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Abstract

This paper provides the first causal evidence of the effect of evictions on crime. I leverage the exogenous variation in evictions due to the staggered adoption of nuisance ordinances in Ohio's cities from 2000 to 2014—a policy that sanctions landlords for nuisances on their properties. I find that each 10 percent increase in evictions leads to 5.5 percent higher burglary into structures and 8.5 percent higher vehicle theft. Other crimes are not affected. The effect appears to be driven by higher homelessness and the pursuit of shelter by illegal means. Findings highlight an unexplored social cost of evictions.

JEL Classification: I3, K4, R21, R28
Keywords: Evictions, Crime, Homeless, Housing Policy, Nuisance Ordinances

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1 Introduction

The question of how evictions harm tenants has sparked recent research in economics and other social sciences. Findings suggest that evictions increase homelessness and reduce earnings, durable consumption and credit access (Desmond 2016; Collinson, Humphries, Mader, Reed, and van Dijk 2022). However, whether evictions also affect crime is unclear. Anecdotal evidence points to a plausible link between the two phenomena but causal evidence is still limited.

This paper fills this gap by testing the hypothesis that evictions lead to burglary into structures and vehicle theft as evicted individuals pursue shelter so as to not "sleep rough." To investigate this hypothesis, I exploit the exogenous variation in evictions generated by the staggered adoption of nuisances ordinances across cities in Ohio from 2000 to 2014. Nuisance ordinances sanction landlords for disturbances at their properties, increasing landlords' incentives to evict tenants (Kroeger and La Mattina 2020).

The context of nuisance ordinances offers one main advantage in exploring the effects of evictions: it reduces the potential bias due to the existence of informal evictions, which are unobserved. Since evictions are mentioned in nuisance ordinances as a method to abate disturbances, landlords can reasonably expect to win at trial against their tenants. Consistently, formal evictions have been found to occur almost six times more frequently than informal ones in the context of nuisance ordinances (Desmond and Valdez 2013). This is a relevant advantage for identification provided that the number of informal evictions is at least twice as high as the one for formal evictions in the United States (Desmond 2016).

To estimate the effect of evictions on crime, I apply a staggered difference-in-differences (DID) design that compares the change in evictions, burglary into structures, and vehicle theft in cities with versus those without a nuisance ordinance. The DID estimate captures the effect of evictions on crime assuming parallel trends in the outcomes and that the effect of nuisance ordinances on crime is driven exclusively by evictions.

Several pieces of evidence support interpreting results as the effect of evictions on crime. First, the literature suggests that the adoption of policies involving landlords in crime control, including nuisance ordinances, reflects a political shift in favor of the Republicans rather than changes in crime or housing conditions (Garland 2012). Consistently, I do not find pretrends in the number of evictions or crime levels, while the effects are visible 1–2 years after the adoption of the policy. The causal interpretation is confirmed when using city-month data, which allow me to zoom in with precision around the shock. Second, the balance test suggests that cities with a nuisance ordinance (treated) are similar across observable characteristics to cities without an ordinance (never treated). Third, I find evidence that nuisance ordinances increase crime only through evictions, rejecting alternative explanations such as changes in the housing market or crime misreporting.

Results show that nuisance ordinances lead to an increase of 32–33 percent in the number of evictions and to 18 percent higher burglary into structures, and 28 percent higher vehicle theft offenses, weighting for the city population. These numbers point to large elasticities of these crimes on evictions—0.55 for burglary and 0.85 for vehicle theft—suggesting that each 10 percent increase in evictions leads to 5.5 percent higher burglary and 8.5 higher vehicle theft.

I find indirect evidence that evicted households become homeless and break into structures or steal vehicles in the pursuit of shelter. First, evictions do not increase crimes weakly susceptible to the homeless presence: violent or income-generating crimes (Deshpande and Mueller-Smith 2022).[1] Second, I document an effect on the incidence of arrests for public drunkenness, a crime sensitive to the homeless presence (Snow, Baker, and Anderson 1989), which increases by 24 percent. Third, the effect on crime is present only in cities without homeless shelters. Fourth, the effect is driven by racially heterogeneous cities, where social capital and support networks are weaker (Alesina and La Ferrara 2000). Fifth, the effect on crime is stronger when outdoor conditions are harsher—from October through February. Sixth, the effect on burglaries exists only for public areas and commercial establishments, typical homeless' targets, and involves the theft of basic commodities only (clothes, consumables, etc.), likely to be lost or unstorable because of evictions. Last, the effect on clearances is not present, hinting to a change in the crime composition in favor of the offenses of the homeless, which are more difficult to clear and less serious than the crimes of burglars.

While individually only suggestive, these findings collectively point to homelessness and the pursuit of shelter as the mechanism through which evictions increase burglary into structures and vehicle theft. I also discuss why these same findings appear to

[1] As discussed in Section 5.4, criminology research has found positive associations between homelessness and burglary, vehicle theft, and public drunkenness, but not violent or income-generating offenses (Fischer 1988; Snow, Baker, and Anderson 1989; Faraji, Ridgeway, and Wu 2018). Deshpande and Mueller-Smith (2022) define "income-generating" crime as theft, fraud, forgery, robbery, drug distribution, and prostitution. Following the Federal Bureau Investigation (FBI), robbery is classified here as a violent crime. I focus on the following income-generating offenses: larceny, drug distribution, theft, forgery and counterfeiting, and gambling.

be inconsistent with other potential mechanisms such as changes in income, social interactions with criminals, or community policing.

Results are robust to the use of alternative outcome measures, additional controls and the estimator proposed by de Chaisemartin and D'Haultfœuille (2020) to overcome the issues in estimating treatment effects in staggered difference-in-differences designs (Borusyak and Jaravel 2017; Callaway and Sant'Anna 2021; de Chaisemartin and D'Haultfœuille 2020; Athey and Imbens 2022).

Related Literature.—This paper contributes to three strands of the literature. First, I add to the growing literature on the negative consequences of evictions, which is "perhaps the most understudied process affecting the lives of the urban poor" (Desmond 2012). Recent work in economics has found causal evidence that evictions harm evicted households (Collinson, Humphries, Mader, Reed, and van Dijk 2022).[2] Yet, despite growing interest in evictions, few works have studied how they affect individuals other than the evicted tenants, and the specific link between evictions and crime is almost completely unexplored.[3] This paper expands this emerging literature by providing the first causal evidence of an externality of evictions: crime. I thus also complement research on the social cost of foreclosures (Campbell, Giglio, and Pathak 2011; Anenberg and Kung 2014; Diamond, Guren, and Tan 2020; Guren and McQuade 2020) and cuts to housing affordability (Fetzer, Sen, and Souza 2020).

Second, this paper contributes to the well-established economics literature on the determinants of crime. Most of the crime literature has focused on private incentives, proving to be largely successful in explaining crime in several settings (Becker 1968; Stigler 1970; Ehrlich 1973; see Draca and Machin 2015 for a review of more recent contributions).[4] Instead, other economists have highlighted the importance of social interactions in criminal behavior (Sah 1991; Murphy, Shleifer, and Vishny 1993; Glaeser, Sacerdote, and Scheinkman 1996; Bayer, Hjalmarsson, and Pozen 2009; Dustmann and Landersø 2021).[5] Overall, this second approach has been more successful in explaining how crime is affected by housing conditions: see, for example, the crime

[2]The deleterious effects of evictions are broad and affect several aspects of human life: homelessness, health, credit access, consumption, and earnings. Findings in economics are in line with those in other social sciences. See, for example, Crane and Warnes (2000) and Desmond and Kimbro (2015).

[3]Only very few papers in criminology have investigated the link between evictions and crime. See, for example, Alm (2018), Semenza, Stansfield, Grosholz, and Link (2021), and Kirk (2022).

[4]Private incentives in criminal activity refer to the offense's payoff, the foregone return of noncriminal activity, the probability of convictions, and the severity of the sentence.

[5]The effect of social interactions on crime has been discussed in criminology and sociology as well. See, for example, Shaw and McKay (1942) and Wilson (1987).

effects of buildings' architecture and structure (Glaeser and Sacerdote 2000), housing vouchers (Kling, Ludwig, and Katz 2005; Andersson, Haltiwanger, Kutzbach, Palloni, Pollakowski, and Weinberg 2022), homeless shelters (Corno 2017), public housing demolition (Aliprantis and Hartley 2015; Chyn 2018), and neighborhoods (Ludwig, Duncan, and Hirschfield 2001; Damm and Dustmann 2014; Billings, Deming, and Ross 2019). Consistent with Becker (1968)'s traditional model, this paper finds that reduced housing access via evictions may lead to crime by lowering the private opportunity cost—the individual's return from the legal alternative to crime.

Third, I add to the literature on the social consequences of nuisance ordinances, which are widely used in the United States, with around 2,000 cities, including 37 of the 40 largest American metropolitan areas.[6] Kroeger and La Mattina (2020) document an effect of nuisance ordinances on eviction risk. Other economists have found that these ordinances lead to domestic violence; specifically, Moss (2019), who focuses on municipalities in California, and Golestani (2021) on 40 major metropolitan statistical areas.[7] I expand this literature by highlighting an additional negative externality of this widely used policy: burglary into structures and vehicle theft.

The rest of the paper is organized as follows. Section 2 provides background information on evictions, homelessness, crime, and nuisance ordinances in the United States and Ohio. Section 3 describes the data. I discuss the empirical strategy and the evidence for the identifying assumptions in Section 4. Section 5 presents the empirical results on evictions and crime, together with robustness checks, and evidence on the potential mechanisms. Section 6 concludes. An Online Appendix provides additional analyses.

2 Context

Evictions, Homelessness, and Crime.—In the United States since 2000, over three million households on average have been evicted every year.[8] Numbers are higher when including informal evictions, which are two to three times higher than formal ones (Desmond 2016).[9] In Ohio, eviction statistics reflect the national ones and the

[6] As documented by the Temple University Policy Surveillance Program, accessible at `https://lawatlas.org/datasets/city-nuisance-property-ordinances`.

[7] The social cost of nuisance ordinances has also attracted the attention of sociologists focusing on tenants' incentives to underreport crime to elude evictions (Desmond and Valdez 2013; Desmond 2016).

[8] Data are from Gromis, Fellows, Hendrickson, Edmonds, Leung, Porton, and Desmond (2022).

[9] The number of evictions is even higher when counting "no-cause" evictions, whereby landlords decline tenants' requests for lease extensions.

institutional environment surrounding formal evictions in the state also exemplifies that in other US states.

The landlord starts the eviction process for alleged violations of the lease terms, typically with a "three-day notice." If the tenant does not fix the condition that led to the breaking of the lease within the set number of days in the notice, the landlord can file a "forcible entry and detainer" lawsuit at the local court. If the landlord is successful at the hearing, the judge issues a "writ of restitution," authorizing the local law enforcement agency to evict the tenant.

Once evicted, households look for new homes. Relocation is usually a costly process that can stretch over months due to several sources of friction in the search and matching of prospective tenants and landlords. First, since eviction records are public, evicted households face a reputation loss. Second, evictions often involve people employed in low-wage jobs without paid leave or advanced scheduling notice (Kalleberg 2009).

Because of these and other frictions discussed in Section 5.4, evicted households risk joining the around 600,000 homeless people in the United States.[10] Consistently, recent causal evidence in economics point to evictions as a cause of homelessness (Collinson, Humphries, Mader, Reed, and van Dijk 2022). Due to lack of housing, homeless people thus face incentives to engage in crime to procure shelter (Fischer 1988), specifically burglary into structures and vehicle theft, for which they are accused disproportionately with respect to the non-homeless population (Snow, Baker, and Anderson 1989).

Nuisance Ordinances.—Beginning in the 1980s, city councils started to adopt nuisance ordinances, which sanction landlords for nuisances in their properties, increasing their incentives to abate them. Since the main objective of the policy is to reduce public expenditure for policing services and to involve private actors in crime control, the adoption of nuisance ordinances reflects political preferences shifting towards conservative positions (Garland 2012).

Although nuisance ordinances often lack a clear definition of a "nuisance," this typically includes both criminal and non-criminal events. However, case studies indi-

[10] The homeless are "individuals and families who are residing in emergency or transitional shelters and those whose primary nighttime residence is a public or private place not meant for human habitation" (US Department of Housing and Urban Development's definition in Meyer, Wyse, Grunwaldt, Medalia, and Wu 2021). According to the US Department of Housing and Urban Development, around 600,000 individuals "sleep rough" or in homeless shelters on a given night in the United States (see `https://www.hudexchange.info/programs/hdx/pit-hic/`).

cate that nuisance ordinances are mostly enacted against petty occurrences, such as noise and kids playing (Desmond and Valdez 2013).[11]

The typical nuisance ordinance stipulates around $1,000 fines to landlords if the police are called to a property owned by the landlord at least three times in ninety days.[12] Nuisance ordinances also usually apply to "buffer zones" surrounding the premises. In Ohio, the profusion of nuisance ordinances in the last two decades has increased the number of evictions (Kroeger and La Mattina 2020). Consistently, case studies point to evictions as landlords' preferred nuisance abatement strategy (Desmond and Valdez 2013).

Today, more than 2,000 cities have an active nuisance ordinance in place, including 37 of the 40 largest cities in the United States. In Ohio, 39 of a total of 246 cities adopted some form of nuisance ordinance between 2000 and 2014 (Online Appendix Table D.6).

3 Data

I combine city-level data from nine sources.

Evictions.—Information on the annual number of formal residential evictions from 2000 to 2014 in Ohio is provided by the Eviction Lab based on court records. An eviction filing is classified as a case of "forcible entry and detainer." If an order to vacate the property is entered, the case is recorded as an eviction. Foreclosures, evictions of commercial tenants, and forced moves from public structures are excluded, while residential evictions by commercial landlords are included. Information on informal evictions is not provided. The numbers of evictions and eviction filings are normalized by the population size. According to the Eviction Lab, eviction data for Ohio is the most reliable in the United States as discussed in Online Appendix D.1 which provides additional information on this dataset.

[11] Based on 294,641 service calls in Milwaukee, Winsconsin, from 2008 to 2009, Desmond and Valdez (2013) find that the two most frequent nuisances are "trouble with subjects" and "noise."

[12] For example, the nuisance ordinance in the city of Lakewood, Ohio, states: "If a third nuisance activity . . . occurs within twelve months after the first of the two nuisance activities . . . the Director of Public Safety . . . may declare the property to be a nuisance . . . The cost of responding to the nuisance activity shall be assessed . . . The City shall provide notice to the owner of the nuisance property to pay the costs of abatement . . . If the same is not paid within thirty days of the mailing of the notice, such amount may be certified . . . for collection as other taxes" (Lakewood Ordinance §510.01c).

Crime.—I use annual crime data from 2000 to 2014 from the FBI's Part I Uniform Crime Reporting (UCR) Program, which reports offenses and clearances of the most serious crime categories in the United States. Offenses are reported by the general public or recorded directly by police officers and are either founded or unfounded. Clearances are offenses that have been "closed," usually by arrest of the offender. Information is provided at the law enforcement agency level, which I then aggregate at the city level. When studying crime by the season of the year, I rely on city-month-level information.

Burglary is the unlawful entry of a structure with the intention to commit a felony or theft. Structures include, but are not limited to, residences, construction sites, grocery stores, or restaurants. Cases are divided into burglary with forcible entry, burglary without forcible entry, and attempted burglary. Around 62 percent of the 1,047,132 burglaries in Ohio from 2000 to 2014 occurred with forcible entry. Importantly, burglary with forcible entry—henceforth, burglary—does not overlap with the "forcible entry and detainer" lawsuit linked to an eviction, which is a civil, not a criminal, case. I also use data on the 372,933 motor vehicle theft offenses in Ohio from 2000 to 2014, of which car theft constitutes 86 percent.

In the context of this study, the sum of burglaries and vehicle thefts can be interpreted as measuring crime against "habitable property." Burglary offers the most reliable measure of the concept for at least two reasons. First, since the existence of an intention to commit a felony or theft is based on the interpretation of the arresting officer, trespassing, a low-level "quality-of-life" offense, may be reported as burglary. The discretionary element in the reporting of burglaries is relevant for trespassing involving theft of petty objects, such as clothes or consumable goods, which may be stolen by homeless individuals whose primary intention is to find shelter. Second, due to the FBI's "hierarchy rule," whereby, in the case of multiple offenses, only the most serious one is reported, vehicle theft in the context of a burglary into a structure is recorded as a burglary.

For more extensive analysis, I use information on arrests for public drunkenness, larceny, drug violations, stolen property, forgery and counterfeiting, and gambling. As for Part I offenses, arrests are reported at the law enforcement agency level from 2000 to 2014 and then aggregated at the city level. I also rely on data on the 424,144 incidents in which burglary was recorded as the most serious offense in the National Incident-Based Reporting System (NIBRS) from 2000 to 2014 in Ohio. The dataset provides information on the location, victim, and property involved in each incident. Details on crime data are discussed in Online Appendix D.2.

Nuisance Ordinances.—Information on nuisance ordinances' adoption years from 2000 to 2014 across cities in Ohio was collected by Mead et al. (2017) in collaboration with the American Civil Liberties Union. Nuisance ordinances in this dataset charge fees to finance the police's intervention, plus a fine, to nuisance property owners who do not abate nuisances within the set time limit. The adoption year refers to the timing of the actual codification of a nuisance ordinance. The first city appearing in the dataset as having adopted a nuisance ordinance in Ohio is Cleveland Heights in 2003. By 2014, 39 cities in the state had an active nuisance ordinance (Online Appendix Table D.6).

House Prices.—I use the house price index (HPI) from 2000 to 2014 at the five-digit ZIP code level by the Federal Housing Finance Agency (FHFA). The HPI is set equal to 100 in year 2000 and measures the movement of single-family house prices by computing average price changes in repeat sales or refinancings on the same properties. Online Appendix D.3 presents how I compute the HPI at the city level based on information at the five-digit ZIP code level.

Demographic Characteristics.—Annual population data from 2000 to 2014 for each enforcement agency in Ohio are obtained from the UCR Program and then aggregated at the city level. Information on the number of tenant households and the number of residents by race at the city level is provided by the 2000 and 2010 US Census Bureau Decennial Censuses, and the 2005–2009 and 2011–2015 five-year US Census Bureau's American Community Survey (ACS) estimates.[13] Residents are divided into the following race categories: (i) White; (ii) Black; (iii) Hispanic or Latino; (iv) Asian; (v) American Indian and Alaska Native; (vi) Native Hawaiian and Other Pacific Islander; (vii) two or more races; or (viii) any other race. Racial heterogeneity is computed as in Alesina and La Ferrara (2000), specifically 1 minus the Herfindahl-Hirschman Index of the share of the population of each race.[14] I consider as racially heterogeneous any city above or equal to the median racial heterogeneity value.

Homeless Shelters.—Information on the presence of homeless shelters for cities in Ohio is provided by the Homeless Shelter Directory, a not-for-profit organization list-

[13] ACS estimates are based on sixty months of data for all US cities, including those with fewer than 65,000 residents for which the one-year ACS information is not available.

[14] $1 - \sum_k s_{kc}^2$, where s is the population share, c the city, and k the race.

ing the names and addresses of all homeless shelters in the United States as of 2022.[15]

Table 1 provides statistics for the main variables.

Table 1: Summary Statistics

	Min	Mean	Max	SD	Observations
Evictions per 10,000 Residents, 2000–2014					
Evictions	0.000	39.85	405.04	39.31	3452
Eviction Filings	0.000	78.45	870.84	80.72	3452
Crimes per 10,000 Residents, 2000–2014					
Burglary Offenses	0.000	35.82	239.47	38.75	2926
Vehicle Theft Offenses	0.000	17.16	248.72	21.46	2926
Car Theft Offenses	0.000	14.27	243.01	19.15	2925
Public Drunkenness Arrests	0.000	0.279	1.000	0.449	3690
Treatment, 2000–2014					
Nuisance Ordinance Adoption	0.000	0.077	1.000	0.266	3690
City Characteristics (Pre-Treatment Average)					
Population	4,456	27,138	760,726	64,702	246
Tenant Households	111	4,424	169,886	14,158	246
Homeless Shelters Presence	0.000	0.191	1.000	0.394	246
Racial Heterogeneity	0.033	0.207	0.625	0.141	246

Notes: The unit of observation is the 246 cities in Ohio. Car Theft Offenses is a subset of Vehicle Theft Offenses. Variables are presented in Section 3.
Sources: evictions: Eviction Lab; crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); city characteristics: ACS; Homeless Shelter Directory.

4 Empirical Strategy

To investigate whether evictions lead to crime, I exploit the staggered adoption of nuisance ordinances across cities in Ohio from 2000 to 2014 in a DID setting. The context of nuisance ordinances offers one main advantage for identification. Since evictions are mentioned in nuisance ordinances as a method to abate disturbances, landlords can reasonably expect to win at trial against their tenants. This feature of the setting reduces the potential bias due to the existence of informal (and hence unobserved) evictions. While formal evictions have been found to occur almost six times

[15] Accessible at https://www.homelessshelterdirectory.org/state/ohio.html.

more frequently than informal ones in the context of nuisance ordinances (Desmond and Valdez 2013), the number of informal evictions is at least twice as high as the one for formal evictions in the United States (Desmond 2016).[16]

I estimate the following OLS specification

$$Y_{ct} = \beta Treat_{ct} + \chi_c \delta_t + \gamma_c + \delta_t + \varepsilon_{ct}, \tag{1}$$

where Y_{ct} is the number of evictions, burglary into structures, or vehicle theft offenses (per 10,000 residents); $Treat_{ct}$ is an indicator of whether city c has an active nuisance ordinance at year t; χ_c are the two baseline controls chosen based on the balance test in Online Appendix Table A.1: average pretreatment population and number of tenant households; γ_c are city fixed-effects absorbing time-invariant city characteristics; and δ_t are year fixed-effects controlling for year-specific common shocks. Standard errors are clustered at the city level. The coefficient of interest β is the estimated effect of evictions on crime based on the comparison of outcome changes in treated and control cities and under the two assumptions presented in Section 4.1.

While no city had an active nuisance ordinance in place in 2000, 39 cities had adopted a nuisance ordinance by 2014 (Online Appendix Figures A.1 and A.2, and Online Appendix Table D.6). Around 85 percent of cities in the sample are never treated, suggesting that the issues discussed in the recent literature on staggered difference-in-difference—which arise mainly when the control group is composed of a high share of already-treated units—are not particularly worrisome in this context, as shown in Online Appendix B.2 (de Chaisemartin and D'Haultfœuille 2020; Callaway and Sant'Anna 2021; Athey and Imbens 2022).

4.1 Identifying Assumptions

The identification of the effect of evictions on crime relies on two assumptions. First, I assume parallel trends in the outcomes across cities with versus without a nuisance ordinance after its adoption, in the counterfactual scenario in which the adoption had not occurred. Reassuringly, the qualitative literature suggests that the adoption of policies involving landlords in crime control, including nuisance ordinances, reflects a political shift in favor of the Republicans, which is plausibly unrelated to evictions and crime (Garland 2012). Second, I assume that nuisance ordinances affect crime

[16] This is a relevant advantage for identification compared to studies that exploit the random assignment of eviction cases to judges who vary in their tendency to evict. The reason is that tenants who are formally non-evicted can be forced to leave informally after winning the trial.

only by increasing landlords' incentives to evict tenants. Under the two assumptions, the estimate β measures an intent-to-treat effect (ITT) of evictions on crime at the city level. I discuss evidence in favor of the two assumptions in the next paragraphs.

4.1.1 Evidence for Assumption One: Parallel Trends

Pretrends.—As a first step to test the parallel trends assumption, I begin by inspecting pretrends. This also allows me to rule out anticipation effects whereby landlords evict nuisance tenants expecting the future adoption of a nuisance ordinance. Exploring pretrends is also informative as to whether nuisance ordinances are adopted because of pretreatment changes in the outcomes. I run the following regression

$$Y_{ct} = \sum_{k=-5, k\neq -1}^{5} \beta_k L_{ck} + \chi_c \delta_t + \gamma_c + \delta_t + \varepsilon_{ct}, \tag{2}$$

where L_{ck} are event study dummies equal to 1 when year t is k years since the adoption of a nuisance ordinance in city c;[17] and χ_c are the two baseline controls: average pretreatment population and number of tenant households. Standard errors are clustered at the city level. The coefficients β_k measure changes in the outcomes in cities with a nuisance ordinance k years since its adoption compared to: (i) the year before its passage in switcher cities (when they are not yet treated); (ii) any year in non-switcher cities: never treated or already treated.[18] Figures 1 and 2 plot coefficients from equation (2) and show the absence of pretrends, lending credibility to the parallel trends assumption. Using a revised version of equation (2) for crime data at the city-month level, I zoom in close to the period around the policy shock and confirm the absence of pretrends (Online Appendix Figure A.3).

I also find that house prices display no pretrends in the four years before the adoption of an ordinance (Online Appendix Figure A.4).[19] Last, against the presence of unobservable pretrends due to crime misreporting, I find no pretrends in violent crime (Online Appendix Figure A.5), which is the most reliably measured crime in the United States (Sampson and Earls 1997).

[17] If k is below -5, then k is set equal to -5. If k is above 5, then k is set equal to 5.

[18] In both cases, when k is equal to -1.

[19] Notice also that the HPI starts to decline one year after the adoption of an ordinance, strengthening the interpretation that the nuisance ordinances caused this decline. This result is consistent with at least two explanations. First, lower house prices may be due to the increase in crime brought about by nuisance ordinances and evictions. Second, they may reflect the fact that nuisance ordinances make homeownership riskier (because of the sanction's risk).

Correlated Shocks.—As a second step to test the parallel trends assumption, I explore whether results are confounded by concurrent shocks unrelated to the adoption of nuisance ordinances. Since the analysis is restricted to cities in Ohio, estimates cannot be driven by annual variation at the state level such as economic shocks, or changes in sentencing practices or policing technology. However, if cities with a nuisance ordinance have different characteristics relative to cities without an ordinance, then shocks at the Ohio level (or higher) may differentially affect the outcomes across the two groups.

I begin by running a balance test exploring whether treated cities have different pretreatment observable characteristics with respect to never-treated cities. Only the population size and the number of tenant households differ significantly across the two groups (Online Appendix Table A.1). Therefore, controlling for trends in the two variables reduces the concern that common shocks, such as the Great Recession after 2007, led to differential changes in the outcomes in large versus small cities, and in cities with high versus low homeownership rates.

Although balanced in observable characteristics, cities with and without a nuisance ordinance may differ in unobservables and still react differently to common shocks, such as increasing poverty or lower police presence. Against this possibility, I show that the adoption of nuisance ordinances does not coincide with a general increase in crime (Online Appendix Figures A.5 and A.6). Another concern is related to correlated shocks pushing offenders to move across cities. I find that the effect on burglary incidents exists only for residents, mitigating this concern.[20]

Overall, the absence of pretrends and the provided evidence against correlated shocks support the plausibility of the parallel trends assumption.

4.1.2 Evidence for Assumption Two: Nuisance Ordinances Affect Crime Through Evictions Only

Here, I show that explanations other than evictions for the link between nuisance ordinances and crime are implausible.

Housing Market.—In theory, nuisance ordinances might affect burglary into structures and vehicle theft via changes in the housing market unrelated to evictions. Specifically, nuisance ordinances may affect housing supply and demand which could, in turn: (i) increase homelessness (Honig and Filer 1993; O'Flaherty 1996; Quigley,

[20] This same result also excludes geographic spillovers whereby evicted individuals commit crimes in neighboring municipalities.

Raphael, and Smolensky 2001; Quigley and Raphael 2004) and crime; (ii) raise the number of unoccupied units, attracting burglars, homeless people, or squatters; (iii) reduce housing property value, strengthening impoverished landlords' incentives to commit crimes; or (iv) reduce housing property value, hampering public authorities' ability to finance crime deterrents (Levitt 1997; Corman and Mocan 2000; Di Tella and Schargrodsky 2004; Evans and Owens 2007; Feler and Senses 2017).

I collect several pieces of evidence rejecting potential explanations linked to the housing market but unrelated to evictions. I begin by focusing on the larger number of unoccupied units as a potential explanation. First, burglaries are typically focused on obtaining precious objects, such as money, jewelry, and credit cards, all of which are unlikely to be present in unoccupied units. Second, if a higher number of unoccupied units is a valid explanation, then we should observe an effect on burglary into residences, which is not present though (Table 7 panels A–B). Third, greater availability of vacant residences should attract burglars from neighboring cities, but residents drive the effect on burglary (Online Appendix Table A.2). Fourth, unlawful entries by squatters should increase as well, raising the number of unfounded burglary offenses which, however, does not occur (Online Appendix Table A.3).[21] Fifth, the positive effect on vehicle theft further dismisses the larger number of unoccupied units as an explanation because higher vacancies per burglar (or homeless person) should lead to a substitution between burglary and vehicle theft, increasing the former and decreasing the latter.

I now focus on the other potential explanations. First, if nuisance ordinances affect burglary into structures or vehicle theft due to a negative wealth effect on landlords, we should observe an effect on income-generating crime as well which, however, is not present (Figure A.6). Second, if the effect is driven by changes in the tax revenue to finance crime deterrents—for example, via lower housing property values—then it is reasonable to expect also an effect on violent crime. Yet, violent crime is not affected (Figure A.5).

Crime Misreporting.—Nuisance ordinances are unlikely to push landlords to report nuisances because this action would increase their probability of being sanctioned. For example, this implies that it is unlikely that results are driven by landlords misreporting squatters as burglars. This interpretation is also corroborated by the absence of an effect on the number of unfounded burglary offenses (Online Appendix

[21] Since squatters act based on housing or political considerations, it is difficult to prove their intention to steal, a necessary condition for squatting to be classified as burglary.

Table A.3).[22]

Nuisance ordinances are also unlikely to increase tenants' incentives to report nuisances provided that this would increase the probability of eviction. Consistently, previous literature has found that nuisance ordinances actually lead to underreporting of offenses (Moss 2019; Golestani 2021).[23] If anything, the existence of this selective reporting bias suggests that results measure a lower bound of the true effect of evictions on crime.

Another potential concern is that individuals call the police for nonexistent nuisances to induce their neighbors' eviction. This may occur, for example, in the case of unsolved disputes between neighbors. If this interpretation is correct, then the effect of nuisance ordinances on evictions should be higher in cities with lower social capital. However, Section 5.4.3 presents evidence that the effect on evictions is not higher in racially heterogeneous cities, where social capital is lower (Alesina and La Ferrara 2000).[24]

Burglary by Landlords.—To abate disturbances, landlords may burglarize their rented residential property to informally force out nuisance tenants. If this explanation is correct, it is reasonable to expect that the burglary occurs without forcible entry, given that landlords have plausibly easy access to their properties. However, the effect on burglary without forcible entry is not present (Online Appendix Figure A.7).

Altogether, these findings suggest that nuisance ordinances affect burglary into structures and vehicle theft exclusively through evictions.

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[22] For the reasons referred to in footnote 21, reporting squatters as burglars would increase the number of unfounded burglary offenses.

[23] Nuisance ordinances have been found to reduce reporting of domestic violence and burglary by partners, as in this case in Euclid, Ohio `https://www.dropbox.com/s/01kisa4g01vn2s6/mm.pdf?dl=0.%20S`. Since nuisance ordinances often apply to "buffer zones" surrounding the premises, underreporting of vehicle theft may also occur.

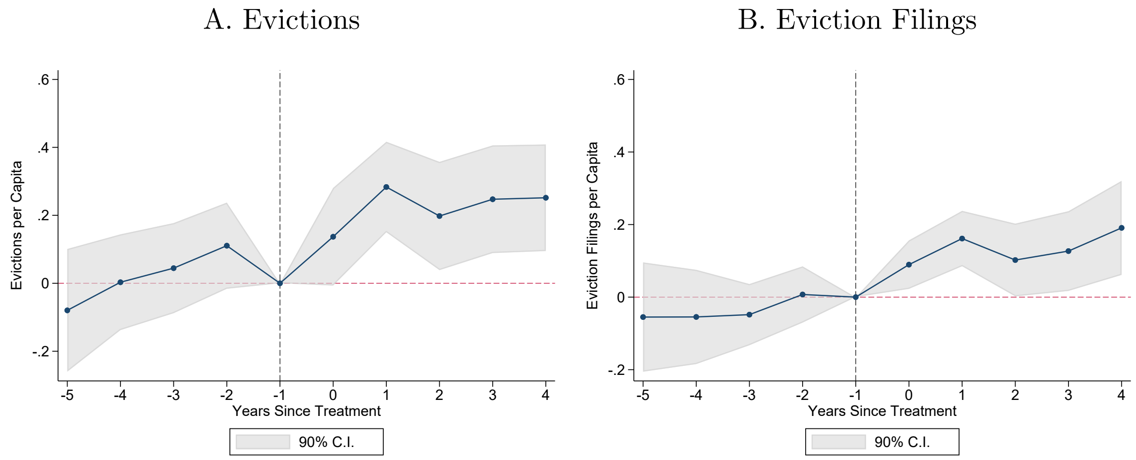
[24] The fact that nuisance ordinances do not increase the number of unfounded burglaries (Online Appendix Table A.3), as it should if the police is called for nonexistent nuisances, provides further evidence against this interpretation.

5 Results

5.1 Evictions

Figure 1 shows results on evictions, plotting coefficients from equation (2). After the adoption of nuisance ordinances, estimates for the inverse hyperbolic sine transformation of the number of evictions per 10,000 residents (panel A) and the number of eviction filings per 10,000 residents (panel B) are mostly positive and significant at the 10 percent level.

Figure 1: Timing of Effect on Evictions



Notes: Estimates of equation (2). Panel A: the dependent variable is the number of evictions per 10,000 residents transformed using the inverse hyperbolic sine method to take into account the zero values. Panel B: the dependent variable is the number of eviction filings per 10,000 residents transformed using the inverse hyperbolic sine method to take into account the zero values.
Sources: evictions: Eviction Lab; nuisance ordinances: Mead et al. (2017); controls: ACS.

Table 2, based on estimates of equation (1), suggests that the effect on evictions is positive and significant at the 5 percent level. Nuisance ordinances lead to 32–33 percent higher number of evictions per 10,000 residents (columns 1–2) while the number of eviction filings per 10,000 residents increases by 27–29 percent (columns 3–4).[25] Overall, these results are similar to those in Kroeger and La Mattina (2020).[26]

[25]Estimates point to an increase of around 12–13 evictions per 10,000 residents from a pretreatment mean of 38 per 10,000 residents and to an increase of around 21 eviction filings per 10,000 residents from a pretreatment mean of 75 per 10,000 residents.

[26]Coefficients are similar but not identical to those in Kroeger and La Mattina (2020) because I: (i) use evictions and eviction filings per 10,000 residents, while they normalize the variables by the number of tenant households; (ii) employ a different set of control variables; (iii) include average

Table 2: Effect on Evictions

	Evictions		Eviction Filings	
	(1)	(2)	(3)	(4)
Treat	12.728***	12.254***	21.536***	20.444***
	(4.510)	(4.239)	(6.792)	(6.361)
Observations	3452	3452	3452	3452
Mean DV	38.215	38.215	75.384	75.384
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Adjusted R^2	0.806	0.812	0.888	0.892

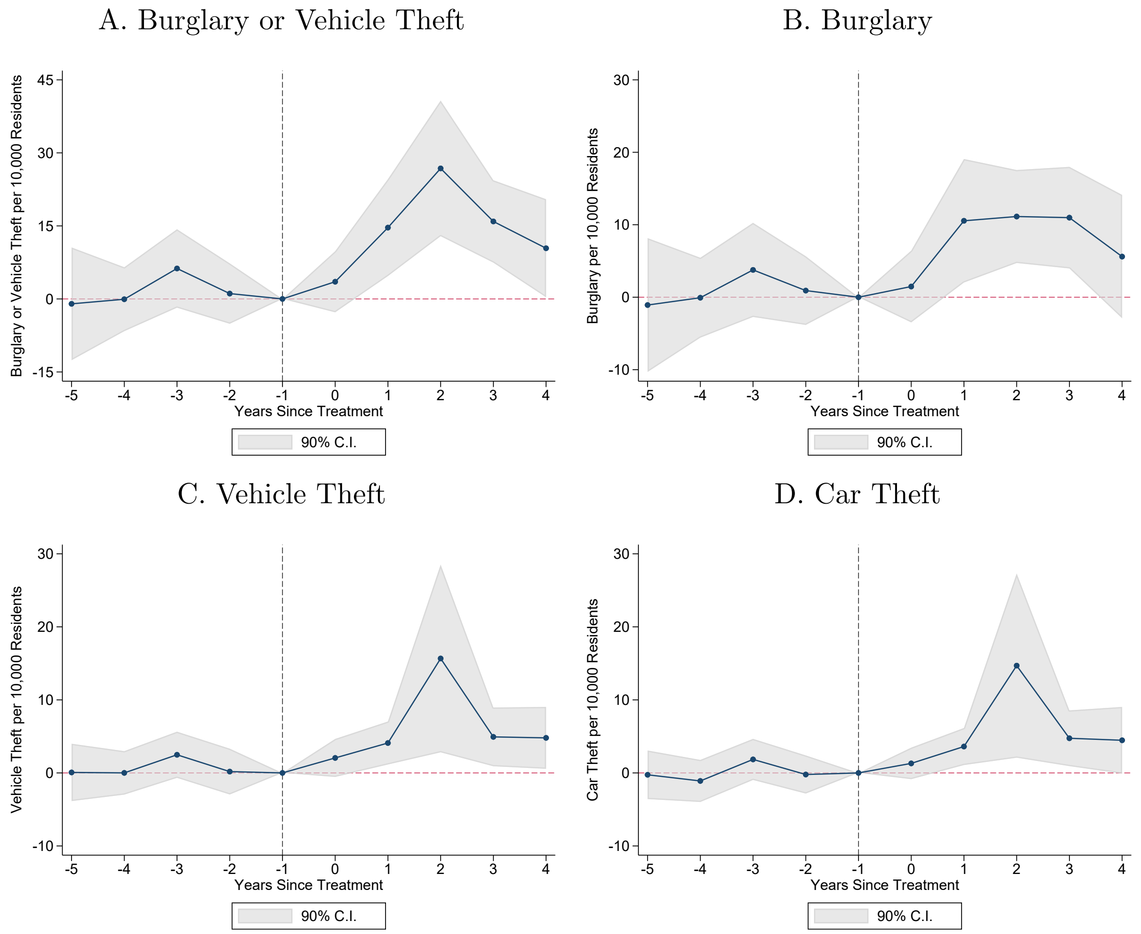
Notes: Estimates of equation (1). Columns 1–2: the dependent variable is the number of evictions per 10,000 residents. Columns 3–4: the dependent variable is the number of eviction filings per 10,000 residents. Treat: indicator of whether a given city has an active nuisance ordinance in a given year. Mean DV: average pretreatment dependent variable. Controls: average pretreatment population and number of tenant households times Year FE. Standard errors clustered at the city level are in parentheses. Significance levels: *** $p < .01$, ** $p < .05$, * $p < .1$.
Sources: evictions: Eviction Lab; nuisance ordinances: Mead et al. (2017); controls: ACS.

5.2 Burglary into Structures and Vehicle Theft

Figure 2 summarizes the main results of the paper, plotting coefficients from equation (2). The graphs provide a visualization of the relationship between the adoption of nuisance ordinances and the number of burglary into structures or vehicle theft offenses (panel A), broken down into burglary (panel B), vehicle theft (panel C), and car theft (panel D). After the adoption of nuisance ordinances, coefficients are positive and mostly significant at the 10 percent level. Consistently, the effect on crime appears to follow the one on evictions by one year.

pretreatment characteristics-by-year FE, while they control for time-varying characteristics; (iv) omit city-specific linear trends.

Figure 2: Timing of Effect on Burglary into Structures and Vehicle Theft



Notes: Estimates of equation (2). Panel A: the dependent variable is the number of burglary into structures or vehicle theft offenses per 10,000 residents. Panel B: the dependent variable is the number of burglary into structures offenses per 10,000 residents. Panel C: the dependent variable is the number of vehicle theft offenses per 10,000 residents. Panel D: the dependent variable is the number of car theft offenses per 10,000 residents.
Sources: crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); controls: ACS.

Table 3 formalizes these findings, estimating equation (1). The number of burglary into structures and vehicle theft offenses increases because of nuisance ordinances: 11 additional cases per 10,000 residents (column 1), broken down into six burglaries (column 2) and five vehicle thefts (column 3), the latter of which driven by cars (column 4). The effects are sizable, amounting to 21 percent for the sum of burglary into structures and vehicle theft (18 percent for burglary and 28 percent for vehicle theft).

Under the two identifying assumptions discussed in Section 4.1, estimates point to high elasticities of these crimes on evictions—0.55 for burglary and 0.85 for vehicle theft. These elasticities imply that each 10 percent increase in evictions raises burglary by 5.5 percent and vehicle theft by 8.5 percent.

Table 3: Effect on Burglary into Structures and Vehicle Theft

	Burglary or Vehicle Theft	Burglary	Vehicle Theft	Car Theft
	(1)	(2)	(3)	(4)
Treat	11.202***	6.309**	4.893**	4.848**
	(3.592)	(3.114)	(2.463)	(2.271)
Observations	2924	2924	2924	2923
Mean DV	52.676	35.113	17.563	14.523
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.859	0.839	0.754	0.741

Notes: Estimates of equation (1). Column 1: the dependent variable is the number of burglary into structures or vehicle theft offenses per 10,000 residents. Column 2: the dependent variable is the number of burglary into structures offenses per 10,000 residents. Column 3: the dependent variable is the number of vehicle theft offenses per 10,000 residents. Column 4: the dependent variable is the number of car theft offenses per 10,000 residents. Treat: indicator of whether a given city has an active nuisance ordinance in a given year. Mean DV: average pretreatment dependent variable. Controls: average pretreatment population and number of tenant households times Year FE. Standard errors clustered at the city level are in parentheses. Significance levels: *** $p < .01$, ** $p < .05$, * $p < .1$.
Sources: crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); controls: ACS.

5.3 Robustness

Online Appendix B shows that results are robust to two main checks. First, findings are robust to the use of alternative outcome measures—outcomes per 10,000 tenants and outcomes weighted by their average numbers in the pretreatment period—and additional controls: average pretreatment poverty share, median gross rent, median household income, median property value, and rent burden times Year FE (Online Appendix B.1). Second, results are robust to the estimator developed by de Chaisemartin and D'Haultfœuille (2020) to overcome the issues in estimating treatment effects in staggered difference-in-differences designs (Online Appendix B.2).

5.4 Mechanism: Homelessness and the Pursuit of Shelter

My hypothesis is that evicted individuals resort to burglary into structures or vehicle theft because they become homeless and are forced into illegal action to find shelter. Evictions may lead to homelessness due to the frictions in housing relocation. First, since eviction records are public, evicted households suffer a reputation loss.[27] Second, landlords and public authorities are authorized to refuse evicted tenants receiving housing assistance.[28] Third, public authorities can end voucher payments in the case of evictions for lease violations, such as nuisances. Fourth, evictions often involve people employed in low-wage jobs without paid leave or advanced scheduling notice (Kalleberg 2009). Last, housing assistance's eligibility requirements are strict, emergency financial assistance is volatile (Evans, Sullivan, and Wallskog 2016) and homeless shelters have long waiting lists.

For all these reasons, evictions are an important cause of homelessness. Recent causal evidence finds that evictions strongly increased the use of homeless shelters in New York City, New York, from 2003 to 2017, and Cook County, Illinois, from 2014 to 2018 (Collinson, Humphries, Mader, Reed, and van Dijk 2022). In a 1996 national study, two of five homeless people attributed their condition to evictions (Burt 2001).[29] In Columbus, Ohio, 35 percent sheltered homeless in 2000 imputed their condition to evictions (Hartman and Robinson 2003). These findings are consistent with popular depictions of the homelessness-eviction link in the media and with the economics literature on the relationship between the housing market and homelessness (Honig and Filer 1993; O'Flaherty 1996; Quigley, Raphael, and Smolensky 2001; Quigley and Raphael 2004).[30]

The plausibility of the homeless mechanism is substantiated by qualitative evidence. For example, a case study in Austin, Texas, suggests that, while arrest rates

[27]Companies such as CoreLogic Rental Property Solutions sell tenant screening reports to landlords.

[28]Low-income households receive housing assistance through the US Department of Housing and Urban Development (HUD) programs. The two most popular assistance policies are public housing, rented below market price, and Section 8 of the Housing Act of 1937, which authorizes voucher payments to landlords on behalf of tenants. In Ohio, apart from the federal government, public rental assistance is provided by the Ohio Department of Job and Family Services, and the Coalition on Homelessness and Housing. The Public Housing Authority in Ohio can refuse evicted tenants receiving housing assistance.

[29]These homeless people owed their homeless conditions to: "couldn't pay rent" (15 percent), "lost job or job ended" (14 percent), or "landlord made client leave" (6 percent). In the case of men with children, 28 percent of respondents declared "landlord made client leave" as the main reason for leaving their last regular residence.

[30]Searching for "evict! /5 homeless!" reveals 400 hits in the *New York Times* alone. See Gottesman (2008) for a discussion of how the media portrays the homelessness-eviction link.

for the homeless and the general population are similar for violent offenses, those for burglary into structures and vehicle theft offenses are respectively 57 and 41 percent higher for homeless people (Snow, Baker, and Anderson 1989).[31] Burglary accusations are often due to breaking into vacant buildings with the purpose of securing shelter (Fischer 1988).

To test the homeless mechanism, I proceed as follows. First, serving as placebo tests, I investigate whether evictions affect violent or income-generating crime, which should not increase, as indicated by the criminology literature. Second, I focus on arrests for public drunkenness, a crime susceptible to the homeless presence (Snow, Baker, and Anderson 1989). Third, I explore the heterogeneous effects by the presence of homeless shelters. Fourth, I test whether the effect is stronger in racially heterogeneous cities, where social capital and support networks are weaker (Alesina and La Ferrara 2000). Fifth, I inquire whether the effect of evictions is stronger during months with harsher outdoor conditions, when "living rough" is life-threatening. Sixth, I study whether the effect is driven by burglarizing commercial or public areas, and involves theft of petty rather than precious objects, as is reasonable to expect in the case of homeless' behavior. Last, by looking at clearances, I measure whether police effectiveness or officers' incentives to track offenders is negatively affected, hinting to a change in the crime composition in favor of the offenses of the homeless, which are more difficult to clear and less serious than the actions of thieves. Section 5.5 discusses potential mechanisms other than homelessness.

5.4.1 Placebo Tests on Other Crimes

Consistent with the criminology literature which suggests that only burglary into structures and vehicle theft should be affected by the presence of homeless people, I find that evictions do not lead to violent nor income-generating crime (Online Appendix Figures A.5 and A.6).

5.4.2 Public Drunkenness Arrests

According to Snow, Baker, and Anderson (1989), the homeless population constitutes "a disproportionate number of all arrests for public drunkenness . . . the homeless are unable to drink . . . in the privacy of a home . . . . If they choose to drink, then,

[31] The study finds that 44 out of 1,000 homeless adult males are arrested for burglary and 9 out of 1,000 homeless adult males are arrested for vehicle theft offenses. The numbers are 28 and 6 respectively for adult males in the general population.

they must do so in public space, which increases the risk of detection and arrest."[32]

Hence, drunkenness arrests are a good proxy for homeless presence for at least three reasons. First, because they lack access to housing, homeless people are more likely to drink alcohol in public spaces than the general population.[33] Second, the harsh conditions of living on the street may push homeless people to alcoholism. Third, alcohol consumption might cause homelessness.[34] Thus, although the empirical strategy does not allow to distinguish between the three specific channels, the existence of an effect of evictions on public drunkenness arrests provides evidence in support of the homeless mechanism.

Estimates from equation (2) plotted in Figure 3 show that nuisance ordinances lead to higher public drunkenness arrests.[35] Running equation (1) with the two baseline controls provides a coefficient of 0.11 and a standard error of 0.05—an effect of 24 percent, given the 0.45 average pretreatment incidence of public drunkenness arrests.

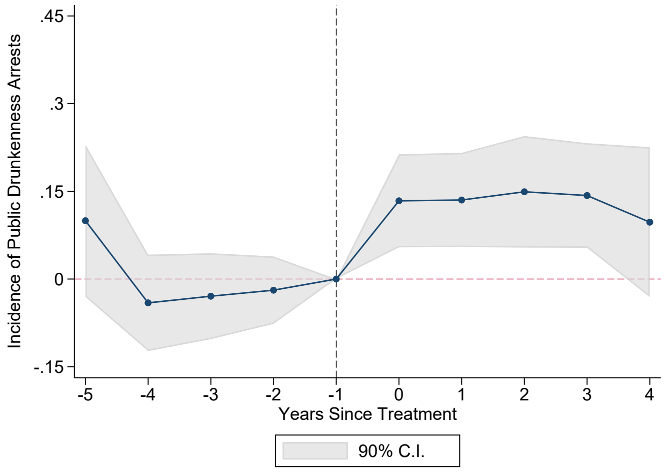
[32] Public drunkenness arrests comprise nearly 50 percent of all homeless arrests in the study.

[33] This is true even assuming identical alcohol consumption habits across homeless versus non-homeless people.

[34] Notice that this third link is not a threat to the identification since evictions may be a cause of psychological stress and alcoholism.

[35] The analysis relies on the extensive margin of public drunkenness arrests to reduce the concern related to the duplication of criminal offenses. Duplication may occur because of computational error or due to the same occurrence being reported by more than one law enforcement agency. Although not worrisome for the serious criminal offenses listed in the UCR Part I, including burglary and vehicle theft, the presence of false positives is a relevant concern when using data on less serious crimes, such as those in the UCR Part II. To confirm the relevance of this concern, I compute the total number of arrests for each one of these crime categories, aggregating information by age versus by race groups, and find different results. However, the incidence of these arrests is the same using both computational methods. This suggests that using the extensive margin is appropriate for UCR Part II arrests.

Figure 3: Timing of Effect on Public Drunkenness Arrests



Notes: Estimates of equation (2). The dependent variable is the incidence of public drunkenness arrests.
Sources: crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); controls: ACS.

5.4.3 Heterogeneous Effects by Homeless Shelters Presence, Racial Heterogeneity, and Outdoor Conditions

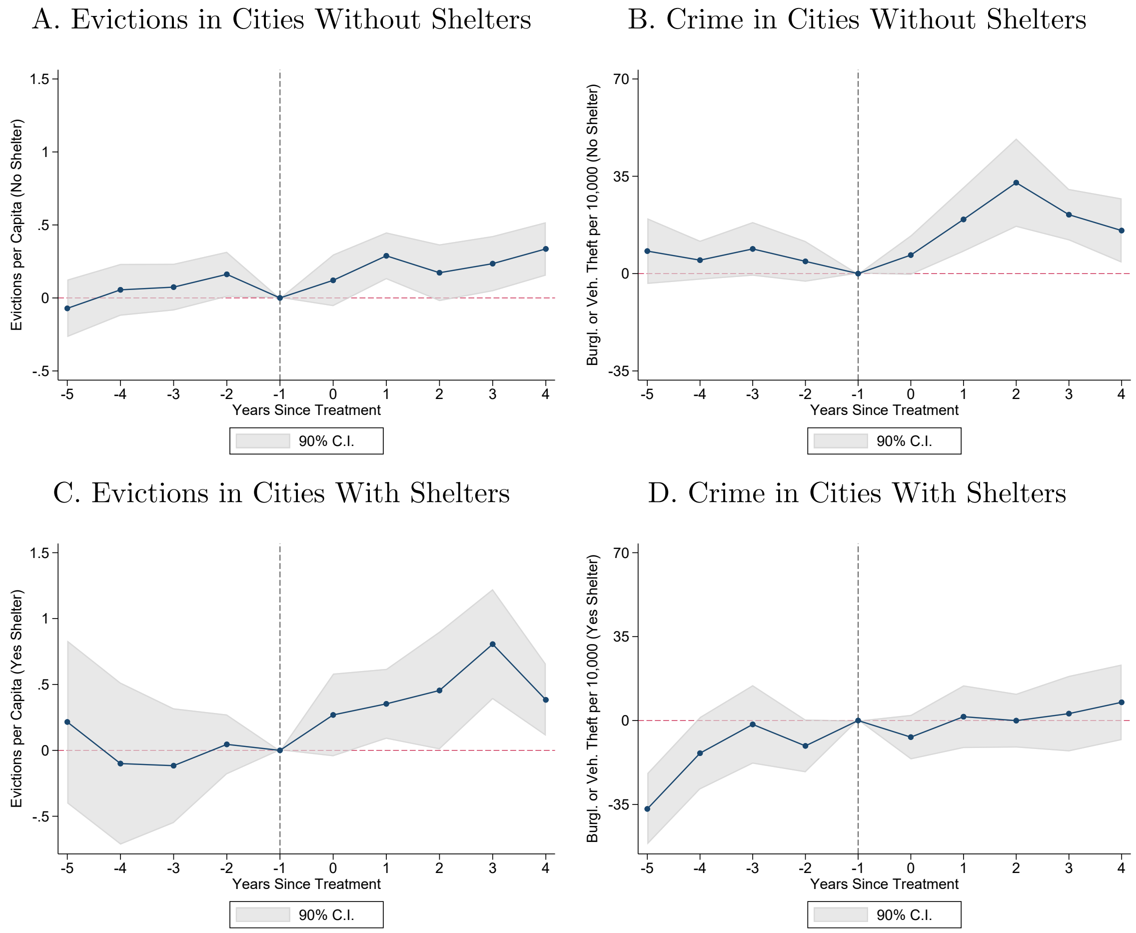
Homeless Shelters.—If evictions lead to burglary into structures and vehicle theft by reducing housing opportunities for evicted households, then the presence of homeless shelters should mitigate this effect. The reason is that homeless shelters, by providing an emergency residence, should increase the opportunity cost of these crimes.[36] To explore this hypothesis, I use data on the presence of homeless shelters. Homeless shelters in the dataset were all established before the adoption of the first nuisance ordinance in Ohio—Cleveland Heights in 2003 (Table D.6)—reducing concerns of reverse causality.[37]

Figure 4 shows the timing of the heterogeneous effects of evictions on burglary into structures and vehicle theft by the presence of homeless shelters, plotting coefficients from equation (2). In cities without homeless shelters (panels A–B), the coefficient plots for both evictions and crime look similar to those at the baseline. On the

[36]Consistently, research in criminology has found that the opening of homeless shelters is associated with lower incidence of burglary (Faraji, Ridgeway, and Wu 2018).
[37]Whereby the stronger the effect of evictions on crime, the weaker the incentives to establish homeless shelters.

contrary, in cities with homeless shelters, the effect on crime appears to be nonexistent (panel D), despite the one on evictions being present (panel C). Consistently, the coefficient plots for public drunkenness arrests also hint to a causal effect of evictions in cities without homeless shelters only (Online Appendix Figure C.9).

Figure 4: Timing of Heterogeneous Effects by Presence of Homeless Shelters



Notes: Estimates of equation (2) in cities without homeless shelters (panels A–B) and in cities with homeless shelters (panels C–D). Panels A–C: the dependent variable is the number of evictions transformed using the inverse hyperbolic sine method to take into account the zero values. Panels B–D: the dependent variable is the the number of burglary into structures or vehicle theft offenses per 10,000 residents.

Sources: evictions: Eviction Lab; crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); homeless shelters: Homeless Shelter Directory; controls: ACS.

Table 4 formalizes these results, showing estimates from equation (1). The effects on burglary and vehicle theft offenses, and public drunkenness arrests exist only in cities without homeless shelters (panels A–B).[38]

[38]These findings suggest that, in the context of this study, the negative effect of homeless shelters on the homeless individuals' incentives to commit crimes more than outweighs its positive effect due to social interactions with criminals found in Corno (2017).

Table 4: Heterogeneous Effect on Crime by Homeless Shelters Presence

Panel A: Cities Without Homeless Shelters				
	Burglary	Vehicle Theft	Car Theft	Drunkenness
	(1)	(2)	(3)	(4)
Treat	6.685**	4.962*	4.945**	0.097*
	(2.681)	(2.651)	(2.428)	(0.053)
Observations	2315	2315	2314	2985
Mean DV	26.064	14.157	11.542	0.265
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.729	0.614	0.581	0.521
Panel B: Cities With Homeless Shelters				
	Burglary	Vehicle Theft	Car Theft	Drunkenness
	(5)	(6)	(7)	(8)
Treat	9.669	6.777	5.987	0.206
	(10.051)	(6.854)	(6.118)	(0.140)
Observations	609	609	609	705
Mean DV	69.509	30.509	25.851	0.349
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.864	0.847	0.838	0.505

Notes: Panel A: estimates of equation (1) in cities without homeless shelters. Panel B: estimates of equation (1) in cities with homeless shelters. Columns 1, 5: the dependent variable is the number of burglary offenses per 10,000 residents. Columns 2, 6 : the dependent variable is the number of vehicle theft offenses per 10,000 residents. Columns 3, 7: the dependent variable is the number of car theft offenses per 10,000 residents. Columns 4, 8: the dependent variable is the incidence of public drunkenness arrests. Treat: indicator of whether a given city has an active nuisance ordinance in a given year. Mean DV: average pretreatment dependent variable. Controls: average pretreatment population and number of tenant households times Year FE. Standard errors clustered at the city level are in parentheses. Significance levels: *** $p < .01$, ** $p < .05$, * $p < .1$.
Sources: crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); homeless shelters: Homeless Shelter Directory; controls: ACS.

Racial Heterogeneity.—If homelessness is a mechanism, then it is reasonable to expect that the effect of evictions is present only where social capital is low, with scarce community life, trust, and connections (Putnam 2000). This may be because, in cities with high social capital, landlords trust their prospective tenants, even if they had been previously evicted.[39] Moreover, where social capital is stronger, connections to families and friends allow evicted people to find a temporary residence if needed.[40] Last, in cities with a larger amount of social connections, evicted individuals can more easily access information about housing opportunities, facilitating the searching and matching.

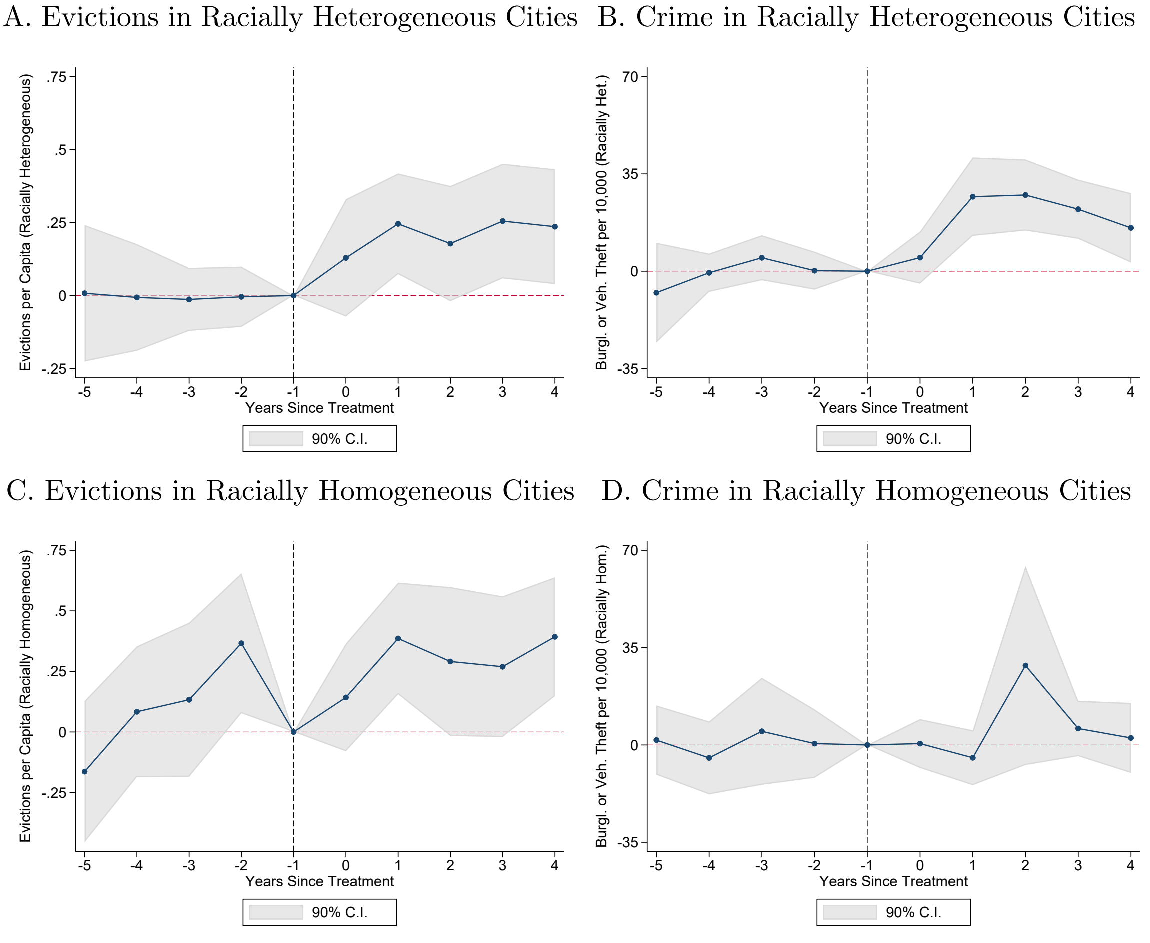
As in Alesina and La Ferrara (2000), I measure social capital as racial heterogeneity which, "seems to have the strongest negative effect on participation" (Alesina and La Ferrara 2000). As presented in Section 3, I compute racial heterogeneity as 1 minus the Herfindahl-Hirschman Index of the share of the population in each racial category of the census.

Figure 5 shows the timing of the heterogeneous effects of evictions on burglary into structures and vehicle theft by racial heterogeneity, plotting coefficients from equation (2). While in racially heterogeneous cities (panels A–B), results for both evictions and crime are similar to those at the baseline, in racially homogeneous cities the effect on crime is nonexistent (panel D), despite the effect on evictions being present (panel C). Consistently, the effect on public drunkenness arrests exists also only in racially heterogeneous cities (Online Appendix Figure C.10).

[39] Consistently, in close-knit cities where "people . . . are willing to help their neighbors and . . . can be trusted" crime is lower (Sampson and Earls 1997).

[40] This is exemplified by the following quote: "The tenant gets evicted, moves in with a family member . . . gets kicked out, moves to a friend's couch, eventually gets kicked out . . . and so on until the evicted tenant has exhausted his support network and has nowhere to go" (Gottesman 2008).

Figure 5: Timing of Heterogeneous Effects by Racial Heterogeneity



Notes: Estimates of equation (2) in racially heterogeneous cities (panels A–B) and in racially homogeneous cities (panels C–D). Panels A–C: the dependent variable is the number of evictions transformed using the inverse hyperbolic sine method to take into account the zero values. Panels B–D: the dependent variable is the number of burglary into structures or vehicle theft offenses per 10,000 residents. Racially heterogeneous: above or equal to the median racial heterogeneity value (as in Alesina and La Ferrara (2000), specifically 1 minus the Herfindahl-Hirschman Index of the share of the population that is: (i) White; (ii) Black; (iii) Hispanic or Latino; (iv) Asian; (v) American Indian and Alaska Native; (vi) Native Hawaiian and Other Pacific Islander; (vii) two or more races; or (viii) any other race). Racially homogeneous: below the median racial heterogeneity value.
Sources: evictions: Eviction Lab; crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); racial heterogeneity and controls: ACS.

Table 5 shows estimates from equation (1) by racial heterogeneity. The effects on burglary and vehicle theft offenses, and public drunkenness arrests exist only in racially heterogeneous cities.

Table 5: Heterogeneous Effect on Crime by Racial Heterogeneity

Panel A: Racially Heterogeneous Cities				
	Burglary	Vehicle Theft	Car Theft	Drunkenness
	(1)	(2)	(3)	(4)
Treat	11.617***	6.451**	6.264**	0.124*
	(3.876)	(3.219)	(2.940)	(0.065)
Observations	1504	1504	1504	1845
Mean DV	45.464	23.505	19.906	0.311
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.868	0.826	0.812	0.523
Panel B: Racially Homogeneous Cities				
	Burglary	Vehicle Theft	Car Theft	Drunkenness
	(5)	(6)	(7)	(8)
Treat	0.119	3.708	4.258	0.037
	(3.481)	(4.348)	(4.071)	(0.090)
Observations	1420	1420	1419	1845
Mean DV	24.149	11.269	8.817	0.251
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.654	0.424	0.356	0.500

Notes: Panel A: estimates of equation (1) in racially heterogeneous cities. Panel B: estimates of equation (1) in racially homogeneous cities. Columns 1, 5: the dependent variable is the number of burglary offenses per 10,000 residents. Columns 2, 6 : the dependent variable is the number of vehicle theft offenses per 10,000 residents. Columns 3, 7: the dependent variable is the number of car theft offenses per 10,000 residents. Columns 4, 8: the dependent variable is the incidence of public drunkenness arrests. Treat: indicator of whether a given city has an active nuisance ordinance in a given year. Mean DV: average pretreatment dependent variable. Controls: average pretreatment population and number of tenant households times Year FE. Racially heterogeneous: above or equal to the median racial heterogeneity value (as in Alesina and La Ferrara (2000), specifically 1 minus the Herfindahl-Hirschman Index of the share of the population that is: (i) White; (ii) Black; (iii) Hispanic or Latino; (iv) Asian; (v) American Indian and Alaska Native; (vi) Native Hawaiian and Other Pacific Islander; (vii) two or more races; or (viii) any other race). Racially homogeneous: below the median racial heterogeneity value. Standard errors clustered at the city level are in parentheses. Significance levels: *** $p < .01$, ** $p < .05$, * $p < .1$.
Sources: crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); racial heterogeneity and controls: ACS.

Outdoor Conditions.—Winter "is the period of greatest environmental threat to unsheltered homeless people in the northern parts of the country" (Turnham, Wilson, and Burt 2008). Because of the harsher outdoor conditions, homeless people face stronger incentives to procure shelter during winter. Consistent with this hypothesis, lower outdoor temperatures predict a higher share of sheltered as opposed to unsheltered homeless people (Corinth and Lucas 2017). On the contrary, burglars in the United States are more active during summer because residents are more likely to be outdoor or on vacations. Hence, the presence of a stronger effect of evictions on burglary into structures and vehicle theft during months in which outdoor conditions are harsher provides evidence in favor of the homeless mechanism. Using a triple DID approach, I estimate the following OLS specification

$$Y_{cmt} = \beta_1 Treat_{cmt} + \beta_2 Treat_{cmt} Harsh_m + \chi_c \delta_t + \zeta_m \delta_t + \gamma_c + \delta_t + \zeta_m + \varepsilon_{cmt}, \quad (3)$$

where m indexes months; $Harsh_m$ is an indicator of the months from October through February; ζ_m are month fixed-effects; and $\zeta_m \delta_t$ are month-by-year fixed-effects.

Table 6 shows coefficients from equation (3). Column 1 suggests that the effect on burglary into structures or vehicle theft is more than 40 percent higher during harsh outdoor months (October through February). In those same months, the effect on burglary is 32 percent higher (column 2), while the one on vehicle theft is 53 percent higher (column 3), and is driven by car theft (column 4).

Table 6: Heterogeneous Effect on Burglary into Structures and Vehicle Theft by Outdoor Conditions

	Burglary or Vehicle Theft	Burglary	Vehicle Theft	Car Theft
	(1)	(2)	(3)	(4)
Treat	0.942***	0.525**	0.416**	0.400**
	(0.299)	(0.249)	(0.191)	(0.176)
Treat × Harsh Outdoor Months	0.392**	0.166*	0.220**	0.211**
	(0.158)	(0.093)	(0.098)	(0.091)
Observations	36176	36239	36194	36179
Mean DV	4.315	2.876	1.441	1.192
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Month × Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.660	0.622	0.432	0.422

Notes: Estimates of equation (3). Column 1: the dependent variable is the number of burglary into structures or vehicle theft offenses per 10,000 residents. Column 2: the dependent variable is the number of burglary offenses per 10,000 residents. Column 3: the dependent variable is the number of vehicle theft offenses per 10,000 residents. Column 4: the dependent variable is the number of car theft offenses per 10,000 residents. Treat: indicator of whether a given city has an active nuisance ordinance in a given month of a given year. Harsh Outdoor Months: indicator of months from October through February. Mean DV: average pretreatment dependent variable. Controls: average pretreatment population and number of tenant households times Year FE. Standard errors clustered at the city level are in parentheses. Significance levels: *** $p < .01$, ** $p < .05$, * $p < .1$.
Sources: crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); controls: ACS.

5.4.4 Evidence from Offenses' Location, Victim Type, and Stolen Property

The circumstances of burglary offenses offer details to test the homeless mechanism. First, the location and the victim type can provide hints as to the motives of the offenses. While burglars typically target residential units, homeless people tend to search for shelter in vehicles, public spaces, or commercial establishments (Turnham, Wilson, and Burt 2008). By focusing on the type of stolen property, we can also plausibly infer whether burglars or the homeless account for burglary incidents. The reason is that burglars usually steal precious objects (money, jewelry, credit cards, etc.), while the homeless are more likely to appropriate goods lost during the eviction process or difficult to store because of lack of housing, such as clothes and consumables (Desmond 2016).

Guided by these insights, I use the NIBRS information on the 424,144 burglary incidents in Ohio from 2000 to 2014. This dataset provides the circumstances of crimes, including the location, the victim type, and the stolen property.

Table 7 based on estimates of equation (1) supports the homeless mechanism.[41] The effect on burglary exists only for construction sites, grocery stores, supermarkets, or restaurants—typical homeless' targets—while residences—mainly burglars' and squatters' objectives—are unaffected (panel A). Similarly, structures involving businesses, financial institutions, the government or the public are targeted, while private individual structures are not (panel B). The stolen property includes necessary commodities (vehicles, alcohol, clothes, consumables, etc.), while precious objects (money, jewelry, credit cards, etc.) are unaffected. The effects are strong: 49 percent for construction sites (column 2), 26 percent for grocery stores, supermarkets, or restaurants (column 3), 28 percent for businesses or financial institutions (column 6), 48 percent for governmental or public structures (column 7), 36 percent for burglaries involving vehicles (column 9), and 22 percent for burglaries involving petty objects (column 11).

[41] The analysis focuses on the intensive margin due to the impossibility of distinguishing between missing and zero values.

Table 7: Effect on Burglary into Structures by Location, Victim Type, and Stolen Property

Panel A: Location				
	Residence	Construction Site	Grocery, Supermarket, or Restaurant	Other
	(1)	(2)	(3)	(4)
Treat	4.655	0.323**	0.367***	0.689
	(3.110)	(0.127)	(0.138)	(1.199)
Observations	1394	236	644	1325
Mean DV	17.580	0.658	1.410	8.567
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.859	0.500	0.433	0.691
Panel B: Victim Type				
	Individual	Business or Financial Institution	Government or Public	Other
	(5)	(6)	(7)	(8)
Treat	4.067	1.863**	0.483**	0.112
	(3.202)	(0.800)	(0.225)	(0.306)
Observations	1425	1252	354	433
Mean DV	19.408	6.713	1.015	1.454
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.855	0.690	0.351	0.434
Panel C: Stolen Property				
	Vehicle	Precious Objects	Petty Objects	Other
	(9)	(10)	(11)	(12)
Treat	0.388*	2.136	0.671**	0.514
	(0.217)	(1.475)	(0.291)	(0.987)
Observations	355	1308	891	1257
Mean DV	1.091	8.527	3.090	6.917
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.521	0.812	0.818	0.692

Notes: Panel A: estimates of equation (1) by location. Panel B: estimates of equation (1) by victim type. Panel C: estimates of equation (1) by stolen property. The dependent variables are the number of incidents involving burglary as the first recorded offense per 10,000 residents (intensive margin). Column 1: location is a residence. Column 2: location is a construction site. Column 3: location is a grocery store, a supermarket, or a restaurant. Column 4: any other location. Column 5: victim is an individual. Column 6: victim is a business or a financial institution. Column 7: victim is a governmental or public structure. Column 8: victim is any other type. Column 9: theft of cars, buses, trucks, or other motor vehicles. Column 10: theft of money, jewelry, precious metals, TVs, computers, credit cards, debit cards, radios, or VCRs. Column 11: theft of clothes, furs, consumable goods, vehicle parts, alcohol, drugs, or narcotics. Treat: indicator of whether a given city has an active nuisance ordinance in a given year. Mean DV: average pretreatment dependent variable. Controls: average pretreatment population and number of tenant households times Year FE. Standard errors clustered at the city level are in parentheses. Significance levels: *** $p < .01$, ** $p < .05$, * $p < .1$. Details on crime incidents are in Section D.2.3.

Sources: crime: NIBRS by FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); controls: ACS.

5.4.5 Evidence from Clearances

The absence of an effect on burglary and vehicle theft clearances may further support the homeless mechanism for at least two reasons. First, it may point to reduced police effectiveness, suggesting that the offenses occur at night or in areas with a low police presence, consistent with the location choices of the homeless described in the literature (Turnham, Wilson, and Burt 2008). Second, the absence of an effect on clearances may point to the weaker incentives of police officers to track offenders, attributed to the homeless that are "not generally regarded as dangerous by the police" (Snow, Baker, and Anderson 1989). Estimating equation (1), Table C.5 shows that nuisance ordinances do not affect the number of burglary into structures or vehicle theft clearances, strengthening the plausibility of the homeless mechanism.

While individually only suggestive, findings collectively point to homelessness and the pursuit of shelter as the mechanism through which evictions increase burglary into structures and vehicle theft.

5.5 Other Potential Mechanisms

In theory, mechanisms such as changes in income or credit access, recruitment by criminal networks, community policing, or retaliatory action against evicting landlords may also be in place. In Online Appendix C.2, I discuss why findings in this study appear to be inconsistent with these other potential mechanisms.

6 Conclusion

This paper provides the first causal evidence of the effect of evictions on crime. By exploiting the increase in evictions due to the staggered adoption of nuisance ordinances sanctioning landlords for nuisances in Ohio's cities from 2000 to 2014, I find that evictions lead to a strong increase in burglary into structures and vehicle theft offenses. These crimes appear to be motivated by evicted individuals becoming homeless and resorting to illegal action to secure shelter.

The existence of an effect of evictions on crime bears welfare implications on homeownership and housing policies on efficiency grounds. In the presence of this negative externality of evictions, higher homeownership as opposed to renting levels might be preferable. Likewise, the social benefit of policies such as homeless shelter provision or the "right-to-counsel"—publicly funded legal counsel to tenants in eviction cases—is likely higher than previously considered. Further research might help elucidate these implications.

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Appendix
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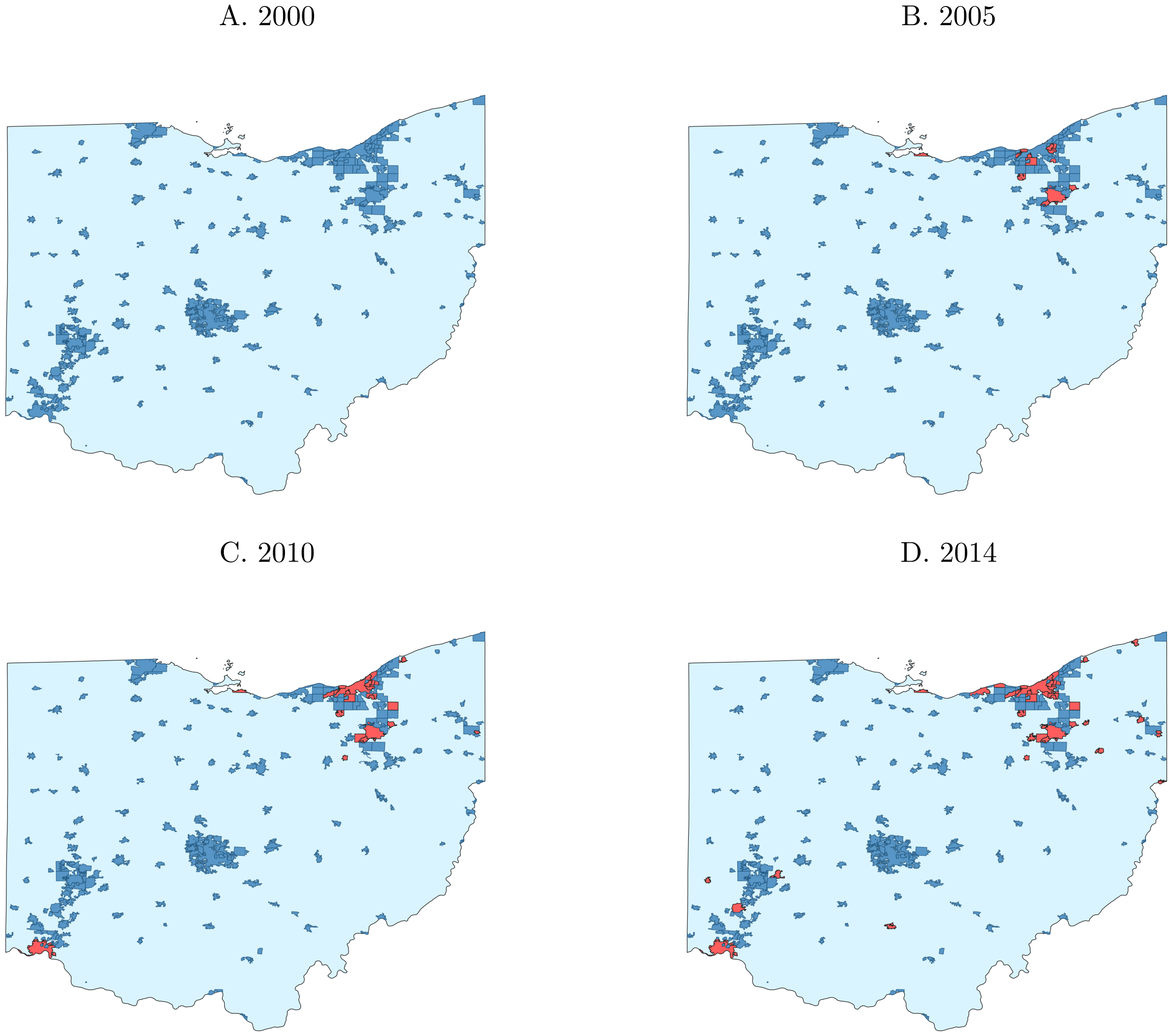
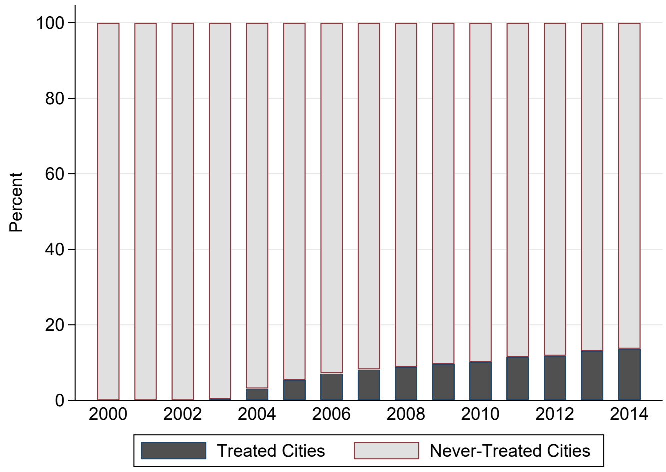
A Empirical Strategy and Tests of Assumptions

Figure A.1: Adoption of Nuisance Ordinances in Ohio's Cities, 2000–2014



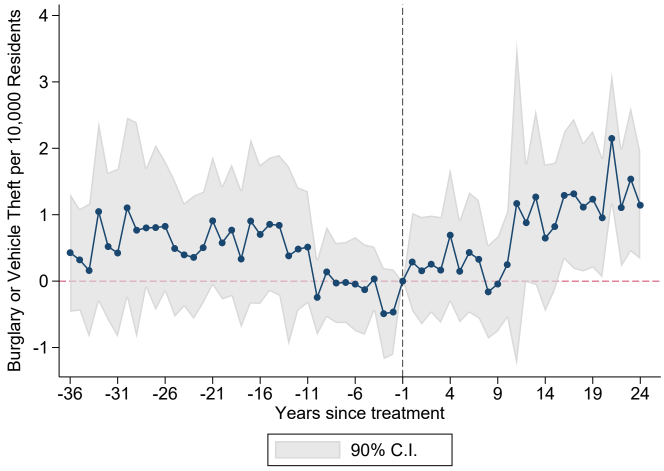
Notes: Adoption of nuisance ordinances (red) across Ohio's cities (dark blue) from 2000 to 2014.
Source: Mead et al. (2017).

Figure A.2: Adoption of Nuisance Ordinances in Ohio's Cities (Shares), 2000–2014



Notes: The number of cities having adopted a nuisance ordinance as the share of the total in Ohio from 2000 to 2014 (dark blue). 39 of 246 cities in Ohio adopted a nuisance ordinance by 2014.
Source: Mead et al. (2017).

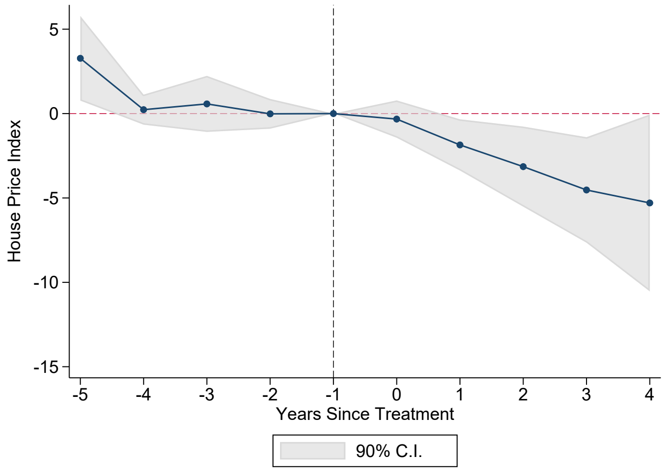
Figure A.3: Timing of Effect on Burglary into Structures or Vehicle Theft at the City-Month Level



Notes: Estimates of the following regression: $Y_{cmt} = \sum_{k=-36,k\neq-1}^{25} \beta_k L_{ck} + \chi_c \delta_t + \gamma_c + \delta_t + \zeta_m + \varepsilon_{cmt}$ where m indexes months and L_{ck} are event study dummies equal to 1 when month of the year mt is k months since the adoption of a nuisance ordinance in city c (if k is below -36, then k is set equal to -36; if k is above 25, then k is set equal to 25). The dependent variable is the number of burglary into structures or vehicle theft offenses per 10,000 residents.

Sources: crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); controls: ACS.

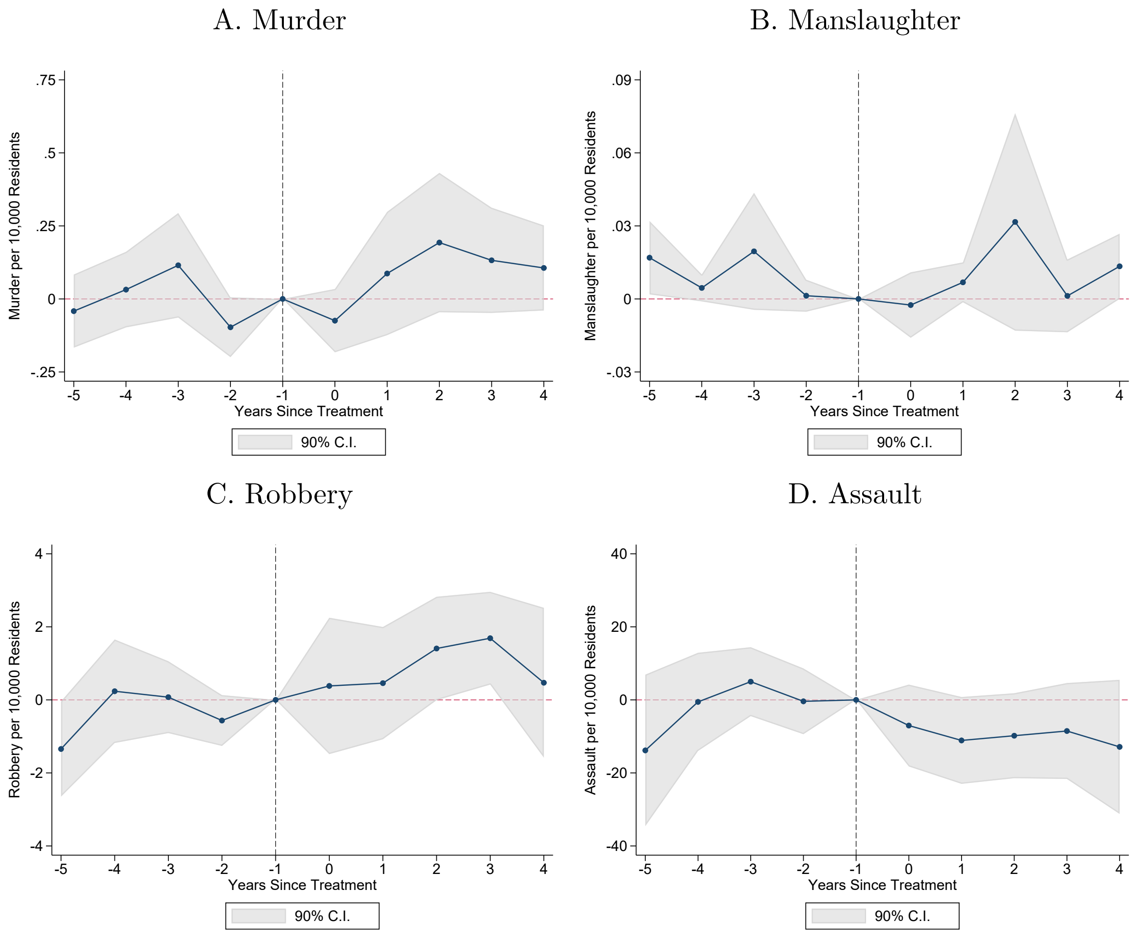
Figure A.4: Timing of Effect on House Price Index



Notes: Estimates of equation (2). The dependent variable is the House Price Index (HPI), which measures the movement of single-family house prices by computing average price changes in repeat sales or refinancings on the same properties. The dependent variable is presented in Appendix Section D.3.

Sources: HPI: Federal Housing Finance Agency; nuisance ordinances: Mead et al. (2017); controls: ACS.

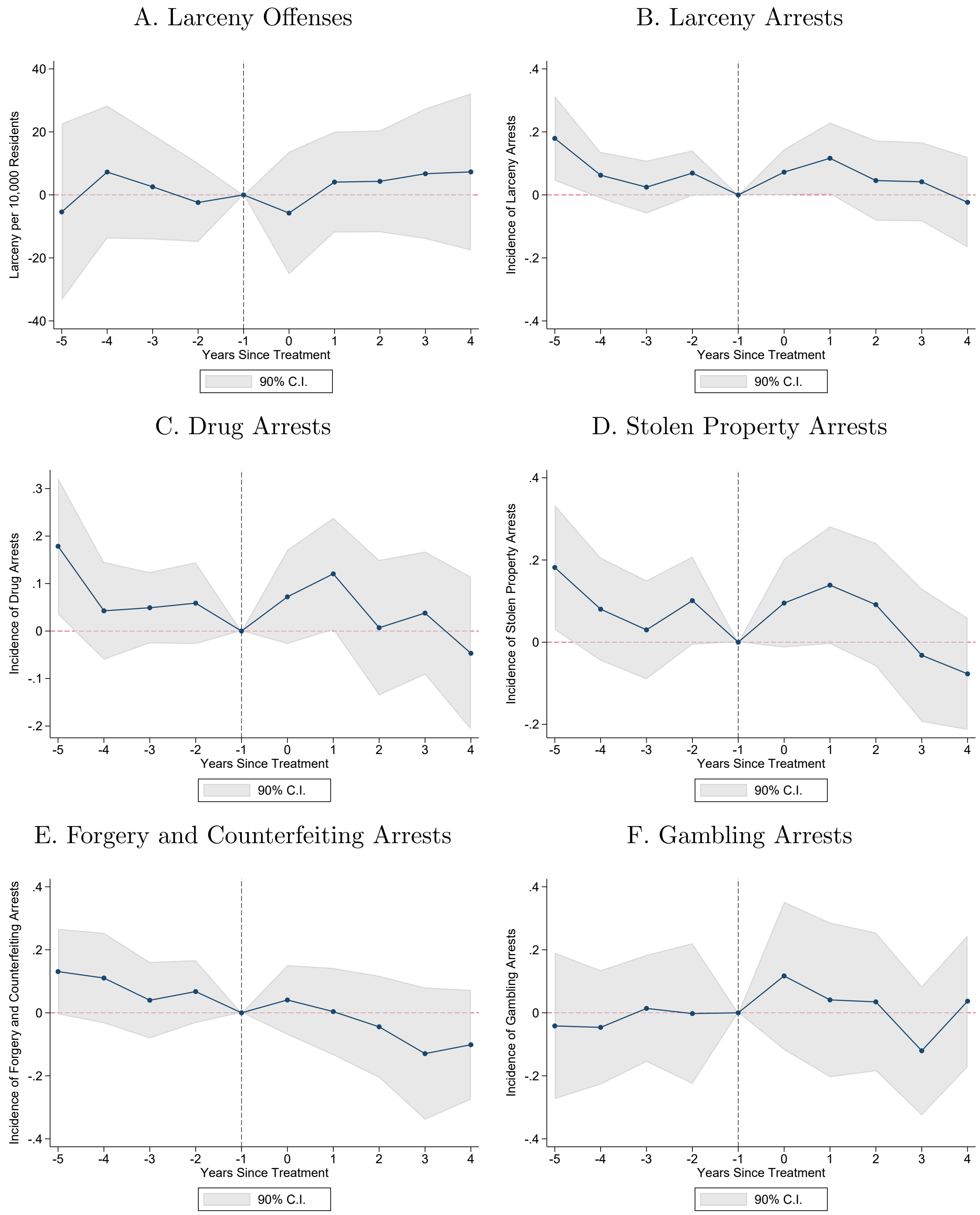
Figure A.5: Placebo Tests on Violent Crime



Notes: Estimates of equation (2). Panel A: the dependent variable is the number of murder offenses per 10,000 residents. Panel B: the dependent variable is the number of manslaughter offenses per 10,000 residents. Panel C: the dependent variable is the number of robbery offenses per 10,000 residents. Panel D: the dependent variable is the number of assault offenses per 10,000 residents. Details on crime data are in Section D.2.

Sources: crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); controls: ACS.

Figure A.6: Placebo Tests on Income-Generating Crime

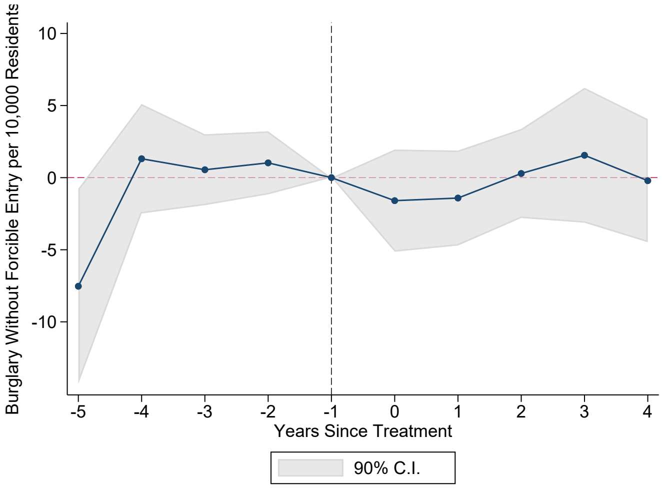


Notes: Estimates of equation (2). Panel A: the dependent variable is the number of larceny offenses per 10,000 residents. Panel B: the dependent variable is the number of larceny arrests per 10,000 residents. Panel C: the dependent variable is the number of drug arrests per 10,000 residents. Panel D: the dependent variable is the number of stolen property arrests per 10,000 residents. Panel E: the dependent variable is the number of forgery and counterfeiting arrests per 10,000 residents. Panel

F: the dependent variable is the number of gambling arrests per 10,000 residents. Details on crime data are in Section D.2.

Sources: crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); controls: ACS.

Figure A.7: Timing of Effect on Burglary Without Forcible Entry



Notes: Estimates of equation (2). The dependent variable is the number of burglary without forcible entry offenses per 10,000 residents.
Sources: crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); controls: ACS.

Table A.1: Balance Test

	Treated	Never Treated	Difference	p-value (Equality)
Population	48559.324	23102.549	25456.775	0.024
Tenant Households	8917.127	3577.386	5339.741	0.030
Tenant Households (Share)	34.947	32.318	2.629	0.230
Rent Burden (Share)	26.699	27.410	-0.711	0.285
Poverty (Share)	11.290	9.714	1.576	0.179
Homeless Shelters Presence	0.205	0.188	0.017	0.808
Racially Heterogeneous	0.615	0.478	0.137	0.117
Observations	39	207		

Notes: Results from the balance t-test comparing average pretreatment city characteristics in treated versus never-treated cities. Rent Burden (Share): median gross rent as a share of the median household income. Poverty (Share): share of the population with income below the poverty level. Racially heterogeneous: above or equal to the median racial heterogeneity value (as in Alesina and La Ferrara (2000), specifically 1 minus the Herfindahl-Hirschman Index of the share of the population that is: (i) White; (ii) Black; (iii) Hispanic or Latino; (iv) Asian; (v) American Indian and Alaska Native; (vi) Native Hawaiian and Other Pacific Islander; (vii) two or more races; or (viii) any other race).

Sources: crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); city characteristics: ACS; Homeless Shelter Directory.

Table A.2: Effect of Nuisance Ordinances on Burglary into Structures by Residence of Offender

	Burglary Resident	Burglary Non-Resident	Burglary Unknown
	(1)	(2)	(3)
Treat	0.845*	-0.497	5.052
	(0.445)	(0.334)	(3.946)
Observations	682	113	1461
Mean DV	2.329	0.660	24.027
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Adjusted R^2	0.501	0.733	0.843

Notes: Estimates of equation (1). The dependent variables are the number of incidents involving burglary with forcible entry as the most serious recorded offense per 10,000 residents (intensive margin). Column 1: by residents. Column 2: by non-residents. Column 3: by offender whose residence is unknown. Treat: indicator of whether a given city has an active nuisance ordinance in a given year. Mean DV: average pretreatment dependent variable. Controls: average pretreatment population and number of tenant households times Year FE. Standard errors clustered at the city level are in parentheses. Significance levels: *** $p < .01$, ** $p < .05$, * $p < .1$.

Sources: crime: NIBRS by FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); controls: ACS.

Table A.3: Placebo Test on Unfounded Burglary into Structures and Vehicle Theft Offenses

	Unfounded Burglary or Vehicle Theft	Unfounded Burglary	Unfounded Vehicle Theft	Unfounded Car Theft
	(1)	(2)	(3)	(4)
Treat	-6.868	-7.307	0.440	0.420
	(7.583)	(7.368)	(0.426)	(0.416)
Observations	2691	2692	2700	2699
Mean DV	2.583	1.849	0.733	0.657
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.456	0.457	0.381	0.371

Notes: Estimates of equation (1). Column 1: the dependent variable is the number of unfounded burglary into structures or vehicle theft offenses per 10,000 residents. Column 2: the dependent variable is the number of unfounded burglary into structures offenses per 10,000 residents. Column 3: the dependent variable is the number of unfounded vehicle theft offenses per 10,000 residents. Column 4: the dependent variable is the number of unfounded car theft offenses per 10,000 residents. Treat: indicator of whether a given city has an active nuisance ordinance in a given year. Mean DV: average pretreatment dependent variable. Controls: average pretreatment population and number of tenant households times Year FE. Standard errors clustered at the city level are in parentheses. Significance levels: *** $p < .01$, ** $p < .05$, * $p < .1$.
Sources: crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); controls: ACS.

B Robustness

B.1 Alternative Outcome Measures and Additional Controls

Table B.4: Alternative Outcome Measures and Additional Controls

Panel A: Evictions		
	Per 10,000 Tenants	Per Pre-Treat. Average
	(1)	(2)
Treat	48.550**	0.414***
	(20.317)	(0.109)
Observations	3452	3452
Mean DV	258.939	1.000
City FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes
Additional Controls	Yes	Yes
Adjusted R^2	0.713	0.306
Panel B: Burglary into Structures or Vehicle Theft		
	Per 10,000 Tenants	Per Pre-Treat. Average
	(3)	(4)
Treat	41.128*	0.196**
	(23.350)	(0.079)
Observations	2750	2924
Mean DV	374.941	1.000
City FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes
Additional Controls	Yes	Yes
Adjusted R^2	0.767	0.080

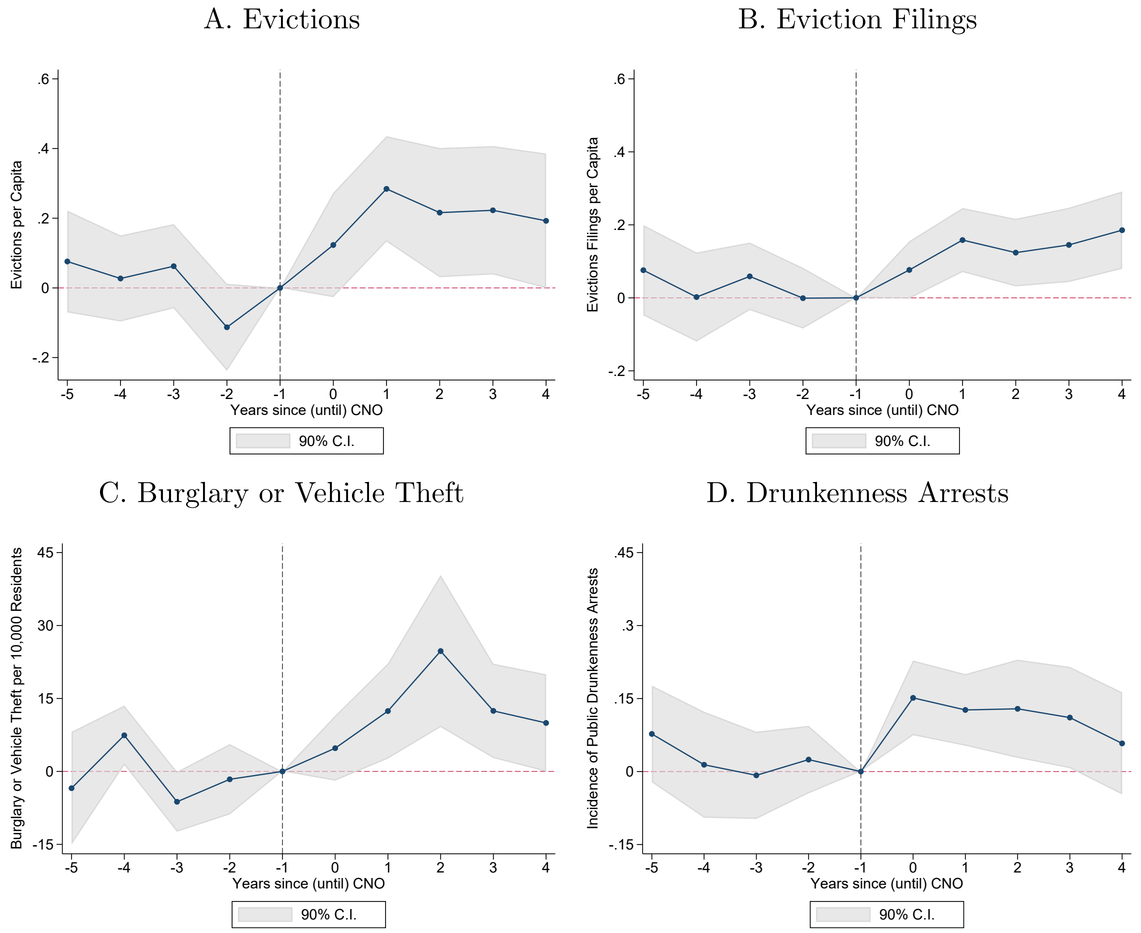
Notes: Estimates of equation (1). Column 1: the dependent variable is the number of evictions per 10,000 tenants. Column 2: the dependent variable is the number of evictions divided by the average pretreatment number of evictions. Column 3: the dependent variable is the number of burglary into structures or vehicle theft offenses per 10,000 tenants. Column 4: the dependent variable is the number of burglary into structures or vehicle theft offenses divided by the average pretreatment value of the variable. Treat: indicator of whether a given city has an active nuisance ordinance in a given year. Mean DV: average pretreatment dependent variable. Controls: average pretreatment population and number of tenant households times Year FE. Additional Controls: average pretreatment poverty share, median gross rent, median household income, median property value, and rent burden times Year FE. Standard errors clustered at the city level are in parentheses. Significance levels: *** $p < .01$, ** $p < .05$, * $p < .1$.
Sources: evictions: Eviction Lab; crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); controls: ACS.

B.2 Alternative Estimator

A recent literature highlights the estimation issues linked to two-way fixed effects estimators with staggered treatment timing (Callaway and Sant'Anna 2021; de Chaisemartin and D'Haultfœuille 2020; Athey and Imbens 2022). In the presence of staggered treatment, as in the context of this paper, the comparison between already-treated and not-yet-treated cities enters in the estimation with a negative weight. Negative weights are an issue if treatment effects are heterogeneous across groups and periods, as it is reasonable to assume in most settings. In theory, it is thus possible that the estimated coefficients in Section 5 have an opposite sign to the true average treatment effect (de Chaisemartin and D'Haultfœuille 2020).

The issues discussed in the new literature on staggered difference-in-difference are not particularly worrisome for the results in this paper because around 85 percent of cities in the sample are never treated. To corroborate this statement, I estimate the effects on the main outcome variables using the estimator proposed by de Chaisemartin and D'Haultfœuille (2020). Coefficients displayed in Online Appendix Figure B.8 are similar to those using the baseline estimation method.

Figure B.8: Timing of Effect on Evictions, Burglary into Structures and Vehicle Theft Offenses, and Public Drunkeness Arrests (de Chaisemartin and D'Haultfœuille estimator)



Notes: Estimates of equation (2) using the estimator proposed in de Chaisemartin and D'Haultfœuille 2020. Panel A: the dependent variable is the number of evictions per 10,000 residents transformed using the inverse hyperbolic sine method to take into account the zero values. Panel B: the dependent variable is the number of eviction filings per 10,000 residents transformed using the inverse hyperbolic sine method to take into account the zero values. Panel C: the dependent variable is the number of burglary into structures or vehicle theft offenses per 10,000 residents. Panel D: the dependent variable is the incidence of public drunkenness arrests.

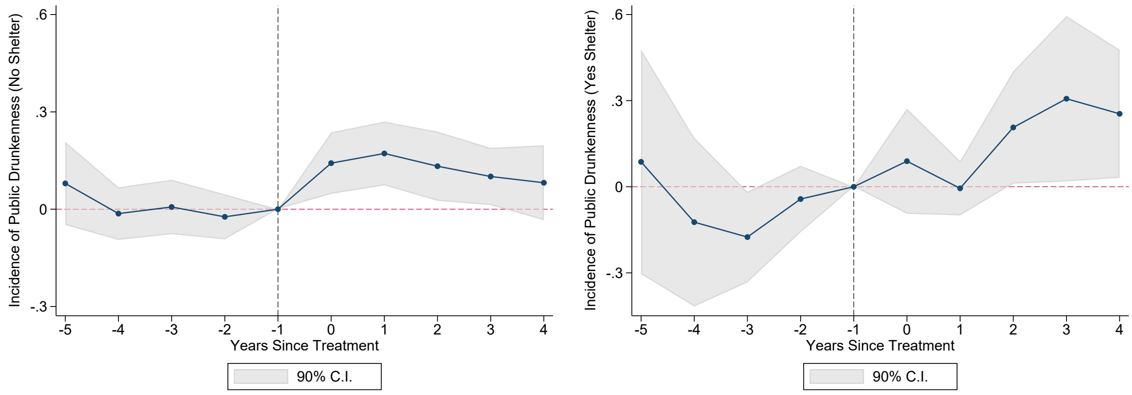
Sources: evictions: Eviction Lab; crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); controls: ACS.

C Mechanism

C.1 Additional Results on Homeless Mechanism

Figure C.9: Timing of Heterogeneous Effects by Presence of Homeless Shelters

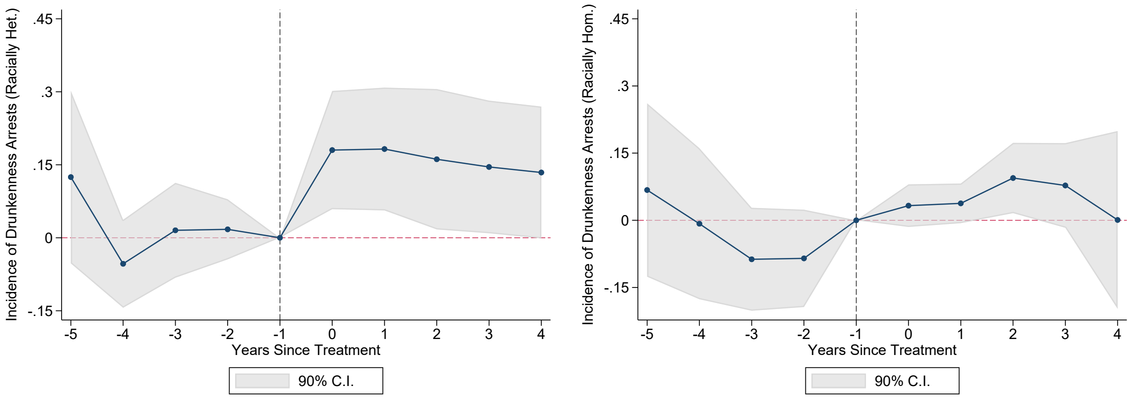
A. Drunk. Arrests in Cities Without Shelters B. Drunk. Arrests in Cities With Shelters



Notes: Estimates of equation (2) in cities without homeless shelters (panel A) and in cities with homeless shelters (panel B). The dependent variable is the incidence of public drunkenness arrests. *Sources:* crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); homeless shelters: Homeless Shelter Directory; controls: ACS.

Figure C.10: Timing of Heterogeneous Effects by Racial Heterogeneity

A. Drunk. Arrests in Racially Het. Cities B. Drunk. Arrests in Racially Hom. Cities



Notes: Estimates of equation (2) in racially heterogeneous cities (panel A) and in racially homogeneous cities (panel B). The dependent variable is the incidence of public drunkenness arrests. Racially heterogeneous: above or equal to the median racial heterogeneity value (as in Alesina and La Ferrara (2000), specifically 1 minus the Herfindahl-Hirschman Index of the share of the population that is: (i) White; (ii) Black; (iii) Hispanic or Latino; (iv) Asian; (v) American Indian and Alaska Native; (vi) Native Hawaiian and Other Pacific Islander; (vii) two or more races; or (viii) any other race). Racially homogeneous: below the median racial heterogeneity value.
Sources: crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); racial heterogeneity and controls: ACS.

Table C.5: Effect on Burglary into Structures and Vehicle Theft Clearances

	Burglary or Vehicle Theft	Burglary	Vehicle Theft	Car Theft
	(1)	(2)	(3)	(4)
Treat	1.514	0.226	0.761	0.754
	(1.355)	(0.460)	(0.723)	(0.636)
Observations	3572	3572	3572	3572
Mean DV	4.509	2.842	2.426	2.083
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.279	0.502	0.291	0.264

Notes: Estimates of equation (1). Column 1: the dependent variable is the number of burglary into structures or vehicle theft clearances per 10,000 residents. Column 2: the dependent variable is the number of burglary into structures clearances per 10,000 residents. Column 3: the dependent variable is the number of vehicle theft clearances per 10,000 residents. Column 4: the dependent variable is the number of car theft clearances per 10,000 residents. Treat: indicator of whether a given city has an active nuisance ordinance in a given year. Mean DV: average pretreatment dependent variable. Controls: average pretreatment population and number of tenant households times Year FE. Standard errors clustered at the city level are in parentheses. Significance levels: *** $p < .01$, ** $p < .05$, * $p < .1$.

Sources: crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); controls: ACS.

C.2 Other Potential Mechanisms

Findings in the mechanism Section 5.4 appear to be inconsistent with potential mechanisms other than homelessness. First, evictions may lead to crime by increasing financial hardship (Desmond 2012; Collinson, Humphries, Mader, Reed, and van Dijk 2022). The literature has shown that: (i) after an eviction, families' belongings are often lost or not easily accessible because stored by moving companies; (ii) households usually endure extra–expenses due to the trial and to procure a transitional shelter; and (iii) evictions damage credit's rating and lead to unemployment because of the frictions in resettling in new residences. However, the fact that I find no effect on income-generating crime (Appendix Figure A.6) suggests that financial hardship is unlikely to be the driver of the effect of evictions on burglary into structures and vehicle theft.

Second, evicted individuals may face a higher probability of joining criminal networks. This may occur because of the negative income shock due to the evictions or via social interaction with criminals in homeless shelters and poor neighborhoods (Desmond and Shollenberger 2015; Corno 2017). If this effect was in place, then it is reasonable to expect that any type of crime would be affected. Yet, the absence of an effect on income-generating or violent crimes (Appendix Figures A.5 and A.6) together weakens the plausibility of this potential mechanism.

Third, evictions may hit tenants involved in community policing of their neighborhoods, reducing crime prevention and control (Semenza, Stansfield, Grosholz, and Link 2021). But, again, the absence of an effect on crimes other than burglary and vehicle theft is inconsistent with this explanation.

Last, evicted households might burglarize their ex–residence to retaliate against evicting landlords. Although difficult to test, looking at burglary offenses without forcible entry can provide hints to whether this mechanism is in place. The reason is that evicted individuals are likely to have easy access into their ex–residences even after an eviction.[42] In contradiction with this potential explanation, Online Appendix Figure A.7 shows no effect on burglary offenses without forcible entry.

[42]For example because they possess entrance keys and knowledge of alarm systems or of policing behavior in the neighborhood.

D Data

D.1 Evictions

Eviction information is provided by the Eviction Lab, a research center at Princeton University, based on residential eviction court records. The unit of analysis is the household. To pinpoint the location of an eviction, the Eviction Lab geocodes each defendant address and then aggregates them at the Census-designated place level—city, towns and villages. Of the 1,204 Census places in Ohio, I only focus on cities, namely the 246 urban entities with at least 5,000 residents. This data is acquired from states, counties, courts and two independent companies. The two independent companies are LexisNexis Risk Solutions (LexisNexis) and American Information Research Services Inc. (AIRS). Foreclosures or commercial cases in which at least one defendant was identified as a commercial entity, such as bars, auto repair shops and laundries are excluded. Cases of residential evictions with commercial landlords are included. The unit of analysis is the households—single individuals, families or multiple families living in one residential unit.

In the case of dismissals "with prejudice," the landlord cannot file another eviction with the same allegations against the tenant, while this is possible in dismissals "without prejudice." In dismissals by "settlement" or "stipulation," the landlord and the tenant agree on how to solve the contention, usually with the tenant voluntarily relocating or paying a stipulated amount of money. Because evictions can occur informally in the case of dismissal, eviction filings offer a more precise, although imperfect, measure of landlords' willingness to evict tenants. In the United States, the difference between informal and formal evictions is amplified by the existence of "no-cause" evictions which allow landlords to evict tenants without filing a complaint by simply declining the request of a lease extension.

To pinpoint the location of an eviction, information on the defendant address linked to a specific court case is geocoded and then matched with a standardized dataset of street addresses and their corresponding latitudes and longitudes as provided by Environmental Systems Research Institute (ESRI) and US Census geographies. Data is then aggregated at the Census-designated place level (namely city, towns, and villages) using 2010 Census boundaries.

Eviction data for Ohio is among the most reliable in the United States. In fact, the ratio of aggregated individual-level eviction cases to county-level cases, a measure capturing the underestimation of the number of evictions, is 0.94 in Ohio, the closest to 1 among US states together with Pennsylvania (Desmond et al. 2018). More information on how this dataset is created and relative sources of information can be found in Desmond et al. (2018).

D.2 Crime

I use annual crime data from 2000 to 2014 by the Federal Bureau Investigation (FBI)'s Uniform Crime Reporting (UCR) Program at the law enforcement agency level. This dataset provides information on Part I offenses, namely felonies susceptible to be punished with over one-year prison sentence. Criminal offenses are either reported to the police by the general public or recorded directly by police officers, distinguishing between completed, attempted and unfounded cases. Clearances are founded criminal offenses that have been "closed," usually by arrest of the offender.[43] In the United States, the share of property crimes cleared by arrests or exceptional means is substantially lower than the one for violent crime.[44]

To construct crime information at the city level, I match each law enforcement agency to its city of operation using the crosswalk provided by the National Archive of Criminal Justice Data (2005).[45] All cities in Ohio have reported at least one burglary and one motor vehicle theft offenses from 2000 to 2014. Around 94 percent of these cities have provided information on these offenses based on one unique law enforcement agency in the same period.[46]

Burglary is defined by the UCR as the unlawful entry of a structure to commit a felony or theft. Structure includes, but is not limited to, apartment, barn, cabin, church, condominium, dwelling house, factory, garage, house trailer, office, public building, railroad car, school, storage facility and warehouse. Cases are divided into burglary with forcible entry, burglary without forcible entry, and attempted burglary. Burglary with forcible entry—henceforth, burglary—involves the use of force to enter the premises. Around 62 percent of the 1,047,132 completed burglaries in Ohio from 2000 to 2014 occurred with forcible entry. Since this dataset excludes civil cases, information on burglary does not overlap with "forcible entry and detainer" lawsuit

[43] To be cleared, an offense needs to meet three conditions: at least one person has been arrested, charged with commission of the offense and turned over to court for prosecution. In special circumstances, the offense can be cleared by "exceptional means," meaning that the law enforcement agency encountered a circumstance outside its control forbidding the arrest, charge and prosecution.

[44] In 2018, around 18 percent of property crimes were cleared, the share being around 46 percent for violent offenses. The numbers were 13.9 percent for burglary offenses, and 13.8 percent for motor vehicle theft offenses (US Department of Justice, Federal Bureau of Investigation 2019).

[45] The crosswalk allows to match law enforcement agencies to cities linking the Originating Agency Identifier (ORI) number of the former to the identifier of the Census Place (FIPS) of the latter.

[46] Columbus, the largest and most populated city in Ohio, relied on data from five law enforcement agencies during the same period.

linked to an eviction. I also use data on the 372,933 completed motor vehicle theft offenses in Ohio from 2000 to 2014, of which car theft constitutes 86 percent.[47]

Law enforcement agencies apply the "hierarchy rule" whereby if more than one criminal offense is produced in one event, then only the most serious crime is reported. Therefore, burglary offenses are, by definition, the subset of trespassing cases in which police officers esteem the existence of an intention to commit a felony or a theft. Since this intention may be considered to exist after investigation even in the absence of the actual occurrence of the felony or theft, the recording of a burglary event is in part discretionary and likely to capture less serious trespassing occurrences. The hierarchy rule also implies that a vehicle theft occurrence involving a burglary into a structure is recorded as a burglary, a more serious offense than vehicle theft.

Information on arrests for public drunkenness is provided in the Part II offenses of the UCR Program. Drunkenness is defined as the drinking of alcoholic beverages until one's impairment of mental faculties and physical coordination. Around 62 percent of the cities in Ohio—153 of 246—have at least one recorded arrest for public drunkenness from 2000 to 2014. Around 96 percent of these cities have provided information on these arrests based on one unique law enforcement agency in the same period. Data on arrests for larceny, drug abuse violations, stolen property, forgery and counterfeiting, and gambling are also provided in the Part II offenses of the UCR Program.

I complement the UCR crime data using the 424,144 incidents in which a completed burglary was recorded as the most serious offense in the National Incident-Based Reporting System (NIBRS) from 2000 to 2014 in Ohio. This database provides details on the location, victim, and property involved in each incident.

D.2.1 Part I

Assault.—An unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury.

Burglary.—The unlawful entry of a structure to commit a felony or a theft.

Larceny.—The unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another (except motor vehicle theft).

[47] The rest is and bus or truck theft (7 percent), theft of other motor vehicle such as sport utility vehicles, motorcycles, motor scooters, all-terrain vehicles, snowmobiles, etc. (6 percent), and unknown (1 percent).

Manslaughter.—The killing of another person through gross negligence.

Motor Vehicle Theft.—The theft or attempted theft of a motor vehicle. A motor vehicle is self-propelled and runs on land surface and not on rails. Motorboats, construction equipment, airplanes, and farming equipment are specifically excluded from this category.

Murder.—The willful (nonnegligent) killing of one human being by another.

Robbery.—The taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear.

D.2.2 Part II

Drug Abuse Violations.—The violation of laws prohibiting the production, distribution, and/or use of certain controlled substances. The unlawful cultivation, manufacture, distribution, sale, purchase, use, possession, transportation, or importation of any controlled drug or narcotic substance. Arrests for violations of state and local laws, specifically those relating to the unlawful possession, sale, use, growing, manufacturing, and making of narcotic drugs. The following drug categories are specified: opium or cocaine and their derivatives (morphine, heroin, codeine); marijuana; synthetic narcotics—manufactured narcotics that can cause true addiction (demerol, methadone); and dangerous nonnarcotic drugs (barbiturates, benzedrine).

Drunkenness.—To drink alcoholic beverages to the extent that one's mental faculties and physical coordination are substantially impaired.

Forgery and Counterfeiting.—The altering, copying, or imitating of something, without authority or right, with the intent to deceive or defraud by passing the copy or thing altered or imitated as that which is original or genuine; or the selling, buying, or possession of an altered, copied, or imitated thing with the intent to deceive or defraud.

Fraud.—The intentional perversion of the truth for the purpose of inducing another person or other entity in reliance upon it to part with something of value or to surrender a legal right. Fraudulent conversion and obtaining of money or property by false pretenses. Confidence games and bad checks, except forgeries and counterfeiting, are included.

Gambling.—To unlawfully bet or wager money or something else of value; assist, promote, or operate a game of chance for money or some other stake; possess or transmit wagering information; manufacture, sell, purchase, possess, or transport gambling equipment, devices, or goods; or tamper with the outcome of a sporting event or contest to gain a gambling advantage.

Stolen Property.—Buying, receiving, possessing, selling, concealing, or transporting any property with the knowledge that it has been unlawfully taken, as by burglary, embezzlement, fraud, larceny, robbery, etc.

D.2.3 National Incident-Based Reporting System (NIBRS)

NIBRS provides details on each crime incident including information on location, victim, and property involved.

Location. Air or Bus or Train Terminal, Bank or Savings and Loan, Bar or Nightclub, Church or Synagogue or Temple, Commercial or Office Building, Construction Site, Convenience Store, Department or Discount Store, Drug Store or Drs Office or Hospital, Field or Woods, Government or Public Building, Grocery or Supermarket, Highway or Road or Alley, Hotel or Motel or Etc., Jail or Prison, Lake or Waterway, Liquor Store, Parking Lot or Garage, Rental Storage Facility, Residence or Home, Restaurant, School or College, Service or Gas Station, Specialty Store (TV, Fur, Etc.), Other or unknown, (M) NA LT 3 records, (M) NA Window Record.

Victim Type. Individual, Business, Financial Institution, Government, Law Enforcement Officer, Religious Organization, Society or Public, Other, (M) NA LT 3 records, (M) Unknown or missing or DNR, (M) NA Window Record.

Stolen Property. Aircraft, Alcohol, Automobiles, Bicycles, Buses, Clothes or Furs, Computer Hardware or software, Consumable Goods, Credit or Debit Cards, Drugs or Narcotics, Drug or Narcotic Equipment, Farm Equipment, Firearms, Gambling Equipment, Heavy Construction or Industrial Equipment, Household Goods, Jewelry or Precious Metals, Livestock, Merchandise, Money, Negotiable Instruments, Nonnegotiable Instruments, Office–Type Equipment, Other Motor Vehicles, Purses or Handbags or Wallets, Radios or TVs or VCRs, Recordings–Audio or Visual, Recreational Vehicles, Structures–Single Occupancy Dwellings, Structures–Other Dwellings, Structures–Commercial or Business, Structures–Industrial or Manufacturing, Structures–Public or Community, Structures–Storage, Structures–Other, Tools–Power or Hand, Trucks, Vehicle Parts or Accessories, Watercraft, Other, Pending Inventory (of Property), Special Category, (M) NA LT 3 records, (M) Not applicable, (M) NA Window Record.

D.3 House Price Index

To calculate the House Price Index, the Federal Housing Finance Agency (FHFA) relies on information in repeat mortgage transactions on single-family properties with mortgages purchased or securitized by Fannie Mae or Freddie Mac. When matching five-digit ZIP codes with city codes, I calculate the average HPI per city-year based on the five-digit ZIP codes within the city. I drop the observations from the five-digit ZIP codes present in more than one city, yielding 1,980 observations in 132 cities (19 treated and 133 never treated). Results are robust to keeping the five-digit-ZIP-code HPI values present in more than one city.

D.4 Nuisance Ordinances

Table D.6: Cities

City	Year
Akron	2005
Ashtabula	2011
Aurora	2010
Barberton	2005
Bedford	2005
Bedford Heights	2007
Brooklyn	2005
Brunswick	2005
Campbell	2006
Cheviot	2007
Chillicothe	2014
Cincinnati	2006
Cleveland	2006
Cleveland Heights	2003
East Liverpool	2011
Eaton	2013
Euclid	2006
Fairview Park	2004
Garfield Heights	2011
Kent	2004
Lakewood	2004
Lorain	2013
Lyndhurst	2009
Maple Heights	2006
Niles	2013
North College Hill	2007
North Olmsted	2008
Norton	2010
Orrville	2009
Painesville	2008
Parma	2005
Ravenna	2011
Sandusky	2004
Shaker Heights	2004
South Euclid	2004
Struthers	2012
University Heights	2004
Wadsworth	2013
Warrensville Heights	2014

Notes: List of the 39 of the 246 Ohio's cities having adopted a nuisance ordinance from 2000 to 2014 and corresponding adoption year.
Source: Mead et al. (2017).