would be even larger when using the panel D estimates with both types of crime in the same equation; the coefficient for property crime is larger and its standard error a bit smaller.

Potential mechanisms explaining the elastic response of homelessness to property crime are difficult to parse. Certainly, increased destruction and theft of homeless individuals' property can increasingly perpetuate the victims' homeless status. For example, repeated "break-ins" to one's house may make an individual or family less likely to pay rent and face eviction. Motor vehicle theft may also create a burden, potentially not allowing individuals to remain employed and lead to homelessness. Alternatively, homeless people may instead be the perpetrators of property crime, be convicted in court, and end up incarcerated. It is often challenging to find a sufficiently paid and stable job after serving prison sentences (Visher et al., 2011), thus increasing the likelihood former prisoners join and increase the homeless population. It is important to recognize that our data cannot identify whether homeless individuals are the perpetrators of a property crime or the victims. Indeed, Tsai (2017) finds that substantial proportions of homeless people in that study's large sample were victims of property destruction (27%) or theft (32%).

4.3 Effect of Homelessness on Crime

Now we turn to the effect that the number of homeless individuals may have on crime. As before, our results depend on the types of crimes we are examining. The estimates in Table 4 suggest there is no evidence that an increase in homelessness leads to a change in property crime, but an increase in homelessness does increase violent crime. Specifically, in the AB/BB estimation procedure's column 4 results, a 1 percent increase in homelessness per capita will increase violent crime per capita by 0.075 percent. This result suggests that violent crime demonstrates an inelastic response to homelessness and is similar to the 0.09 estimate in Corinth and Grace (2017). Although this coefficient may at first appear small, further examination suggests a substantial effect. At mean values, each additional 32.39 homeless individuals in an area correspond with an increase in violent crimes by 3.27. In other words, 10 additional homeless individuals corresponds to approximately one more violent crime. The lower bound estimate of the confidence interval is 0.013. This corresponds to one additional crime for every 57 additional homeless individuals. It is interesting to note that the coefficient in our preferred estimation (column 4) is twice as large as in the second estimation of OLS with controls, which again highlights the importance of using a more sophisticated modeling/estimation strategy that accounts for endogeneity.

Potential mechanisms are again difficult to ascertain since once more we cannot decipher whether homeless individuals are the perpetrators or victims of the violent crimes in these data. However, like with property crime, it is clear from the literature that homeless individuals are at great risk of being victims of violent crimes (Meinbresse et al., 2014). Yet the literature also contains results suggesting homeless individuals may be more likely to commit crimes (Mulvey, 1994; Fischer et al., 2008). This study's results seem to suggest that, at minimum, increases in homelessness can lead to higher rates of violent crime in a region, but there is no evidence of an effect on property crime.

4.4 Robustness and Falsification Checks

In this section we explore alternative model specifications to test the robustness and validity of the primary model. We start by estimating the models with alternative versions of our dependent variables. Specifically, we explore whether removing the population from the denominator of the dependent variable will change the results. We persist in using logged versions of our dependent variables due to their relative symmetrical distributions. The first two columns of Table 5 present the results of estimations whose specifications correspond entirely with those in columns 4 and 5 of Tables 3 and 4, except for the change in the dependent variables. In the interest of space, we only present the results for the independent variable of interest. These results qualitatively replicate our main results found in Tables 3 and 4 and are quantitively similar. All results in Table 5 retain their statistically significant or insignificant statuses from Tables 3 and 4 and are similar in size. For example, the coefficient for violent crime in column 3 of Table 3 is statistically insignificant at a value of 0.231; its analogous value in column 1 of Table 5 is also statistically insignificant with a similar value of 0.255. More importantly, the coefficient for property crime in column 3 of Table 3 is statistically significant at 1.209 and in Table 5 the corresponding coefficient has a statistically significant and similar coefficient value of 1.163. The approximate equivalencies continue when comparing the column 4 and 5 results in Table 4 with the column 1 and 2 results in the bottom panel of Table 5. Thus, removing population from the dependent variable's denominator has little or no effect on the results.

Next, we explore whether the results change when adding additional IV (instrumental variable) lags. The second two columns of Table 5 examine our primary AB/BB 1 models by including additional lags of the instruments. As an illustration, the Table 3 homelessness estimates in column 4 include 3 lags of the dependent variable as instruments ($h_{i,t-2}$, $h_{i,t-3}$, and $h_{i,t-4}$). When possible in Table 5's top panel, so as not to reduce the working sample's size, column 3 estimates add a fourth lag as an IV ($h_{i,t-4}$) and column 4 estimates add a fourth and fifth lag as IVs ($h_{i,t-5}$ and $h_{i,t-6}$), respectively. The additional instruments do not meaningfully alter the main results.[16]

Third, we conduct a falsification check by estimating our preferred model with our main independent variables of interest led one period. In theory, the coefficient on these variables should show no impact with this incorrect structure. However, if the statistically significant relationships remain significant with the incorrect structure, or if insignificant relationships become significant, then our modeling/estimation technique is likely incorrect and the significant results likely spurious. The first two columns in Table 6 portray the results when the incorrect structures are applied to the column 3 and 4 models in Tables 3 and 4. None of the coefficients are statistically significant, providing further evidence the estimation technique is sound.

Finally, determining the correct dynamic structure is difficult. While we believe the correct structure does not involve lagging the independent variable of interest, it is possible any insignificant results stem from a necessary longer period of time between crime and homelessness incidences. Perhaps it takes time for crime to affect homelessness and vice versa. In other words, there may be a timing issue. To explore these possibilities, we examine the homelessness equation with the independent crime variables lagged one year and then again with crime lagged two years. We apply the same lag strategy to the homelessness variable when

[16] It is also possible to estimate models with more complicated structures, such as allowing moving averaged (MA) errors. We do not present the results from these types of estimations since our main preferred models' estimates meet all the validity conditions. Consequently, we do not believe it is necessary to further complicate the models' structure.

crime is the dependent variable. The results are shown in columns 3 and 4 of Table 6. None of the coefficients of the lagged variables are statistically significant, suggesting that the insignificance found in some of the estimates in Tables 3 and 4 are not due to the independent variables' contemporaneous timing with the dependent variables.

4.5 Discussion/Policy Discussion

Our primary findings first suggest that reducing property crime carries the additional benefit of reducing homelessness. Second, reducing homelessness can reduce violent crime. Based on these results, a bold policy prescription to reduce crime and homelessness might focus municipalities and law enforcement agencies on reducing property crime, since this can reduce homelessness, which may in turn reduce violent crime. However, efforts to reduce property crimes can end up criminalizing homelessness in the process, as in some applications of the "broken-windows" approach to policing (Berk and MacDonald, 2010). Moreover, policing intended to maintain social order, at least in part by reducing misdemeanor offenses such as minor property crimes, can have the negative side effect of displacing homeless people and further destabilizing their lives (Sparks, 2018). Thus, while our results suggest efforts to reduce property crime can lead to reductions in both homeless populations and violent crime, local law enforcement agencies must carefully adopt approaches that will not criminalize homeless or enflame the homelessness crisis.

5. Conclusion

This paper examines the relationship between crime and homelessness utilizing a panel dataset from the state of California. California contains a disproportionate quantity of homeless individuals, so it is a natural laboratory for measuring homelessness and its relationships with other social phenomena. Crime is also a commonly discussed social problem in Californian media, so crime and homelessness are often linked in media accounts and social discussions. Much of the academic literature focuses on local or small regional policies to measure the relationship between crime and homelessness. While these are important in disentangling these relationships, wider studies are important to make sure the results apply to a wider population, geographic region, and time period. Indeed, crime and homelessness are difficult to randomly assign.

While the approaches in the literature are highly informative, the main advantages of using panel data methods to approach the crime-homelessness relationship is that we account for area heterogeneity and dynamics along with addressing endogeneity and feedback effects. Additionally, we examine a wider geographic area over a longer period of time. In this study we first examine California as a whole over multiple years rather than snapshots of local areas and/or times. Second, we seek causal (or at minimum semi-structural causal) relationships by including regional fixed effects in a dynamic panel data model that corrects for endogeneity (creating quasi-random variation) by incorporating lagged values of the endogenous regressors. The results indicate that increases in property crime can lead to increases in homelessness, and that increases in homelessness can increase violent crime. These relationships are statistically significant and substantial in magnitude. Further, we find no evidence that changes in violent crimes affects homelessness and no evidence that a change in homelessness affects property crime.

There remain potential caveats to our study. First, we could not employ random control trials or locate naturally random variation in crime or homelessness to correct for endogeneity in a cleaner way. Second, we examine only one state over a specific time period, which may not be ideal from an external validity perspective. Yet, California itself is a large economy and we examine it over a fairly long time period. Thus, studying California may be valuable in its own right. Finally, reducing property crime is a worthy endeavor, but our results indicate that there could be policy implications. Allocating resources to reduce property crime may have the added benefit of reducing homelessness, and reducing homelessness could, in turn, create the additional benefit of reducing violent crime. At minimum, this study's results invite further examination of the relationship between crime and homelessness.

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Figure 1: CoC homelessness and crime averages over time

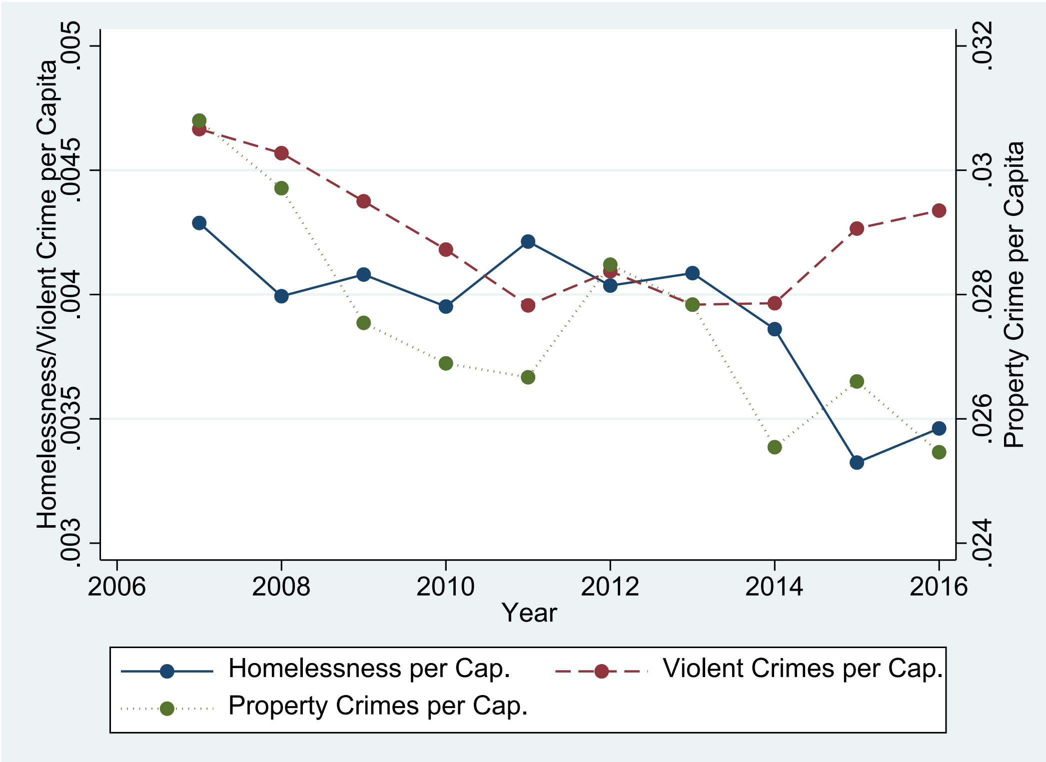

Figure 2: Kernal Density Estimates

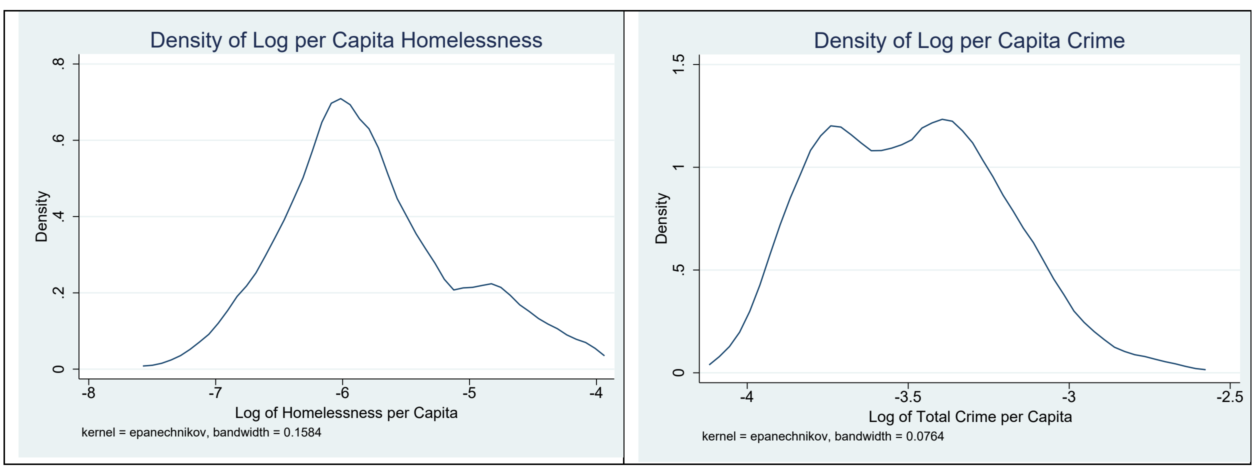

Table 1: Summary Statistics of Homelessness and Crime

Variable	Mean	Standard Deviation
Homelessness		
Homelessness	3,238.979	6,742.495
Homelessness per Capita	0.004	0.003
Log of Homelessness per Capita	-5.795	0.672
Total Crime		
Crime	31,097.290	48,492.510
Crime per Capita	0.031	0.009
Log of Crime per Capita	-3.500	0.275
Violent Crime		
Violent Crime	4,363.361	8,171.541
Violent Crime per Capita	0.004	0.002
Log of Violent Crime per Capita	-5.552	0.393
Property Crime		
Property Crime	26,733.930	40,468.270
Property Crime per Capita	0.027	0.008
Log of Property Crime per Capita	-3.644	0.279
n	338	

Each observation is a CoC/year.
There are 41 observations over 10 years and means are presented in total per year terms

Table 2: Summary Statistics of Control Variables

Variable	**Mean**	**Standard Deviation**
Log of Police Per Capita	-6.527	0.335
Unemployment Rate	9.909	4.356
Precipitation	21.118	14.942
Number of days with temperature below 32°F	31.748	33.972
Number of days with temperature above 90°F	58.693	37.834
Log of Income	10.955	0.256
Percentage Black	5.065	3.765
Percentage Hispanic	32.658	16.368
Percentage Female	49.982	0.951
Percentage with High School Diploma Only	21.709	4.276
Percentage with Some Col. Assoc. but no 4-year	32.387	5.054
Percentage of 4-year degree or more	28.539	11.292
Percentage of individuals aged 20 to 29	14.353	2.534
Percentage of individuals aged 30 to 49	26.117	2.474
Percentage of individuals aged 50 or older	32.669	5.666
Log of Population	13.111	1.142
n	338	

Table 3: Effect of Crime on Homelessness

	Dependent Variable: Log of Homelessness Per Capita				
	(1)	(2)	(3)	(4)	(5)
	OLS No Controls	OLS Controls	With FE	AB/BB 1	AB/BB 2
A. Total					
Crime	0.095	-0.030	0.526	0.891	0.555
	(0.133)	(0.114)	(0.269)	(0.516)	(0.548)
Homelessness $_{t-1}$		0.726**		0.436**	0.478**
		(0.035)		(0.118)	(0.111)
Homelessness $_{t-2}$					-0.093
					(0.077)
AR1 p-value (s=1)				0.01	0.01
AR2 p-value (s=2)				0.10	0.11
AR3 p-value (s=3)				0.16	0.14
B. Violent					
Crime	0.300**	0.121	0.547**	0.231	0.095
	(0.092)	(0.080)	(0.179)	(0.349)	(0.334)
Homelessness $_{t-1}$		0.710**		0.431**	0.521**
		(0.036)		(0.126)	(0.127)
Homelessness $_{t-2}$					-0.006
					(0.092)
AR1 p-value (s=1)				0.01	0.03
AR2 p-value (s=2)				0.12	0.08
AR3 p-value (s=3)				0.16	0.20
C. Property					
Crime	-0.006	-0.080	0.362	1.209*	0.967
	(0.132)	(0.108)	(0.248)	(0.538)	(0.567)
Homelessness $_{t-1}$		0.726**		0.467**	0.509**
		(0.035)		(0.121)	(0.115)
Homelessness $_{t-2}$					-0.098
					(0.076)
AR1 p-value (s=1)				0.01	0.01
AR2 p-value (s=2)				0.13	0.16
AR3 p-value (s=3)				0.18	0.19
D. Both Crime Variables in the Same Equation					
Violent Crime	0.508**	0.176*	0.515**	-0.240	-0.221
	(0.118)	(0.087)	(0.183)	(0.296)	(0.274)
Property Crime	-0.461**	-0.179	0.217	1.298*	1.134*
	(0.166)	(0.119)	(0.251)	(0.535)	(0.512)
Homelessness $_{t-1}$		0.706**		0.547**	0.622**
		(0.036)		(0.112)	(0.095)
Homelessness $_{t-2}$					-0.067
					(0.075)
AR1 p-value (s=1)				0.00	0.01
AR2 p-value (s=2)				0.19	0.17
AR3 p-value (s=3)				0.27	0.25
Observations	338	338	379	338	297

Standard errors in parentheses; * $p < .05$, ** $p < .01$

Estimations (2), (3), (4) and (5) include the full set of controls found in Table 2 and time dummies.

Table 4: Effect of Homelessness on Crime

	Dependent Variable: Log of Crime Per Capita				
	(1)	(2)	(3)	(4)	(5)
	OLS No Controls	OLS Controls	With FE	AB/BB 1	AB/BB 2
A. Total					
Homelessness	0.016	0.009	0.023	0.036	0.034
	(0.022)	(0.007)	(0.012)	(0.020)	(0.029)
Crime $_{t-1}$		0.910**		0.722**	0.704**
		(0.023)		(0.096)	(0.107)
Crime $_{t-2}$					-0.040
					(0.078)
AR1 p-value (s=1)				0.00	0.00
AR2 p-value (s=2)				0.13	0.13
AR3 p-value (s=3)				0.07	0.16
B. Violent					
Homelessness	0.102**	0.033**	0.053**	0.075*	0.074*
	(0.031)	(0.012)	(0.017)	(0.031)	(0.030)
Crime $_{t-1}$		0.868**		0.694**	0.706**
		(0.026)		(0.093)	(0.093)
Crime $_{t-2}$					0.073
					(0.093)
AR1 p-value (s=1)				0.00	0.00
AR2 p-value (s=2)				0.73	0.64
AR3 p-value (s=3)				0.79	0.91
C. Property					
Homelessness	-0.001	0.005	0.019	0.033	0.028
	(0.023)	(0.008)	(0.013)	(0.022)	(0.032)
Crime $_{t-1}$		0.907**		0.696**	0.654**
		(0.024)		(0.094)	(0.099)
Crime $_{t-2}$					0.005
					(0.083)
AR1 p-value (s=1)				0.00	0.00
AR2 p-value (s=2)				0.19	0.07
AR3 p-value (s=3)				0.08	0.15
Observations	338	338	379	338	297

Standard errors in parentheses; * $p < .05$, ** $p < .01$
Estimations (2), (3), (4) and (5) include the full set of controls found in Table 2 and time dummies.

Table 5: Robustness Checks

Dependent Variable: Log of Homelessness	(1) Not Per Capita AB/BB 1	(2) Not Per Capita AB/BB 2	(3) Four lags as IVs AB/BB 1	(4) Five lags as IVs AB/BB 1
A. Total				
Crime	0.901	0.529	0.905	0.953
	(0.499)	(0.505)	(0.514)	(0.499)
B. Violent				
Crime	0.255	0.057	0.198	0.193
	(0.296)	(0.288)	(0.337)	(0.323)
C. Property				
Crime	1.163*	0.875	1.255*	1.286*
	(0.502)	(0.500)	(0.547)	(0.522)
Observations	338	297	338	338

Dependent Variable: Log of Crime	(1) Not Per Capita AB/BB 1	(2) Not Per Capita AB/BB 2	(3) Four lags as IVs AB/BB 1	(4) Five lags as IVs AB/BB 1
A. Total				
Homelessness	0.035	0.033	0.039*	0.035
	(0.018)	(0.026)	(0.020)	(0.020)
B. Violent	0.079**	0.072*	0.071*	0.074*
Homelessness	(0.030)	(0.030)	(0.030)	(0.029)
C. Property				
Homelessness	0.030	0.024	0.037	0.034
	(0.021)	(0.030)	(0.022)	(0.022)
Observations	338	297	338	338

Standard errors in parentheses; * $p < .05$, ** $p < .01$
Estimations in top of this table have the same estimation techniques and same controls as Table 3 (the final two results) and the bottom of this table has the same techniques and controls as Table 4. The only difference is the specification of the dependent variable.

Table 6: Falsification Checks and Exploring Potential Timing Issues

Dependent Variable: Log of Homelessness Per Capita				
	(1)	(2)	(3)	(4)
	AB/BB 1 Crime led	AB/BB 2 Crime led	Once Lagged Crime AB/BB 1	Twice Lagged Crime AB/BB 1
A. Total				
Crime	0.359	-0.452	0.222	-0.072
	(0.690)	(0.839)	(0.659)	(0.511)
B. Violent				
Crime	0.044	0.032	-0.082	0.056
	(0.353)	(0.394)	(0.268)	(0.344)
C. Property				
Crime	0.510	-0.216	0.498	0.075
	(0.682)	(0.754)	(0.658)	(0.501)
Observations	297	259	338	297

Dependent Variable: Log of Crime Per Capita				
	(1)	(2)	(3)	(4)
	AB/BB 1 Homelessness led	AB/BB 2 Homelessness led	Once Lagged Homelessness AB/BB 1	Twice Lagged Homelessness AB/BB 1
A. Total				
Homelessness	0.026	0.023	-0.032	-0.018
	(0.023)	(0.024)	(0.017)	(0.026)
B. Violent				
Homelessness	0.039	0.026	-0.038	0.023
	(0.054)	(0.053)	(0.033)	(0.043)
C. Property				
Homelessness	0.022	0.016	-0.030	-0.018
	(0.030)	(0.033)	(0.017)	(0.027)
Observations	297	259	338	297

Standard errors in parentheses; * $p < .05$, ** $p < .01$
Estimations in top of this table have the same estimation techniques and same controls as Table 3 (the final two results) and the bottom of this table has the same techniques and controls as Table 4. The only difference is the specification of the dependent variable.