Forcing Out, Breaking In: Do Evictions Increase Crime?

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Abstract

This paper provides the first causal evidence of an external cost of evictions: crime. Leveraging an exogenous increase in evictions in Ohio's cities from 2000 to 2014, I find that evictions increase "crime over inhabitable property:" a 10 percent increase in evictions lead to 5.5 and 8.5 higher percent of forcible entry and vehicle theft, respectively. These elasticities suggest that reducing evictions is at least as effective as increasing police deployment or arrests. The effect is driven by higher homelessness: drunkenness arrests increase; crime effects are stronger in cities without homeless shelters, in cities with lower social capital—where support networks are weaker—and in months with harsher outdoor conditions; forcible entry involves theft of vehicles, clothes and food only. Findings highlight an unexplored social cost of evictions and a neglected determinant of crime.

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1 Introduction

An emerging literature documents the deleterious effects of evictions on evicted households (Collinson and Reed 2018; Humphries, Mader, Tannenbaum, and Van Dijk 2019). Yet whether evictions may also lead to negative externalities is unknown. This is an important question because, if evictions lead to inefficient outcomes, then this changes welfare analysis of homeownership and housing policies.[1] Given the staggeringly high numbers of evictions globally, 2.3 million per year in the US alone, even very small effects of evictions on crime may imply strong inefficiencies.

This paper approaches the question of the evictions' social cost by focusing on one specific negative externality: crime. My hypothesis is that evictions lead to homelessness, thus increasing "crime over inhabitable property:" unlawful entry and vehicle theft, both aimed at procuring shelter not to "sleep rough." Correlations between the numbers of evictions, homeless and burglaries in the US (Figure A.1 panels A–B), coupled with causal evidence on the effect of evictions on homelessness (Collinson and Reed 2018) and case studies on the link between homeless and crime in the pursuit of shelter support the plausibility of the hypothesis.[2]

To investigate this question causally, I exploit the staggered introduction of nuisance ordinances across cities in Ohio from 2000 to 2014. Widely used across the US, nuisance ordinances sanction landlords for disturbances in their properties, increasing landlords' incentive to evict tenants (Kroeger and La Mattina 2020).[3] Thanks to the effort of the American Civil Liberties Union, information on nuisance ordinances' adoption year in Ohio's cities has already been systematized and made publicly available.[4]

The context of nuisance ordinances in Ohio offers several advantages in exploring whether evictions increase crime. First, I believe that the setting more closely mirrors the ideal thought experiment than others found in the literature. In fact, while I focus on landlords' incentive to evict, previous research has mostly relied on comparing individuals formally evicted *versus* formally non-evicted, potentially biasing downward the estimate because tenants can be informally forced to leave after winning trial. Moreover, I study a populous state, Ohio, with eleven million residents and heterogeneous cities' size, making it representative of landlord-tenant relationships in the whole country, and less susceptible to threats to the external validity then studies on judiciary decisions in extremely large cities. Second,

[1] Welfare analysis of homeownership, which has already been found to generate external benefits (Hausman, Ramot-Nyska, and Zussman 2022), would be affected. The same applies to several housing policies, such as the establishment of homeless shelters, the introduction of "right-to-counsel", which provide publicly-funded legal counsel to tenants in eviction cases in the US, or eviction *moratoria*, protecting renters from eviction in bad times, as during the COVID-19 pandemics in the US.

[2] I discuss this literature in Section 5.3.

[3] More than 2,000 cities are estimated to have an active nuisance ordinance in place (Jarwala and Singh 2019), including thirty-seven of the forty largest cities in the US. See `https://lawatlas.org/datasets/city-nuisance-property-ordinances`.

[4] This information is provided by Mead, Hatch, Tighe, Pappas, Andrasik, and Bonham (2017).

the setting also provides measurement advantages: since evictions are explicitly mentioned in nuisance ordinances as a method to abate disturbances, landlords can reasonably expect to win trial, reducing the number of informal and hence unmeasured evictions; furthermore, publicly accessible eviction data for Ohio is presented as the most reliable in the US by the organization that collects the information.[5]

To investigate whether evictions lead to "crime over inhabitable property," I apply a staggered difference-in-difference (DID) comparing the change in evictions, forcible entry and vehicle theft in cities with *versus* without a nuisance ordinance. Assuming parallel trends in outcomes' levels and that nuisance ordinances affect crime only through evictions, the DID estimate captures the effect of evictions on crime. Since nuisance ordinances are mostly applied for occurrences such as noise and kids playing, the effect is arguably not specific to the sub-group of criminal tenants (Desmond and Valdez 2013; Mead et al. 2018).

I provide several evidence in support of the two identifying assumptions allowing a causal interpretation of the DID estimate. In favor of the parallel trends assumption, I begin by providing evidence that results are not driven by shocks correlated with the adoption of nuisance ordinances: cities with a nuisance ordinance (treated) are similar across several observable characteristics to cities without the ordinance (never treated), suggesting that results are unlikely due to common shocks leading to heterogeneous effects across the two groups; in addition, I find no relationship between the adoption of nuisance ordinances and crime not directly related to housing, excluding correlated shocks affecting general drivers of criminal activity; moreover, the effect on forcible entry is driven by residents, ruling out correlated shocks pushing offenders to move across cities.

To further support the parallel trends assumption, I find presence of parallel trends in the number of crime offenses and evictions leading to the adoption of nuisance ordinances, in an event study setting. House prices also show absence of pre-trends, while decreasing since the adoption of nuisance ordinances, consistent with the parallel trends assumption. To confirm that unmeasured pre-trends due to crime misreporting are not a threat to the parallel trends assumption, I proceed as follows. First, I show that the same result holds for violent crime—arguably the most reliably measured crime in the US (Sampson and Earls 1997)—suggesting that unmeasured pre-trends are unlikely to be present. Second, because nuisance ordinances increase crime underreporting (Moss 2019; Golestani 2021), I discuss why this would help support the parallel trends assumption even if unmeasured pre-trends were present.

To test the second assumption, namely that nuisance ordinances increase crime only through evictions, I explore whether the effect is driven by (i) changes in the housing market affecting, for example, the availability of unoccupied residential units and attracting already existing thieves; (ii) crime misreporting; (iii) landlords illegally entering in their premises in the process of informally evict nuisant tenants. I find evidence against all of them,

[5]These two measurement advantages are discussed in Section 4.

supporting the second assumption.

Results show that evictions strongly increase "crime over inhabitable property." While nuisance ordinances lead to 12–13 higher evicted households per 10,000 residents, an increase of 33 percent, they also lead to around 11 additional number of "crime over inhabitable property" per 10,000 residents, an increase of 21 percent: 6 forcible entries and 5 vehicle theft, 18 and 28 percent higher, respectively. These numbers point to large elasticities of "crime over inhabitable property" on evictions—0.55 for forcible entry and 0.85 for vehicle theft. Estimates are higher than the crime-police deployment elasticities found in the literature and in the range of those related to crime-arrests (Levitt 1997; Corman and Mocan 2000; Di Tella and Schargrodsky 2004; Draca, Machin, and Witt 2011; Chalfin and McCrary 2017; Blanes i Vidal and Mastrobuoni 2018).

I find evidence that evicted households struggle to settle in new residences, become homeless and break into structures or steal vehicles to find shelter. First, I document an effect on the incidence of arrests for public drunkenness, a crime susceptible to homeless presence (Snow, Baker, and Anderson 1989), which increases by 24 percent. Second, the effect on crime is present only in cities without homeless shelters, "residence providers of last resort." Third, the effect is driven by racially fragmented cities, where social capital, trust, connections and mutual help are lower (Alesina and La Ferrara 2000), together with housing opportunities at family's, friends' or neighbors' dwellings. Fourth, using city-months data, I find that the effect on crime is stronger when outdoor conditions in Ohio are particularly harsh and life-threatening to the local homeless population—from October to February included. Fifth, relying on incident-level information, I show that "crime over inhabitable property" involves theft of basic commodities (clothes and consumables) but *not* of precious items (money, jewelry, credit cards), pointing to homeless' rather than burglars' behavior. Last, serving as a placebo test, evictions do not increase crime less susceptible to homeless presence according to the criminology literature:[6] violent or "income-generating" (Deshpande and Mueller-Smith 2022).[7]

While individually only suggestive, these findings are, I believe, collectively conclusive, pointing to homelessness and the quest of shelter as the mechanism through which evictions increase crime. Evidence against other potential mechanisms, such as changes in general economic conditions—unemployment, income, and poverty—recruitment by criminal organization, reduction in community policing, or retaliatory action against evicting landlords is also discussed.

[6] As discussed in Section 5.3, research in criminology has found positive associations between homelessness and burglary, vehicle theft and public drunkenness, while homeless arrest rates for violent or other "income-generating" offenses are comparable to those of the general population (Fischer 1988; Snow, Baker, and Anderson 1989; Faraji, Ridgeway, and Wu 2018).

[7] Deshpande and Mueller-Smith (2022)'s definition of "income-generating" crime include theft, fraud, forgery, robbery, drug distribution and prostitution. I follow the Federal Bureau Investigation (FBI) and classify robbery as a violent crime. I focus on the following "income-generating" offenses: larceny, drug distribution, theft, forgery and counterfeiting, and gambling. The concept of "income-generating" is similar in spirit to the one of "economically motivated" in Pinotti, Britto, and Sampaio (2022).

Results are robust to the use of the alternative outcome measures and to the estimator proposed by de Chaisemartin and D'Haultfœuille (2020) to overcome the issues in estimating treatment effects in staggered difference-in-difference designs when the effects differ across groups or periods (Borusyak and Jaravel 2017, Callaway and Sant'Anna 2020, de Chaisemartin and D'Haultfœuille 2020, Sun and Abraham 2020, Athey and Imbens 2021 and Goodman-Bacon 2021).

Related Literature.—This paper contributes to several strands of the literature. First, I add to the growing literature on the negative consequences of evictions, "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 and Reed 2018; Humphries, Mader, Tannenbaum, and Van Dijk 2019), and that housing policies such as rental assistance (Abramson 2022) or eviction moratoria (Jowers, Timmins, Bhavsar, Hu, and Marshall 2021; An, Gabriel, and Tzur-Ilan 2022) can help dampen these negative effects. The deleterious effects of evictions are broad, affecting several aspects of human life: homelessness, health, credit access, consumption and earnings.[8] Despite a growing interest on evictions, few works have explored how they affect non-evicted individuals, and the specific link between evictions and crime has been almost completely neglected,[9] with only very few papers in criminology approaching this question.[10] I expand this emerging literature by providing the first causal evidence of an external cost of evictions, finding a strong effect on crime.

Second, this paper contributes to the well-established literature in economics 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 (see Becker 1968, Stigler 1970 and Ehrlich 1973 for classical works, and Draca and Machin 2015 for a review of more recent contributions).[11] Instead, other economists have highlighted the importance of social interactions or strategic complementarities in criminal behavior (Case and Katz 1991; Sah 1991; Murphy, Shleifer, and Vishny 1993; Glaeser, Sacerdote, and Scheinkman 1996; Bayer, Hjalmarsson, and Pozen 2009; Dustmann and Landersø 2021).[12] Overall, this

[8] These findings are in line with correlations documented in other social sciences between evictions and homelessness (Crane and Warnes 2000), residential instability (Desmond, Gershenson, and Kiviat 2015), and poverty and poor health (Desmond and Kimbro 2015). Forced displacement attracted interest also in developing countries and has been found to lead to social isolation (Barnhardt, Field, and Pande 2017) and lower earnings and education (Rojas-Ampuero and Carrera 2021).

[9] This is even more surprising in light of the fact that the social cost of foreclosures (landlords' evictions) has received attention by economists, mainly focusing on price externalities (Campbell, Giglio, and Pathak 2011; Anenberg and Kung 2014; Guren and McQuade 2020; Diamond, Guren, and Tan 2020).

[10] See, for example, Alm (2018), Gottlieb and Moose (2018) and Semenza, Stansfield, Grosholz, and Link (2021).

[11] Private incentive in criminal activity refer to the offense's payoff, the foregone return in non-criminal activity, and the probability and severity of conviction.

[12] The importance of social interactions has been discussed also in criminology and sociology (Shaw and McKay 1942; Sutherland 1947; Wilson 1987; Sampson and Groves 1989; Massey and Denton 1993).

second approach has been more successful in explaining how crime is affected by housing conditions: see, for example, the crime effects of housing structure (Glaeser and Sacerdote 2000), housing vouchers (Kling, Ludwig, and Katz 2005), homeless shelters (Corno 2017), public housing (Chyn 2018), and neighborhoods (Ludwig, Duncan, and Hirschfield 2001; Damm and Dustmann 2014; Billings, Deming, and Ross 2019), all driven by the "social multiplier" (Becker and Murphy 2000). Consistent with Becker (1968)'s traditional model, I find that housing shocks may lead to crime if they reduce housing access, thus by directly affecting the private individual's opportunity cost—the return from the legal alternative to crime.

Third, I add to the literature on the social consequences of nuisance ordinances, widely used in the US, with around 2,000 cities, including thirty-seven of the forty largest American metropolitan areas (Jarwala and Singh 2019).[13] On the one hand, Kroeger and La Mattina (2020) document an effect of nuisance ordinances on eviction risk. On the other hand, other economists have found that these ordinances lead to domestic violence: Moss (2019), focusing on municipalities in California, and Golestani (2021) in forty major metropolitan statistical areas. The social cost of nuisance ordinances has also attracted attention by sociologists (Desmond and Valdez 2013; Desmond 2016) and legal scholars (Fais 2008; Kastner 2015), all focusing on tenants' incentive to underreport crime to elude evictions, increasing undocumented violence against women in the household. I expand this literature by highlighting an additional external cost of a widely used policy: unlawful entry and vehicle theft.

2 Context

Evictions, Homelessness and Crime.—In the US, 2.3 million individuals are evicted every year on average since 2000 (Desmond et al. 2018b). Numbers are higher when including evictions not ordered by court—informal evictions—estimated to be two to three times higher than formal ones, and "no-cause" evictions, whereby tenants lose access to residence because landlords decline requests for lease extensions.

In the specific case of Ohio, eviction statistics are similar to those for the U.S as a whole,[14] and the correlations between the numbers of evictions, homeless and burglaries offenses also reflect the national ones (Figure A.1). The institutional environment surrounding formal evictions in the state also exemplifies the one in other US states. For all these reasons, Ohio is a case study potentially representative of the whole country.

The landlord starts the eviction process by notifying the tenant about her willingness to vacate the property, typically with a "three-day notice." If the tenant has not moved of her rental unit within the deadline, then the landlord can file a "forcible entry and detainer"

[13] See https://lawatlas.org/datasets/city-nuisance-property-ordinances.

[14] The annual average number of evictions in Ohio from 2000 to 2014 was X, with a total population of 11 million residents (Desmond et al. 2018b).

lawsuit at the local court. If the landlord is successful at the hearing, the judge emits a "writ of restitution," authorizing the federal law enforcement agency to evict the tenant. The tenant is ordered to vacate the property in 85–95 percent of the cases (Geminiani, Chin, and Feldman-Schwartz 2018). This is hardly surprising since tenants have no right to representation by lawyers (Scherer 1988), confront difficulties in navigating the complex landlord-tenant law (Hartman and Robinson 2003) and often do not attend trial.[15]

Once evicted, households look for new homes to relocate. This is usually a costly process that can stretch over months due to the several sources of frictions in the search and matching of prospective tenants and landlords (Desmond, Gershenson, and Kiviat 2015). First, since eviction records are public, evicted households face a reputation loss in relation to prospective landlords (Kleysteuber 2007). Second, evictions often involve people employed in low-wage staff jobs without paid leave or advanced scheduling notice (Kalleberg 2008), and having to deal with schooling rearrangements.

Because of these relocation frictions, evicted households face a high risk of joining the around 600,000 homeless people in the US.[16] Consistently, recent causal evidence in economics (Collinson and Reed 2018) and an extensive criminology literature point to evictions as a cause of homelessness.[17] The same literature also suggests that, due to lack of secure housing, homeless people face an incentive to engage in illegal activity to procure shelter (Fischer 1988): burglary and vehicle theft, for which they are accused disproportionately (Snow, Baker, and Anderson 1989). The link between evictions, homelessness and crime in the pursuit of shelter is discussed in details in Section 5.3, when I present the mechanism.

Nuisance Ordinances.—In an effort to reduce public expenditure for policing services, city councils started since the 1980s to adopt nuisance ordinances, sanctioning landlords for nuisance properties. These ordinances increase landlords' incentive to abate housing nuisances by shifting the external cost of these disturbances on them.

Although nuisance ordinances often lack a clear definition of "nuisance", this typically includes both criminal and non-criminal events. However, case studies indicate that nuisance ordinances are mostly applied for petty occurrences such as noise (Desmond and Valdez 2013) and kids playing (Mead et al. 2018).[18]

[15] Since there is no right to housing in the US, tenants are often unrepresented. In a case study of New York City's Housing Court, lawyers represented 90 percent of landlords and 15 percent of tenants (Chen 2003). In his case study on Milwaukee, Winsconsin, Desmond (2016) finds that 70 percent of tenants summoned to court did not attend the trial.

[16] 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 in a given night in the US, see `seehttps://www.hudexchange.info/programs/hdx/pit-hic/`.

[17] See, for example, Burt (2001) and Hartman and Robinson (2003).

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

The typical nuisance ordinance stipulates around 1,000 US dollars fines to landlords if police is called at least three times in ninety days.[19] Moreover, nuisance ordinances may apply to "buffer zones" surrounding the premises (Gavin 2014). Since, in Ohio, nuisance activity may justify an eviction, the diffusion of nuisance ordinances in the last two decades has been found to increase the number of evictions (Kroeger and La Mattina 2020).[20] Consistently, several case studies point to the eviction of the tenant as the landlord's preferred nuisance abatement strategy (Desmond and Valdez 2013).

Today, more than 2,000 cities are estimated to have an active nuisance ordinance in place (Jarwala and Singh 2019), including thirty-seven of the forty largest cities in the US, as documented by the Temple University Policy Surveillance Program.[21] In Ohio, for which detailed information on nuisance ordinances exists thanks to the effort of the American Civil Liberties Union (Mead et al. 2017), 39 of a total of 246 cities have adopted this ordinance in the 2000–2014 period, involving over 1,8 million residents, 39 percent of the state's urban population. Online Appendix Table E.6 provides nuisance ordinances' adoption years for cities in Ohio.

3 Data

I combine city-level data from six sources.

Evictions.—Information on the annual number of formal residential evictions from 2000 to 2014 at the city level in Ohio is provided by the Eviction Lab based on court records. An eviction is classified as a case of "forcible entry and detainer" in which the judge sentenced a "writ of restitution," namely an order to vacate the property. If the case is dismissed, the case is recorded as an eviction filing. 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 and on "no-cause" evictions whereby landlords evict tenants by declining requests for lease extensions is not provided. Because landlords can evict tenants informally after losing trial, the number of eviction filings is a more precise measure of landlords' willingness to evict than the number of formal evictions. Both the number of evictions and eviction filings are normalized by the popula-

[19] For example, the nuisance ordinance in the city of Lakewood in Ohio states that "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 §510.01 c).

[20] Ohio Revised Code §5321.05 on tenant obligations sanctions that: "A tenant who is a party to a rental agreement shall [...] Conduct himself and require other persons on the premises with his consent to conduct themselves in a manner that will not disturb his neighbors' peaceful enjoyment of the premises", and that if the tenant violates this provision then the landlord has the right "to terminate the rental agreement, to maintain an action for the possession of the premises [...]".

[21] Accessible at `https://lawatlas.org/datasets/city-nuisance-property-ordinances`.

tion size. According to the Eviction Lab, eviction data for Ohio is is the most reliable in the US: in fact, the ratio of aggregated individual-level 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. 2018a). More information on eviction data is in Online Appendix E.1.

Crime.—I use annual crime data from 2000 to 2014 by 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. Crime offenses are reported by the general public or recorded directly by police officers, while clearances are founded crime offenses. Information is provided at the law enforcement agency level, which I then aggregate at the city level using the crosswalk by the National Archive of Criminal Justice Data (2005).

Burglary is the unlawful entry of a structure with the *intention* to commit a felony or theft. Structure includes, but is not limited to, apartments. Cases are divided into forcible entry, burglary without breaking, and attempted burglary. 62 percent of the 1,047,132 burglaries in Ohio from 2000 to 2014 occurred with the use of force. Importantly, burglary with forcible entry—henceforth, forcible entry—, being a criminal category, does not overlap with the "forcible entry and detainer" civil lawsuits linked to evictions, judged according to landlord-tenant law. I also use data on two subcategories of the 372,933 completed motor vehicle theft offenses in Ohio in the same period: car theft and bus or truck theft, 86 percent and 7 percent of the total, respectively.

The sum of forcible entry and vehicle theft define what I classify as "crime over inhabitable property." I argue that forcible entry 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 discretionary, simple trespassing, a low-level "quality-of-life" offense (Chalfin, Hansen, Weisburst, and Williams 2022), may be reported as burglary. The discretionary element in the reporting of burglaries is particularly relevant for unlawful entries involving theft of petty objects, such as clothes or consumable goods, which may be stolen by homeless 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 is reported, vehicle theft in the context of breaking and entering into a structure is recorded as forcible entry.

For the more extensive analysis, I use information on arrests for public drunkenness, larceny, drug abuse violations, stolen property, forgery and counterfeiting, and gambling from 2000 to 2014. As for Part I offenses, arrests are reported at the law enforcement agency level and then aggregated at the city level. To reduce concerns related to the duplication of these crime offenses, I rely on the extensive margin.[22] I also rely on data on the

[22]Duplication may occur because of computational error or due to the failure of de-duplicating the counting of the same occurrence when reported in more than one law enforcement agency. Although not particularly worrisome for serious crime offenses in the UCR Part I, such as burglary and vehicle theft, the presence of false positive is a relevant concern when using data on less serious crimes, such as those in the

424,144 incidents in which forcible entry was recorded as the most serious offense in the National Incident-Based Reporting System (NIBRS) from 2000 to 2014 in Ohio—henceforth, forcible entry incidents. The dataset provides, among others, information on the location, victim and property involved in each incident. Due to the impossibility of distinguishing between missing and zero values, I only focus on the intensive margin. Details on crime data are discussed in Online Appendix E.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. The adoption year refers to the timing of the actual codification of the ordinance which typically qualifies a residential property as a nuisance if at least two disturbances occurred in twelve months. While nuisances in Ohio include both criminal and non-criminal occurrances, noise and kids playing have been found to be the most common (Mead et al. 2018), in line with findings for cities outside Ohio (Desmond and Valdez 2013). 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 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 E.6).

House Price Index.—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 measures the movement of single-family house prices computing average price changes in repeat sales or refinancings on the same properties. To calculate the HPI, the 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 with city codes, I calculate the average HPI per city-year based on all the five-digit ZIP codes overlapping with the city geography. Since five-digit ZIP codes can be present in more than one cities, this computational method implies that several HPI values are counted in more than one city to calculate the average HPI per city-year.

Demographic Characteristics.—Annual population data from 2000 to 2014 for each enforcement agency in Ohio is 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 Eviction Lab based on the 2000 and 2010 US Census Bureau Decennial Censuses, and the 2005–2009 and 2011–2015 five-year US Census

UCR Part II, including drunkenness. 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, finding different results. On the contrary, 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.

Bureau's American Community Survey (ACS) estimates.[23] Residents are divided in the following race categories: American Indian and Alaska Native, Asian, Black, Hispanic or Latinx, Native Hawaiian and Other Pacific Islander, White, two or more races, and any other race. Racial fragmentation is computed as in Alesina and La Ferrara (2000), 1 minus the Herfindahl-Hirschman Index of the share of population of each race. I consider as racially fragmented any city above or equal to the median racial fragmentation 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 listing the name and address of all homeless shelters in the US as of 2022.[24] As shown in Online Appendix Table X, homeless shelters in Ohio's cities listed in this database were already established by 2000, before the introduction of the first nuisance ordinance in the state—Cleveland Heights in 2003.

Table 1 provides statistics for the main variables.

[23] 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. Details on the demographic characteristics used in this study can be found in ACS (2020) and Desmond et al. (2018a).

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

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
Crime Offenses per 10,000 Residents, 2000–2014					
Crime over Inhabitable Property	0.000	52.98	398.61	55.37	2926
Forcible Entry	0.000	35.82	239.47	38.75	2926
Vehicle Theft	0.000	17.16	248.72	21.46	2926
Car Theft	0.000	14.27	243.01	19.15	2925
Arrests Incidence, 2000-2014					
Public Drunkenness	0.000	0.279	1.000	0.449	3690
Treatment, 2000–2014					
Nuisance Ordinance Adoption	0.000	0.077	1.000	0.266	3690
Demographics (Pre-Treatment Average)					
Population	4,456	27,138	760,726	64,702	246
Tenant Households	111	4,424	169,886	14,158	246
Racially Fragmented	0.000	0.500	1.000	0.501	246
Homelessness (Pre-Treatment Average)					
Homeless Shelters Presence	0.000	0.492	15.000	1.735	246

Notes: The unit of observation are the 246 cities in Ohio. "Crime over Inhabitable Property" is the sum of Forcible Entry and Vehicle Theft. Car Theft is a subset of Vehicle Theft. Variables are presented in Section 3.
Sources: evictions: Eviction Lab; crime offenses and arrests: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); demographics: ACS; homeless shelters: Homeless Shelter Directory.

4 Empirical Strategy

To investigate whether evictions lead to "crime over inhabitable property," I begin by running the following endogenous regression

$$CrimeInhabitableProperty_{ct} = \beta Evictions_{ct} + \gamma_c + \delta_t + \varepsilon_{ct} \tag{1}$$

where c indexes cities and t indexes years; $CrimeInhabitableProperty_{ct}$ is the number of forcible entry or vehicle theft offenses per 10,000 residents in; $Evictions_{ct}$ is the number of eviction filings per 10,000 residents; γ_c are city fixed-effects and δ_t are year fixed-effects controlling for year-specific shocks common to all cities.

Consistent with the hypothesis that evictions lead to "crime over inhabitable property," Online Appendix Table B.1 shows that the number of eviction filings is positively correlated with the number of "crime over inhabitable property" and, more specifically, with forcible entry offenses.

However, these suggestive results cannot be interpreted as the effect of evictions on "crime over inhabitable property." In fact, although γ_c absorb time-invariant city characteristics and δ_t controls for year-specific common shocks, the association between the changes in the number of eviction filings and crime offenses may be endogenous. First, these changes might be caused by a third factor, such as increasing unemployment due to macroeconomic adjustments. Second, higher crime levels may lead to increasing number of evictions as, for example, in the case of landlords evicting tenants who are suspected to have committed a crime.

To account for these potential sources of endogeneity, I exploit the staggered adoption of nuisance ordinances across cities in Ohio, relying on the comparison of changes in "crime over inhabitable property" in cities with the ordinance relative to cities without it. While no city had an active nuisance ordinance in place in 2000, 39 cities had adopted a nuisance ordinance by 2014 (Online Appendix Figure B.3 and Online Appendix Table E.6). Since nuisance activity may justify an eviction in the state—see footnote 20—nuisance ordinances increased evictions (Kroeger and La Mattina 2020).

Exploring the effect of evictions on "crime over inhabitable property" in the context of nuisance ordinances in Ohio offers several important advantages. First, the context provides identification advantages: in fact, the study of nuisance ordinances allows to focus on changing landlords' incentive to evict, reducing the potential source of bias in studies comparing individuals formally evicted *versus* formally non-evicted, since the latter can be forced to leave informally after landlords lose trial;[25] moreover, I study a populous state—11 million residents—with both large and small cities, making it representative of landlord-tenant relationships in the whole country, and less susceptible to threats to the external validity then studies on judiciary decisions in extremely large cities.[26] Second, the setting also provides measurement advantages: since evictions are explicitly mentioned as a method to abate nuisances, landlords can reasonably expect to win the trial, reducing the number of informal and hence unmeasured evictions altogether;[27] in addition, as discussed in Section 3, publicly accessible eviction data for Ohio is presented as the most reliable in the US by the organization that collects the information.

I estimate

$$Y_{ct} = \beta Treat_{ct} + \gamma_c + \delta_t + \varepsilon_{ct} \tag{2}$$

[25] This is a relevant concern because, in the US, informal evictions are estimated to be two to three times higher than formal ones and likely used by landlords defeated in court (Desmond 2016).

[26] Collinson and Reed (2018) focus on evictions as mandated by judges in New York City, while Humphries, Mader, Tannenbaum, and Van Dijk (2019) do the same in Cook County (including the City of Chicago). Table 1 shows that, of the 246 cities in Ohio, the smallest one has 4,456 residents, while the most populous one 760,726, with a mean of 27,138 and a standard deviation of 64,702.

[27] Consistently, case studies show that formal evictions are almost six times more frequent than informal ones in the context of nuisance ordinances (Desmond and Valdez 2013).

where Y_{ct} is the number of evictions, "crime over inhabitable property", forcible entry 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. Standard errors are clustered at the city level. The coefficient of interest β is the estimated effect of evictions on "crime over inhabitable property", under the two assumptions discussed in Section 4.1.

The identifying variation relies on the comparison of treated with control cities which, in the staggered DID setting, are: (i) not-yet-treated cities; (ii) never-treated cities.[28] Around 85 percent of cities in the sample are never treated (Figure B.2), suggesting that the empirical strategy does not suffer from the estimation problems highlighted in the recent DID literature (Borusyak and Jaravel 2017, Callaway and Sant'Anna 2020, de Chaisemartin and D'Haultfœuille 2020, Sun and Abraham 2020, Athey and Imbens 2021 and Goodman-Bacon 2021), as discussed in Section 5.2. Since nuisance ordinances are predominantly applied against noise (Desmond and Valdez 2013) and kids playing (Mead et al. 2018), the estimated effect is likely not driven by the specific sub-group of criminal tenants but applies more generally to all evictions.

4.1 Identifying Assumptions

The identification of the effect of evictions on "crime over inhabitable property" relies on two assumptions. First, the parallel trends assumption: I assume parallel trends in the number of evictions and crime offenses across cities with *versus* without the nuisance ordinance after its adoption, in the counterfactual scenario in which the latter had not occurred. Second, I assume that nuisance ordinances affect evictions and "crime over inhabitable property" only by increasing landlords' incentive to evict tenants. Under the two assumptions, the estimate β measures an Intent-To-Treat effect (ITT) of evictions on "crime over inhabitable property" at the city level.[29] Although the two assumptions are not testable by definition, I provide evidence in favor of their plausibility.

4.1.1 Evidence for Assumption One: Parallel Trends

Correlated Shocks.—As a first 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 in economic shocks, incarceration levels, sentencing practices, policing technology and crime recording practices (Mastrobuoni 2020; Chalfin, Hansen, Weisburst, and Williams 2022). However, if cities with the nuisance ordinance

[28] Because not-yet-treated cities are different in different years t, the control group changes over time, as standard in the staggered DID design.

[29] The ITT captures the Average Treatment effect on the Treated (ATT) of the treatment assignment: stronger landlords' incentive to evict tenants. The ATT recovers the Average Treatment Effect (ATE) under the additional assumption that the average treatment effect on the never-treated (cities) is identical to the ATT.

have different characteristics relative to cities without the ordinance, then shocks at the Ohio level (or higher) may differentially affect evictions and crime.

I begin by exploring whether observable city characteristics predict the adoption of nuisance ordinances in the 2000–2014 period. To do so, I run regressions of an indicator for the adoption of the ordinance in the period on average pretreatment socioeconomic characteristics, separately. Online Appendix Table B.2 shows that only the population size and the number of tenant households predict the adoption of nuisance ordinances. Therefore, adding controls for trends in the two variables in equation (2) reduces the concern that common shocks, such as the Great Recession in 2007, led to differential economic losses in large *versus* small cities, and in areas with high *versus* low homeownership.[30]

Although balanced in observable characteristics, cities with *versus* without the nuisance ordinance may differ in unobservables and hence still react differently to common shocks. Against this possibility, I explore whether the adoption of nuisance ordinances coincides with a general increase in crime. If I do not find a relationship between nuisance ordinances and offenses not directly related to housing, then this result is evidence against correlated shocks affecting general drivers of criminal activity, such as increasing poverty or lower police presence. The timing of nuisance ordinances does not coincide with higher violent crime (Online Appendix Figure B.5), nor with increases in "income-generating" crime (Online Appendix Figure B.6), supporting the parallel trends assumption.

Another concern is related to correlated shocks pushing offenders to move across cities. Online Appendix Table B.3 shows that the effect on forcible entry incidents exists only for residents, reassuring against this potential source of bias.[31]

Pre-Trends.—As a second step to test the parallel trends assumption, I begin by inspecting pre-trends in the outcomes. This also allows to rule out anticipation effects (Malani and Reif 2015) whereby landlords in control cities evict nuisant tenants expecting the future adoption of the nuisance ordinance, leading to increasing levels of crime before the shock. Exploring pre-trends is also informative as to whether nuisance ordinances were adopted because of pre-treatment changes in evictions and crime levels. I run the following regression

$$Y_{ct} = \sum_{k=-4, k\neq -1}^{6} \beta_k L_{ck} + \chi_c \delta_t + \gamma_c + \delta_t + \varepsilon_{ct} \tag{3}$$

where L_{ck} are event study dummies equal to 1 when year t is k years since the adoption of the nuisance ordinance in city c;[32] χ_c are the two baseline controls: average pretreatment population and number of tenant households. Standard errors are clustered at the city

[30] In the specific case of the Great Recession, the fact that only X percent of the cities adopted the nuisance ordinance during the crisis, coupled with eviction data excluding foreclosures, further reassure against this potential correlated shock.

[31] This same result also excludes geographic spillovers, namely evicted individuals illegally entering, using or stealing inhabitable property in neighboring municipalities.

[32] I consider as -4 if k is below -4 and as 6 if k is above 6.

level. The coefficients β_k measure the change in evictions and crime levels in cities with the nuisance ordinance k years since its adoption compared to (i) the year before its introduction in not-yet-treated cities; (ii) any year in never-treated cities—in both cases, when k is equal to -1. Section 5 shows absence of pre-trends in the outcomes, lending credibility to the parallel trends assumption.

Then, I explore the effect of nuisance ordinances on house prices. Since nuisance ordinances make homeownership more costly, I expect this to be reflected in lower house prices. Online Appendix Figure B.4 shows absence of strong pre-trends in the HPI before the adoption of nuisance ordinances, while the index starts to decline one year after the introduction of the ordinance.[33] This result further lends credibility to the parallel trend assumption, namely that the adoption of nuisance ordinances is exogenous to evictions and crime.[34]

Last, I explore whether unmeasured pre-trends due to crime misreporting are a threat to the parallel trends assumption. Online Appendix Figure B.5 shows absence of pre-trends for violent crime—arguably the most reliably measured crime in the US (Sampson and Earls 1997)—suggesting then this plausibly applies also to other crimes, including forcible entry and vehicle theft. Online Appendix Figure B.6 confirms this result also for "income-generating" crime, further rejecting the "unmeasured pre-trends" threat.[35] In addition, because nuisance ordinances increase crime underreporting by landlords minimizing the sanction risk and tenants minimizing the eviction risk (Moss 2019; Golestani 2021), the parallel trends assumption would not be necessarily violated even if unmeasured pre-trends were present, as discussed in Section 4.1.2. This applies also to offenses outside the premises, such as vehicle theft, because nuisance ordinances involve landlords in the abatement of disturbances in "buffer zones" around their premises (Gavin 2014). Hence, because of crime underreporting, unmeasured pre-trends are not necessarily a threat to the parallel trends assumption as long as the post-treatment violation of the parallel trends is stronger than the pre-treatment one (Rambachan and Roth 2022).

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

In this section, I discuss evidence in favor of the assumption that nuisance ordinances affect "crime over inhabitable property" only by increasing landlords' incentive to evict their tenants. To do so, I show that explanations other than evictions and linking nuisance ordi-

[33]Since the HPI only measures single-family home prices, the real effect of nuisance ordinances might actually be stronger when accounting for multi-family homes where nuisances are likely to be more frequent.

[34]Although not a threat to the identification, reduced housing values due to nuisance ordinances may themselves affect evictions. On the one hand, lower housing value weakens the incentive to bring the property to the market, reducing evictions (Asquith 2019). But, on the other hand, it pushes landlords to evictions due to the wealth effect, making them more sensitive to non-payment of rent, consistent with results in Stroebel and Vavra (2019). Since available evidence suggests that the former channel dominates the latter (Deshpande and Mueller-Smith 2022), then nuisance ordinances are likely to lead to higher evictions if they did not concurrently reduce house prices.

[35]Similar findings are in Moss (2019) Golestani (2021).

nances to "crime over inhabitable property" are implausible.

Housing Market—Nuisance ordinances might affect the housing market and explain the effect on "crime over inhabitable property" even without affecting evictions. In fact, nuisance ordinances may: (i) increase crime by reducing the supply in the rental housing market and increase homelessness, consistent with the economics literature on the link between the two phenomena (Honig and Filer 1993; O'Flaherty 1996; Quigley, Raphael, and Smolensky 2001; Quigley and Raphael 2004);[36] (ii) change housing demand and supply in a way to raise the number of unoccupied units, attracting burglars, thieves and already-existing homeless; (iii) reduce housing property value, affecting impoverished landlords incentive to commit crimes, or public authorities ability to finance deterrents of crime, such as police deployment, deterrence technology and public goods (Levitt 1997; Corman and Mocan 2000; Di Tella and Schargrodsky 2004; Evans and Owens 2007; Draca, Machin, and Witt 2011; Feler and Senses 2017).

I collect several pieces of evidence that reject the hypothesis that changes in the housing market unrelated to evictions drive the effect of nuisance ordinances on "crime over inhabitable property." First, although nuisance ordinances lead to a lower house price index (Online Appendix Figure B.4), the rental housing market is unaffected (see Table X for results on median rents and rent burden). Second, the larger availability of unoccupied units as a channel is contradicted by both qualitative and quantitative evidence. Since properties stolen in burglaries usually involve precious objects—such as credit cards, money and TVs—unlikely to be present in unoccupied units, then higher numbers of vacant residences should not increase burglaries. On top of this, if higher number of unoccupied units is a channel, we should also observe an effect on forcible entry into residences. Against this hypothesis, Table 5 panels A–B shows that the effect on forcible entry exists only for public or commercial sites, while private units are unaffected. Moreover, while higher availability of vacant residences should attract burglars from neighboring cities, Online Appendix Table B.3 shows that the effect on forcible entry is driven by residents. Furthermore, if higher number of unoccupied units is the driver of the effect, then illegal entries by trespassers (squatters) should also increase as a consequence, leading to an effect on the number of unfounded forcible entry offenses.[37] However, Online Appendix Table B.4 shows no effect on unfounded forcible entry offenses.

Third, if nuisance ordinances affected crime due to a negative wealth effect on landlords, then we should observe an increase in "income-generating" crime (Deshpande and Mueller-Smith 2022). Yet, I find no effect on these crimes (Figure B.6). Fourth, if nui-

[36] The lower supply in the rental housing market may occur, for example, by not renewing existing rental contracts after expiration—sometimes referred to as "no-cause evictions"—and subsequently withdraw the unit from the market.

[37] Since squatters act based on housing or political considerations and, by definition, *stay* in the units they occupy, this makes it extremely difficult to prove an *intention* to steal, a necessary condition for trespassing to be classified as burglary.

sances ordinances reduce housing property value, lowering the tax revenue to finance crime deterrents, such as police deployment, deterrence technology and public goods (Levitt 1997; Corman and Mocan 2000; Di Tella and Schargrodsky 2004; Evans and Owens 2007; Draca, Machin, and Witt 2011; Feler and Senses 2017), then all crimes should increase. Nonetheless, while nuisance ordinances increase "crime over inhabitable property" (Table 2 panel B and Figure 1), violent crime and "income-generating" offenses are unaffected (Figures B.5 and B.6).

Last, the positive effect on vehicle theft further dismisses the interpretation that nuisance ordinances cause "crime over inhabitable property" for reasons unrelated to evictions. In fact, higher presence of unoccupied units per homeless should, if anything, lead to a substitution between vehicle theft and trespassing, decreasing the former.

Crime Misreporting—Nuisance ordinances might push landlords to erroneously report trespassers already squatting in their units as burglars. This explanation is implausible for several reasons. First, because landlords would increase their chances of being sanctioned by the nuisance ordinance if they reported squatters. Second, burglary involves an *intention* to commit a theft or a felony and, in the case of squatters, it can hardly be proved given that their action is clearly motivated by housing or political considerations. Hence, if landlords reported squatters, then nuisance ordinances should increase the number of unfounded forcible entry offenses. However, Online Appendix Table B.4 suggests otherwise. Third, the existence of effects on vehicle theft offenses and public drunkenness arrests further contributes to reject changes in crime reporting as the driver of the results.

Nuisance ordinances may also affect landlords', tenants' and neighbors' incentives to report a nuisance. For landlords and tenants, this is counter-intuitive since, by reporting a nuisance, they would increase their chances of being sanctioned (landlords) or evicted (tenants). In fact, previous literature has found that nuisance ordinances lead to underreporting of offenses such as domestic violence (Moss 2019; Golestani 2021).[38] Since nuisance ordinances may apply to "buffer zones" surrounding the premises (Gavin 2014), underreporting of vehicle theft may also occur. If anything, this suggests that results on "crime over inhabitable property" capture this selective reporting bias and hence measure a lower bound of the true effect of evictions. In the case of neighbors, it is possible that their incentive to report a nuisance is increased by nuisance ordinances, which make abatement more responsive to police calls. However, although plausible for forcible entry, this interpretation is difficult to reconcile with results, such as the effects on vehicle theft and public drunkenness arrests presented in Section 5. In fact, in these cases, landlords would be held unaccountable and hence the ordinance should not increase neighbors' incentive to report the offenses.

[38]Nuisance ordinances may indeed reduce reporting of forcible entries by partners, as in a case in Euclid, Ohio, discussed at https://www.dropbox.com/s/01kisa4g01vn2s6/mm.pdf?dl=0.%20S.

Another concern is that individuals decide to call the police for non-existing nuisance cases with the objective to induce an eviction on their neighbors, and thus solve pre-existing disputes unrelated to nuisances. Again, the fact that nuisance ordinances do not increase the number of *unfounded* forcible entries (Online Appendix Table B.4), together with the increase in *founded* vehicle theft and public drunkenness arrests discussed in Section 5, provide evidence against this interpretation. Moreover, if this interpretation was correct, then the effect of evictions should be higher in cities with lower social capital. However, results in Section 5.3.2 show that the effect on evictions is not higher in racially fragmented cities, where social connections and mutual trust are weaker (Alesina and La Ferrara 2000).

Forcible Entries by Landlords against Tenants—To abate disturbances, landlords may enter unlawfully in their rented residential units to informally force nuisant tenants out. This explanation is implausible for at least two reasons. First, this type of actions would not be recorded as forcible entries since their intention is not to commit a felony or a theft. Second, even in the case in which the unlawful entry is recorded, one would expect that this occurs without breaking provided that landlords have easy access to their properties. However, as shown in Online Appendix Figure B.7, the effect on unlawful entries without breaking is not present.

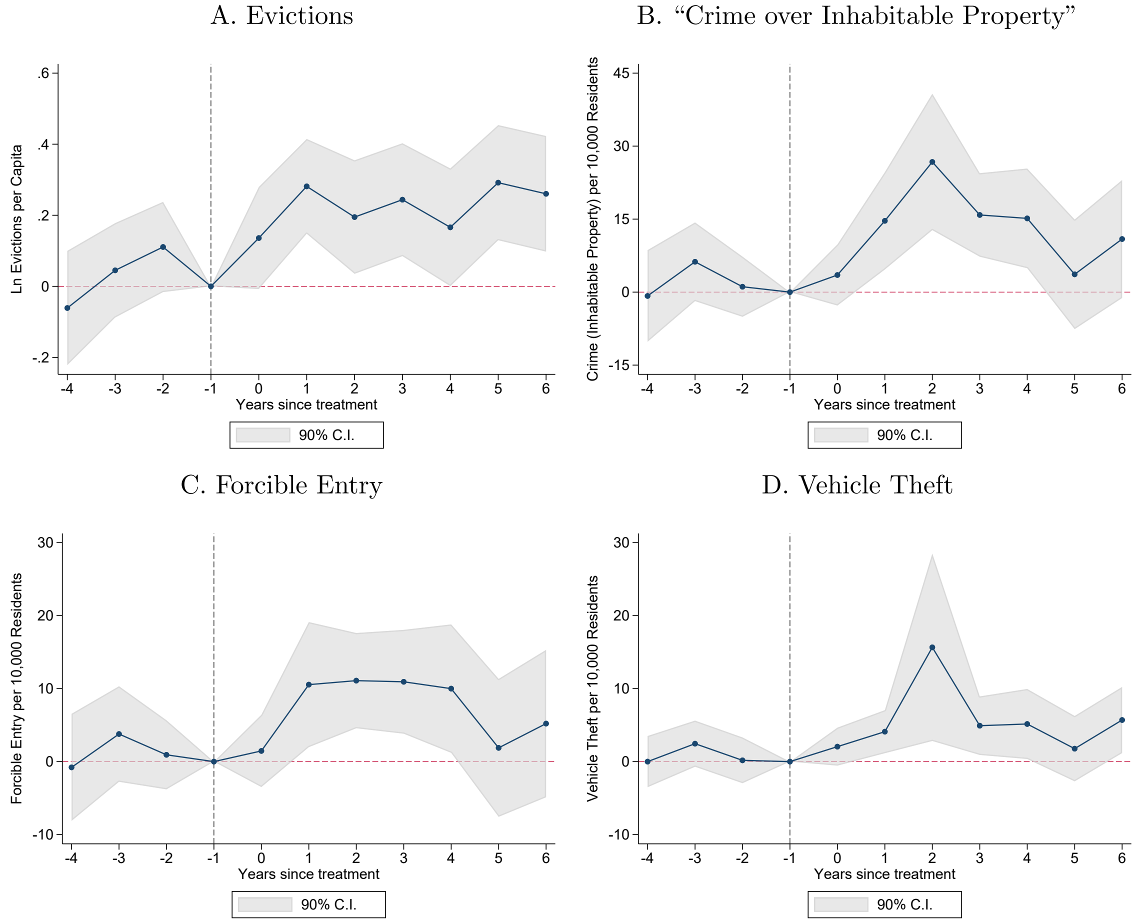
While individually only suggestive, the pieces of evidence discussed in this section collectively corroborate a causal interpretation of the effect of evictions on crime.

5 Results

5.1 Baseline Effects on Evictions and "Crime over Inhabitable Property"

Figure 1 summarizes the main results of the paper. The graphs provide a visualization of the relationship between the adoption of nuisance ordinances and: the inverse hyperbolic sine transformation (IHS) of the number of evictions per 10,000 residents (panel A) and the number of "crime over inhabitable property" offenses per 10,000 residents (panel B), then divided in forcible entry (panel C) and vehicle theft (panel D). After the adoption of nuisance ordinances, coefficients are positive and mostly significant at 10 percent level. Consistently, the effect on evictions appear to anticipate the one on "crime over inhabitable property" by one year.

Figure 1: Timing of Effect on Evictions and "Crime over Inhabitable Property"



Notes: Estimates of equation (3). Panel A: the dependent variable is the number of evictions per 10,000 residents transformed using the inverse hyperbolic sine to take into account the zero values. Panel B: the dependent variable is the number of "crime over inhabitable property" offenses (the sum of forcible entry and vehicle theft) per 10,000 residents. Panel C: the dependent variable is the number of forcible entry offenses per 10,000 residents. Panel D: the dependent variable is the number of vehicle theft offenses per 10,000 residents.
Sources: evictions: Eviction Lab; crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); controls: ACS.

Table 2 formalizes these findings reporting estimates of equation (2). The effect on evictions is positive and significant at 5 percent level (panel A). Nuisance ordinances lead to 33 percent higher number of evictions per 10,000 residents, an increase of 12–13 from a pre-treatment mean of 38 (columns 1–2). Similarly, the number of eviction filings per 10,000 residents increases by 27–29 percent, an increase of around 21 from a pre-treatment mean of 75 (columns 3–4). These results corroborate findings in Kroeger and La Mattina (2020).[39]

[39] Coefficients found here are similar but not identical to those in Kroeger and La Mattina (2020) because

The number of "crime over inhabitable property" offenses also increases because of nuisance ordinances (panel B): 11 additional cases per 10,000 residents (column 5), the sum of 6 forcible entries (column 6) and 5 vehicle thefts (column 7), the latter driven by stealing of cars (column 8). The effects are sizable, amounting to 21 percent for "crime over inhabitable property", 18 percent for forcible entry 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: around 0.55 and 0.85 for forcible entry and vehicle theft, respectively.[40] Findings point to a strong reactivity of forcible entry and vehicle theft on evictions, higher than the crime-police deployment elasticities found in the literature and in the range of those related to crime-arrests (Levitt 1997; Corman and Mocan 2000; Di Tella and Schargrodsky 2004; Draca, Machin, and Witt 2011; see Blanes i Vidal and Mastrobuoni 2018 for estimates specific to burglaries, andChalfin and McCrary 2017 for a review of crime-deterrence elasticities and Bun, Kelaher, Sarafidis, and Weatherburn 2020 for a summary of estimates.)

I: (i) use evictions and eviction filings per 10,000 residents, while they normalize the variables by the number of tenant households; (ii) include average pretreatment Characteristics-by-Year FE, while they control for time-varying characteristics; (iii) omit city-specific linear trends.

[40] This implies that a 10 percent increase in evictions increases forcible entry by 5.5 percent and vehicle theft by 8.5 percent.

Table 2: Effect on Evictions and "Crime over Inhabitable Property"

Panel A: 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
Panel B: Crime over Inhabitable Property				
	Total	Forcible Entry	Vehicle Theft	Car Theft
	(5)	(6)	(7)	(8)
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: Panel A: estimates of equation (2) on evictions. Panel B: estimates of equation (2) on "crime over inhabitable property." 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. Column 5: the dependent variable is the number of "crime over inhabitable property" offenses (the sum of forcible entry and vehicle theft) per 10,000 residents. Column 6: the dependent variable is the number of forcible entry offenses per 10,000 residents. Column 7: the dependent variable is the number of vehicle theft offenses per 10,000 residents. Column 8: 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 (not in log). Controls: average pretreatment population and number of tenant households times Year FE. Standard errors clustered at the city level are in parenthesis. 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.

5.2 Robustness

Online Appendix C shows that results are robust to a large range of checks. First, findings are robust to the use of alternative outcome measures (Online Appendix C.1). Second, results are robust to the use of the alternative estimator in de Chaisemartin and

D'Haultfœuille (2020) (Online Appendix C.2).

5.3 Mechanism: Homelessness and Crime in the Pursuit of Shelter

My hypothesis is that evicted individuals resort to "crime over inhabitable property" because they become homeless and are forced to illegal action to find shelter. Homelessness is a real threat for evicted households because of the frictions inherent in the relocation process. First, since eviction records are public (Kleysteuber 2007), evicted households suffer a reputation loss in relation to prospective landlords (Desmond, Gershenson, and Kiviat 2015).[41] Second, in several US states, including Ohio, landlords and public authorities, such as the Public Housing Authority in Ohio, are authorized to refuse evicted tenants even if under housing assistance.[42] Third, public authorities can decide to 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 protections from termination (Kalleberg 2008), having to deal with schooling rearrangements.[43] Fifth, typically, housing assistance's eligibility requirements are strict, emergency financial assistance is volatile (Evans, Sullivan, and Wallskog 2016) and homeless shelters have long waiting lists. Last, in Ohio, there is no "right to shelter" guaranteeing decent housing to all.[44]

For all these reasons, evictions are an important cause of homelessness. Recent causal evidence found that evictions increased the use of homeless shelters by 14 percentage points in New York City from 2003 to 2017 (Collinson and Reed 2018). These findings are corroborated by an extensive criminology literature. Based on a national sample of homeless people in 1996, around two of five individuals under homeless assistance attributed their condition to involuntary displacement (Burt 2001).[45] In Columbus, Ohio, 35 percent of households in homeless shelters in 2000 imputed their homeless condition to evictions (Hartman and Robinson 2003).[46] These findings are consistent with popular depictions

[41] Several companies, such as CoreLogic Rental Property Solutions, sell tenant screening reports to prospective landlords.

[42] 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 at a price below the market price, and the Section 8 of the Housing Act of 1937, authorizing 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.

[43] In several cases, evicted people are single mothers. Women represented 62 percent of evicted individuals in Chicago in 1996 (Chadha and Ansell 1996), 70 percent in Philadelphia in 2001 (Eldridge 2001) and 61 percent in Milwaukee between 2003 and 2012 (Desmond 2012).

[44] Columbus is the only city in the state with a sanctioned right to shelter.

[45] These homeless owed their homeless conditions to: "couldn't pay rent" (15 percent), "lost job or job ended" (14 percent), "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 place to stay.

[46] For other case studies, see for example: Santa Clara, California, in 2017 accessible at `https://housingmatterssc.org/wp-content/uploads/2019/08/2019-PIT-Count-Full-Report.pdf`; New York City, 2010, accessible at `https://cdn2.hubspot.net/hubfs/4408380/PDF/General-Housing-Homelessness/Housing-Help-Program.pdf`.

of the homelessness-eviction link in the media, and with the economics literature on the relationship between housing market conditions and homelessness (Honig and Filer 1993; O'Flaherty 1996; Quigley, Raphael, and Smolensky 2001; Quigley and Raphael 2004).[47]

The plausibility of the "homeless mechanism", namely that "crime over inhabitable property" is increasing in the presence of homeless people, is substantiated by descriptive and qualitative evidence. A case study in Austin, Texas, suggests that, while arrest rates for male homeless and the male general population are similar for violent offenses such as murder, rape, robbery and assault, those for burglary and vehicle theft offenses are respectively 57 percent and 41 percent higher for homeless people (Snow, Baker, and Anderson 1989).[48] Moreover, public drunkenness comprises nearly 50 percent of all homeless arrests in the study, a disproportionate number. Burglary accusations have been found to be due to breaking into vacant buildings with the purpose of securing shelter (Fischer 1988; Snow, Baker, and Anderson 1989), while the opening of homeless shelters is associated to lower incidence of breaking and entering into commercial buildings (Faraji, Ridgeway, and Wu 2018). The causal relationship between homelessness and vehicle theft is also not far-fetched in light of the numerous households inhabiting cars, with cities such as Los Angeles, California, having documented 18,904 individuals living in their vehicles in 2020.[49]

Consistent with the literature in criminology (Fischer 1988; Snow, Baker, and Anderson 1989; Faraji, Ridgeway, and Wu 2018), evictions do not lead to violence (Online Appendix Figure B.5) nor "income-generating" crime (Online Appendix Figure B.6), providing the first preliminary evidence in favor of the "homeless mechanism". To further test the mechanism and conscious of the empirical challenges in measuring homelessness, absent precise data at the local level (Meyer, Wyse, Grunwaldt, Medalia, and Wu 2021), I proceed as follows. First, I focus on arrests for public drunkenness, a crime susceptible to homeless presence (Snow, Baker, and Anderson 1989). Second, I explore the heterogeneous effects of evictions on "crime over inhabitable property" by: (i) the presence of homeless shelters; (ii) social capital, measured as racial fragmentation (Alesina and La Ferrara 2000). If homelessness is a mechanism, then the effect on crime should be stronger in cities without shelters, where "residence providers of last resort" are absent, or low social capital, where trust and social connections are scarce. Third, I exploit crime information at the city-month level to explore whether the effect of evictions on "crime over inhabitable property" is stronger during months with harsher outdoor conditions, when "living rough" becomes life-threatening. Fourth, focusing on the circumstances of forcible entries—location, type of victim and stolen property—I explore whether the effect is driven by breaking and entering into commercial or restricted public areas and involves theft of petty rather than precious

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

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

[49] The number is provided by the local Homeless Services Authority.

objects, as I would expect in the case of homeless' behavior. Last, by looking at clearances, I can measure whether police effectiveness or agents' incentive to track offenders is negatively affected, indicating a change in the crime composition in favor of homeless' offenses, both more difficult to clear and less serious than thieves'. Section 5.4 discusses other potential mechanisms.

5.3.1 Effect on Public Drunkenness Arrests

The homeless population constitutes "[...] a disproportionate number of all arrests for public drunkenness. While the higher incidence of alcoholism among the homeless may account in part for their frequent arrests for public intoxication, other factors are also clearly at work. Foremost [...] private housing. [...] the homeless are unable to drink [...] in the privacy of a home [...]. If they choose to drink, then, they must do so in public space, which increases the risk of detection and arrest" (Snow, Baker, and Anderson 1989).

Hence, drunkenness arrests is a good proxy for homeless presence for at least three reasons: (i) lacking access to housing, homeless people are more likely to drink alcohol in public spaces than non-homeless individuals;[50] (ii) the harsh conditions of living on the street may push homeless people to alcoholism; (iii) alcohol consumption might cause homelessness.[51]. Thus, although I cannot 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."

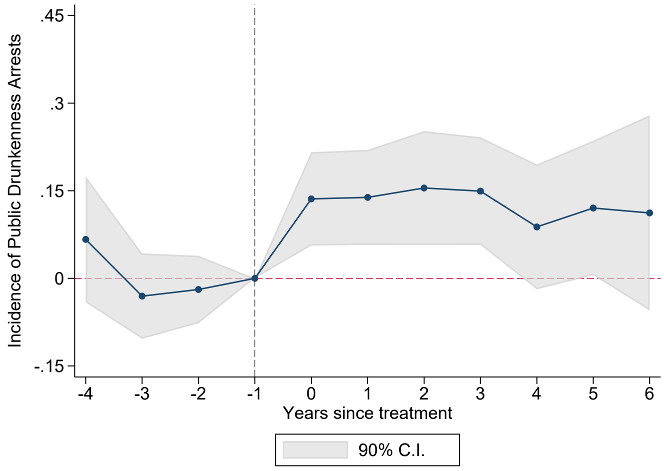
As explained in Section 3, I rely on the extensive margin of public drunkenness arrests to reduce the concern related to the duplication of crime offenses. Estimates in Figure 2 show that nuisance ordinances lead higher incidence of public drunkenness arrests. Given an average pretreatment incidence of public drunkenness arrests of 0.45, results point to a sizeable effect, of 40–50 percent in the first four years after the adoption.[52] This result suggests that the housing access problem that evicted individuals face is shifted, at least in part, onto the jail system which act as a "residence provider of last resort."

[50] This is true by the very definition of homelessness, even assuming identical alcohol consumption habits across homeless *versus* non-homeless people.

[51] This third aspect is understudied and the few available evidence is debated. For a work drawing a causal link from alcoholism to homelessness, see Didenko and Pankratz (2007)

[52] Running equation (2) with the two baseline controls—average pretreatment population and number of tenant households times Year FE—provides a coefficient of 0.11 and a standard error equal to 0.05, an effect of 24 percent.

Figure 2: Timing of Effect on Public Drunkenness Arrests



Notes: Estimates of equation (3). 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.

5.3.2 Heterogeneous Effects

By Presence of Homeless Shelters.—If evictions lead to forcible entry and vehicle theft by reducing housing opportunities, then the presence of homeless shelters should decrease the effect of evictions on these crimes. In fact, homeless shelters provide evicted people an emergency residence, increasing the opportunity cost of illegal activity directed to avoid "sleeping rough." Consistently, prior research in criminology has found that the opening of homeless shelters is associated to lower incidence of breaking and entering into commercial buildings (Faraji, Ridgeway, and Wu 2018). To explore this hypothesis, I use data on the presence of homeless shelters. Importantly, homeless shelters in the dataset were all established before the adoption of the first nuisance ordinance in Ohio—Cleveland Heights in 2003, see Table X. This reduces concerns related to reverse causality whereby the stronger the effect of evictions on crime, the weaker the incentive to establish homeless shelters.[53]

Figure 3 shows the heterogeneous effects of evictions on "crime over inhabitable property" by the presence of homeless shelters. While in cities without homeless shelters (panels A–B), results for both evictions and crime are similar to those at baseline (Figure 1 panels A–B), in cities with homeless shelters (panels C–D), the effect on "crime over inhabitable property" is non-existent (panel D), despite the one on evictions being stronger (panel C) than in the baseline. Table 3 formalizes these results. The effect on "crime over inhabitable

[53]Endogeneity may still occur due to homeless shelters presence being correlated with other city characteristics determining the heterogeneous effects of evictions on crime. Reassuringly, Table Y shows that cities with homeless shelters are not different in several characteristics from cities without them.

property" exists only in cities without homeless shelters (panels A–B). A similar result applies to public drunkenness arrests—comparing columns 4 and 8. Moreover, the effect on "crime over inhabitable property" in cities without homeless shelters is 3.7 percent higher than in the baseline regression (Table 2 panel B).[54] Overall, these results, by pointing to higher evictions increasing "crime over inhabitable property" only where homeless shelters are unavailable, provide additional evidence in favor of the "homeless mechanism."[55] Moreover, findings suggest that homeless shelters might be a cost-effective public intervention to break the link between evictions and crime. This is particularly important in light of the fact that other anti-poverty interventions have been found to backfire, as in the case of emergency financial assistance to homeless people increasing property crime (Corno 2017).[56] Furthermore, the fact that the presence of homeless shelters reduces the effect of evictions on arrests (for drunkenness) suggest that shelters substitute jails as "residences of last resort" for evicted individuals in dire housing conditions.

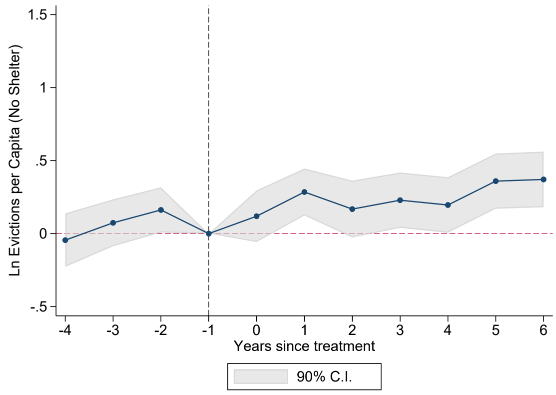
[54] To calculate 3.7 percent, I compute by how much the estimate of forcible entry in cities without homeless shelters (6.685) is higher than the one for the average city (6.309), yielding 5.96 percent. I repeat the procedure for vehicle theft and obtain 1.41 percent. I then calculate the mean of 5.96 percent and 1.41 percent.

[55] These findings also suggest that, in the context of this study, homeless shelters do not provide a place of socialization for potential criminals, complementing previous work on how homeless people coordinate into illegal activities (Corno 2017).

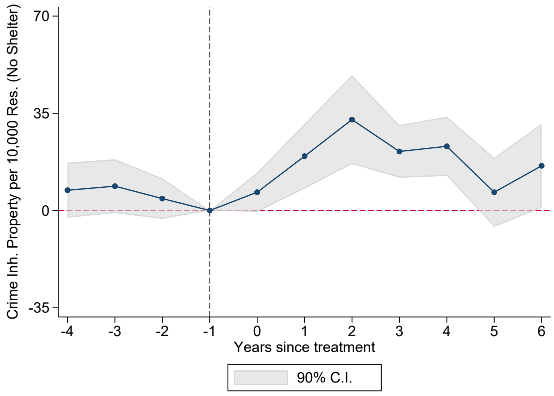
[56] By enabling families to take on financial obligations that they are subsequently unable to meet.

Figure 3: Timing of Heterogeneous Effects by Presence of Homeless Shelters

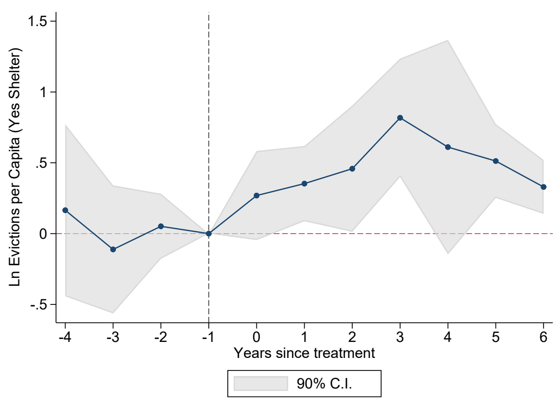
A. Evictions in Cities without Homeless Shelters



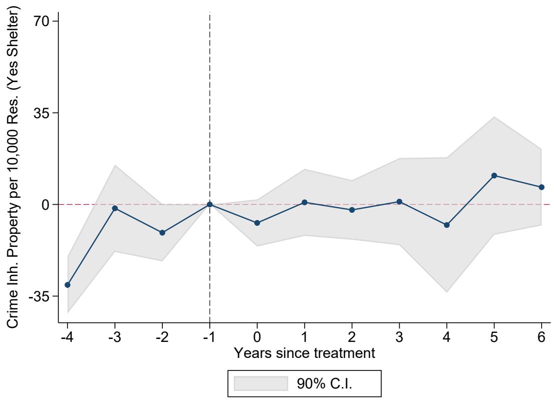
B. Crime in Cities without Homeless Shelters



C. Evictions in Cities with Homeless Shelters



D. Crime in Cities with Homeless Shelters



Notes: Estimates of equation (3) 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 to take into account the zero values. Panels B–D: the dependent variable is the number of "crime over inhabitable property" offenses (the sum of forcible entry and vehicle theft) 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. *Sources:* crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); homeless shelters: Homeless Shelter Directory; controls: ACS.

By Racial Fragmentation.—I expect that evictions lead to "crime over inhabitable property" only in cities where social capital is scarce, with low levels of participation in community life, trust and social connections (Putnam 1992; Putnam 2000). In fact, in cities with high social capital, landlords might for example decide to trust their prospective tenants, even if they were previously evicted. Moreover, where social capital is stronger, networks of families and friends can allow evicted people to stay in their homes until they find a rental opportunity.[57] Last, in cities with a large amount of "weak ties" (Granovetter 1973), evicted individuals can more easily access information about housing opportunities, facilitating the searching and matching in the rental housing market. Consistently, Sampson and Earls (1997) have shown that, in close-knit cities, where "people around here are willing to help their neighbors and [...] can be trusted," crime is lower.

As in Alesina and La Ferrara (2000), I measure social capital as racial fragmentation. In fact, "[a]mong the various forms of heterogeneity, racial fragmentation seems to have the strongest negative effect on participation" (Alesina and La Ferrara 2000). To compute racial fragmentation, I calculate 1 minus the Herfindahl-Hirschman Index of the share of population that is American Indian and Alaska Native, Asian, Black, Hispanic or Latinx, Native Hawaiian and Other Pacific Islander, White, two or more races, or any other race.[58]

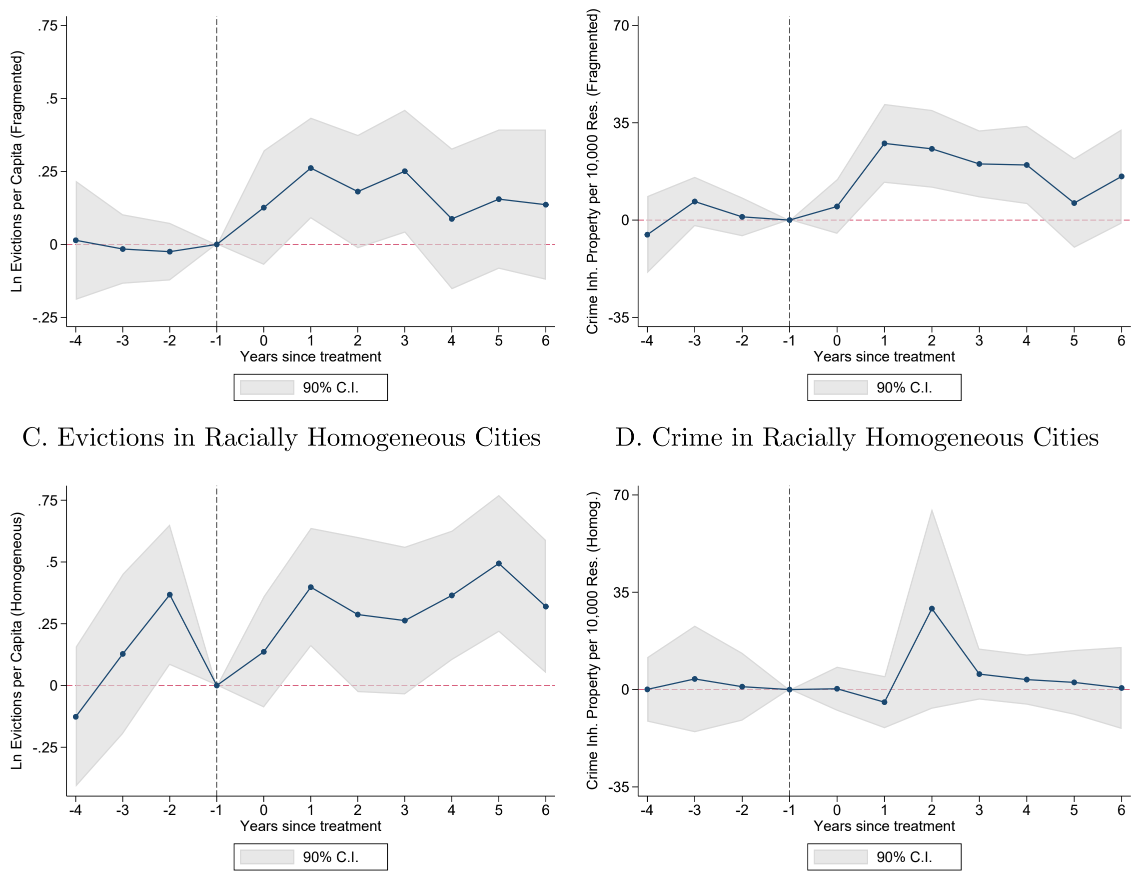
Figure 4: Timing of Heterogeneous Effects by Racial Fragmentation

A. Evictions in Racially Fragmented Cities

B. Crime in Racially Fragmented Cities

C. Evictions in Racially Homogeneous Cities

D. Crime in Racially Homogeneous Cities



Notes: Estimates of equation (3) in racially fragmented cities (panels A–B) and in racially homogeneous

[57] 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).

[58] formula here.

cities (panels C–D). The dependent variable is the number of "crime over inhabitable property" offenses (the sum of forcible entry and vehicle theft) per 10,000 residents. Panel A: in cities without homeless shelters. Panel B: in cities with homeless shelters. Panels C: in racially fragmented cities. Panel D: in racially homogeneous cities. Racially fragmented: above or equal to the median racial fragmentation value (as in Alesina and La Ferrara (2000), 1 minus the Herfindahl-Hirschman Index of the share of population that is American Indian and Alaska Native, Asian, Black, Hispanic or Latinx, Native Hawaiian and Other Pacific Islander, White, two or more races, or any other race). Racially homogeneous: below the median racial fragmentation value.

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

Table 3: Effect on "Crime over Inhabitable Property" by Homeless Shelters Presence or Racial Fragmentation

	Forcible Entry	Vehicle Theft	Car Theft	Drunkenness Arrests
Panel A: Cities without Homeless Shelters				
	(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
Adjusted R^2	0.729	0.614	0.581	0.521
Panel B: Cities with Homeless Shelters				
	Forcible Entry	Vehicle Theft	Car Theft	Drunkenness Arrests
	(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
Adjusted R^2	0.864	0.847	0.838	0.505
Panel C: Racially Fragmented Cities				
	Forcible Entry	Vehicle Theft	Car Theft	Drunkenness Arrests
	(9)	(10)	(11)	(12)
Treat	7.084*	9.777**	9.221**	0.111
	(4.073)	(3.991)	(3.810)	(0.067)
Observations	1504	1504	1504	1845
Mean DV	45.464	23.505	19.906	0.311
Adjusted R^2	0.872	0.833	0.819	0.523
Panel D: Racially Homogeneous Cities				
	Forcible Entry	Vehicle Theft	Car Theft	Drunkenness Arrests
	(13)	(14)	(15)	(16)
Treat	0.104	3.667	4.165	0.048
	(3.516)	(4.392)	(4.108)	(0.089)
Observations	1416	1416	1415	1841
Mean DV	24.167	11.280	8.824	0.250
Adjusted R^2	0.656	0.422	0.353	0.503

Notes: Panel A: estimates of equation (2) in cities without homeless shelter. Panel B: estimates of equation (2) in cities with homeless shelter. Panel C: estimates of equation (2) in racially fragmented cities. Panel D: estimates of equation (2) in racially homogeneous cities. City FE, Year FE and Controls are present in all regressions although not displayed in the table. Columns 1, 5, 9, 13: the dependent variable is the number of forcible entry offenses per 10,000 residents. Columns 2, 6, 10, 14: the dependent variable is the number of vehicle theft offenses per 10,000 residents. Columns 3, 7, 11, 15: the dependent variable is the number of car theft offenses per 10,000 residents. Columns 4, 8, 12, 16: 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 (and average pre-treament racial fragmentation in Panels C–D) × Year FE. Racially fragmented: above or equal to the median racial fragmentation value (as in Alesina and La Ferrara (2000), 1 minus the Herfindahl-Hirschman Index of the share of population that is American Indian and Alaska Native, Asian, Black, Hispanic or Latinx, Native Hawaiian and Other Pacific Islander, White, two or more races, or any other race). Racially homogeneous: below the median racial fragmentation value. Standard errors clustered at the city level are in parenthesis. 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.

Figure 4 and Table 3 panels C–D show that racial fragmentation lead to results qualitative similar to the absence of homeless shelters. In fact, while the effect on evictions is similar across racially fragmented *versus* homogeneous cities, the effect on crime is present only in the former.

By Harsh Outdoor Months—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 this, evicted individuals unable to settle in a new residence face a stronger incentive to procure shelter than in other seasons. Consistently, Corinth and Lucas (2017) find that decreased outdoor temperatures predict a lower share of unsheltered homeless people. Hence, the existence of a stronger effect of evictions on "crime over inhabitable property" during harsh outdoor months provides further evidence in favor of the "homeless mechanism." In line with the latter, Table 4 column 1 finds that the effect on "crime over inhabitable property" is more than 40 percent higher in months from October to February included. In the case of forcible entry, the effect is 32 percent higher (column 2) while, for vehicle theft, it is 1.53 times the one of other months (column 3) and driven by car theft (column 4).

Table 4: Effect on "Crime over Inhabitable Property" by Harsh Outdoor Months

	Crime over Inhabitable Property	Forcible Entry	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	0.133	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 (2) at the city c month m and year t level adding Treat × Cold Months, Month FE and Month × Year FE. Column 1: the dependent variable is the number of "crime over inhabitable property" offenses (the sum of forcible entry and vehicle theft) per 10,000 residents. Column 2: the dependent variable is the number of forcible entry 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 to February, both included. 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 parenthesis. Significance levels: *** $p < .01$, ** $p < .05$, * $p < .1$.
Sources: crime: FBI's Uniform Crime Reporting Program; nuisance ordinances: Mead et al. (2017); controls: ACS.

5.3.3 Additional Evidence on the "Homeless Mechanism" from Incidents and Clearances Data

Location, Victim and Stolen Property.—The circumstances of forcible entry offenses offer precious details to test the "homeless mechanism." First, the location and the type of victim can provide hints as to the motives of the offense. In fact, the qualitative literature suggests that homeless people tend to search for shelter in public spaces, such as construction sites or abandoned building, in commercial establishments where they can also find food, as in the case of all-night coffee shops and grocery stores, and in vehicles (Turnham, Wilson, and Burt 2008). On the contrary, burglars and trespassers (squatters) typically target residential units. Similarly, by studying the property stolen in forcible entry incidents, we can understand whether these offenses are "income-generating" (Deshpande and Mueller-Smith 2022), and hence plausibly enacted by thieves, or "non-income-generating," pointing to homeless action. Since evictions are not a major cause of earnings or benefits reduction (Collinson and Reed 2018), I expect the effect to be present only for "non-income generating" forcible entries. On the contrary, the effect should be present for forcible entries involving goods that are either lost or cannot be stored due to evictions and housing instability, such as clothes and consumables (Desmond 2016). Notice also that, if the effect on forcible entry is present only in structures other than residences, then this result excludes evictions increasing the availability of unoccupied units as a mechanism.[59]

To test these hypothesis, I use information on the 424,144 forcible entry incidents in Ohio from 2000 to 2014 recorded in the NIBRS. This dataset provides the circumstances of crime incidents, including the location, the type of victim and the stolen property. As discussed in Section 3, I only focus on the intensive margin due to the impossibility of distinguishing between missing and zero values in the dataset.

Table 5 supports the “homeless mechanism.” The effect on forcible entry exists only for construction sites, grocery stores, supermarkets and restaurants, while all other structures, including residences, 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 property involved ranges from vehicles to alcohol, clothes and consumable goods, while precious objects are unaffected. The effects are strong: 49 percent (location: construction site; column 2), 26 percent (location: grocery, supermarket or restaurant; column 3), 28 percent (victim: business or financial institution; column 6), 48 percent (victim: government or public; column 7), 36 percent (stolen property: vehicle; column 9) and 22 percent (stolen property: petty objects; column 11).

[59] As explained in Section 3, eviction data does not include forced moves from commercial or public properties. This implies that the result could not be driven neither by evictions increasing the vacancies of these types of structures. Section 4.1.2 discusses other evidence against changes in unoccupied units as a driver of the effect on forcible entry.

Table 5: Effect on Forcible Entry by Location, Type of Victim and Stolen Property

Panel A: Location				
	Residence	Construction Site	Grocery, Supermaket 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: Type of Victim				
	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 (Money, Jewelry etc.)	Petty Objects (Alcohol, Clothes etc.)	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: The dependent variables are the number of incidents involving forcible entry as the first recorded offense per 10,000 residents. Due to impossibility of distinguishing between missing and zero values, only positive values are used (intensive margin). Panel A: estimates of equation (2) by location. Panel B: estimates of equation (2) by type of victim. Panel C: estimates of equation (2) by stolen property. Column 1: homes or residences. Column 2: construction sites. Column 3: groceries, supermarkets or restaurants. 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 the government or society/public. Column 8: victim is of any other type. Column 9: theft of cars, buses, trucks or other motor vehicles. Column 10: theft of precious objects: money, jewelry, precious metals, TVs, radios, VCRs, computers (hardware and software), credit or debit cards. Column 11: theft of petty objects: alcohol, drugs or narcotics (including equipment), clothes or furs, consumable goods or vehicle parts or accessories. 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 parenthesis. Significance levels: *** $p < .01$, ** $p < .05$, * $p < .1$. Details on crime incidents are in Section E.2.3.

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

Clearances.—The absence of an effect on forcible entry and vehicle theft clearances may further support the "homeless mechanism" for at least two reasons. First, no effect on forcible entry clearances may point to reduced police effectiveness (Donohue, Cai, Bondy, and Cook 2022), suggesting that these offenses occur at night and in areas with low presence of people, police or deterrence technology (Draca, Machin, and Witt 2011), such as construction sites, garages or warehouses, typical improvised shelters for homeless people (Turnham, Wilson, and Burt 2008). This hypothesis is consistent with location results in Table 5. Second, it may point to the weaker incentive of police officers to track offenders and hence to the "survival" nature of the crimes, attributed to homeless rather than more dangerous thieves. This is consistent with the literature in criminology claiming that homeless people are "[...] not generally regarded as dangerous by the police" (Snow, Baker, and Anderson 1989). Table X shows that nuisance ordinances do not affect the number of clearances per capita for "crime over inhabitable property," corroborating this interpretation.[60]

5.4 Other Potential Mechanisms

In theory, mechanisms other than homeless may contribute to drive the results. However, these other potential mechanism are difficult to reconcile with all the accumulated evidence: (i) a positive effect on public drunkenness arrests; (ii) effects being present only in cities without homeless shelters or racially fragmented (low social capital); (iii) stronger effect during harsh outdoor months; (iv) effect on forcible entry involving business or public places, and theft of non-precious objects. On the contrary, the "homeless mechanism" appear as the only plausible explanation consistent with the general picture. In Online Appendix D, I provide further evidence against potential mechanisms such as changes in general economic conditions—unemployment, income, and poverty—recruitment by criminal organizations, reduction in community policing, or retaliatory action against evicting landlords.

6 Conclusion

This paper provides the first causal evidence of an external cost of evictions, documenting an effect on crime. 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 burglaries and vehicle theft. Evidence suggests that these crimes are motivated by evicted individuals becoming homeless and resorting to illegal action to secure shelter as a survival strategy. These findings highlight an unexplored social cost of evictions, a neglected determinant of crime, and suggest that homeless shelters may break the link between the two phenomena.

[60] The alternative interpretation that nuisance ordinances attract burglars sufficiently skillful to avoid arrest is contradicted by: (i) residences, typical burglars' targets, being unaffected (Table 5); (ii) house prices being decreasing, pointing to impoverishment and lower "prize" per burglary (Figure B.4).

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Appendix

FOR ONLINE PUBLICATION ONLY

A General Trends in Evictions, Homeless and Burglaries

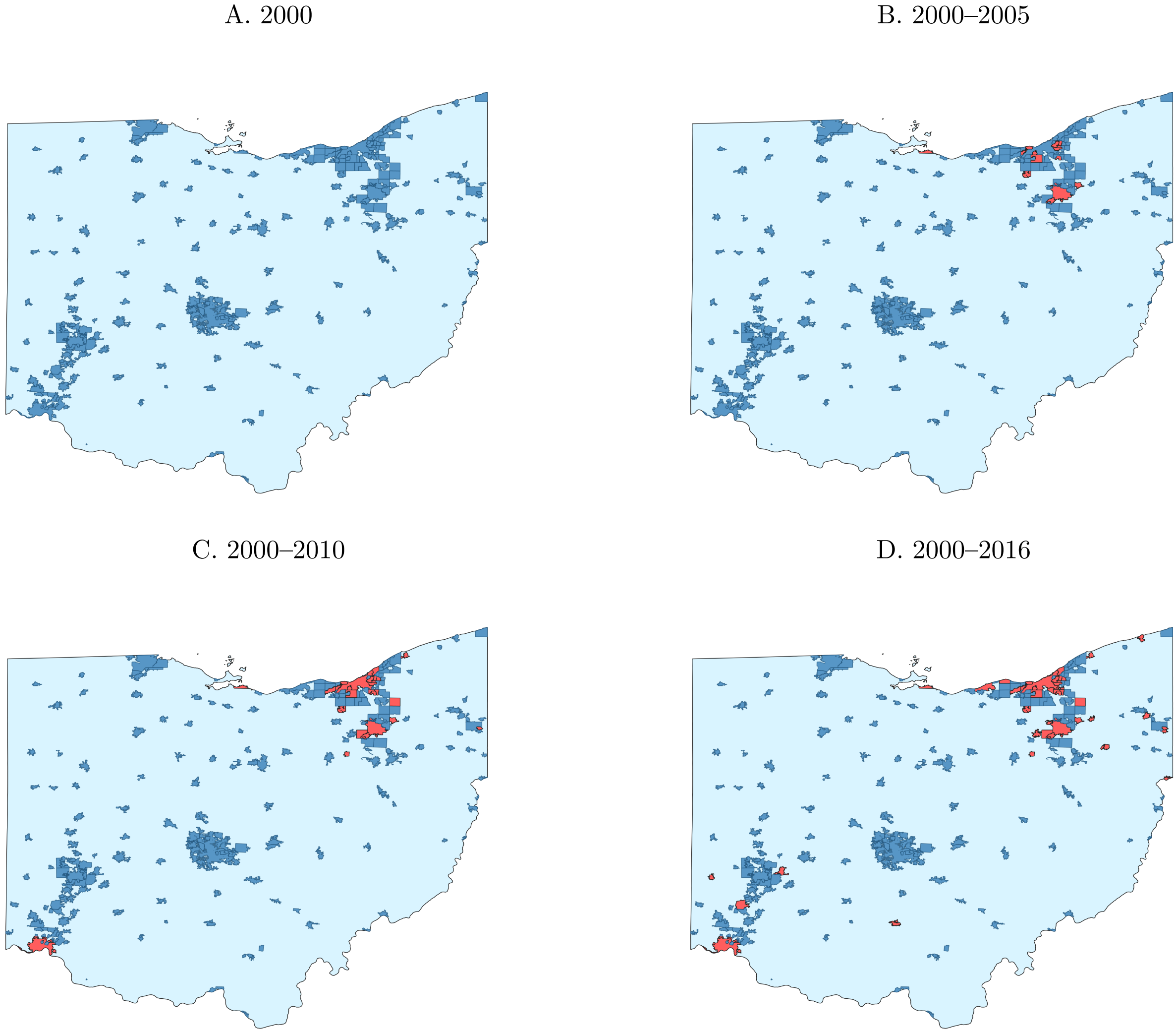
Figure A.1: Trends in Number of Evictions, Burglaries and Homeless

Notes: Panels A–C: number of burglary offenses (continuous blue) and number of evictions (dashed red) from 2000 to 2014. Panel B–D: number of homeless (continuous blue) and number of evictions (dashed red) from 2006 to 2014.

Sources: evictions: Eviction Lab; burglaries: FBI's Uniform Crime Reporting Program; homeless: US Department of Housing and Urban Development.

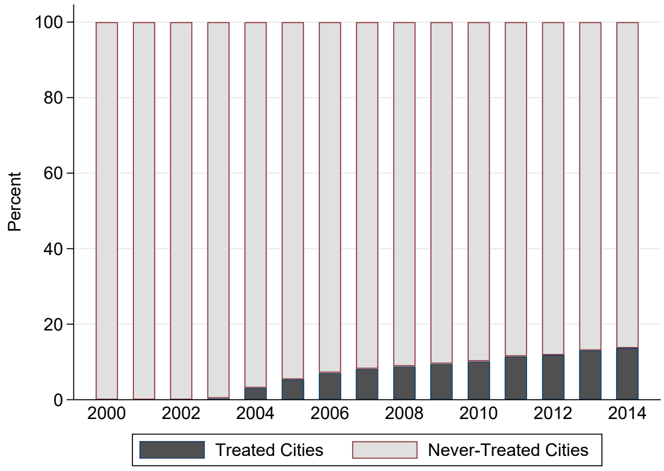
B Empirical Strategy and Tests of Identifying Assumptions

Figure B.2: Adoption of Nuisance Ordinances in Ohio, 2000–2016



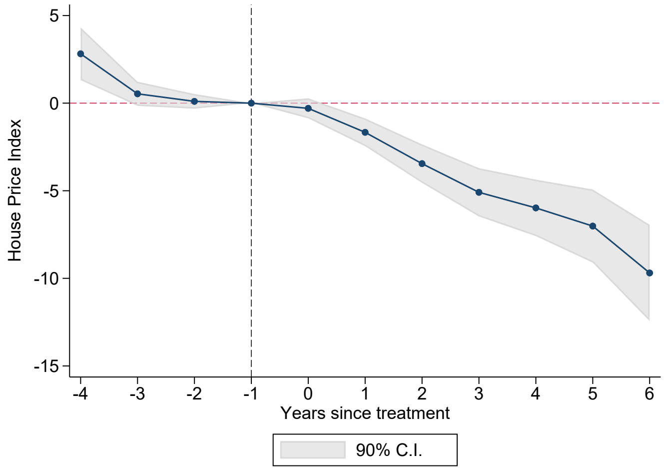
Notes: Adoption of nuisance ordinances (red) across Ohio's cities (dark blue) in the 2000–2016 period.
Source:

Figure B.3: Adoption of Nuisance Ordinances across Cities in Ohio, 2000–2014



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

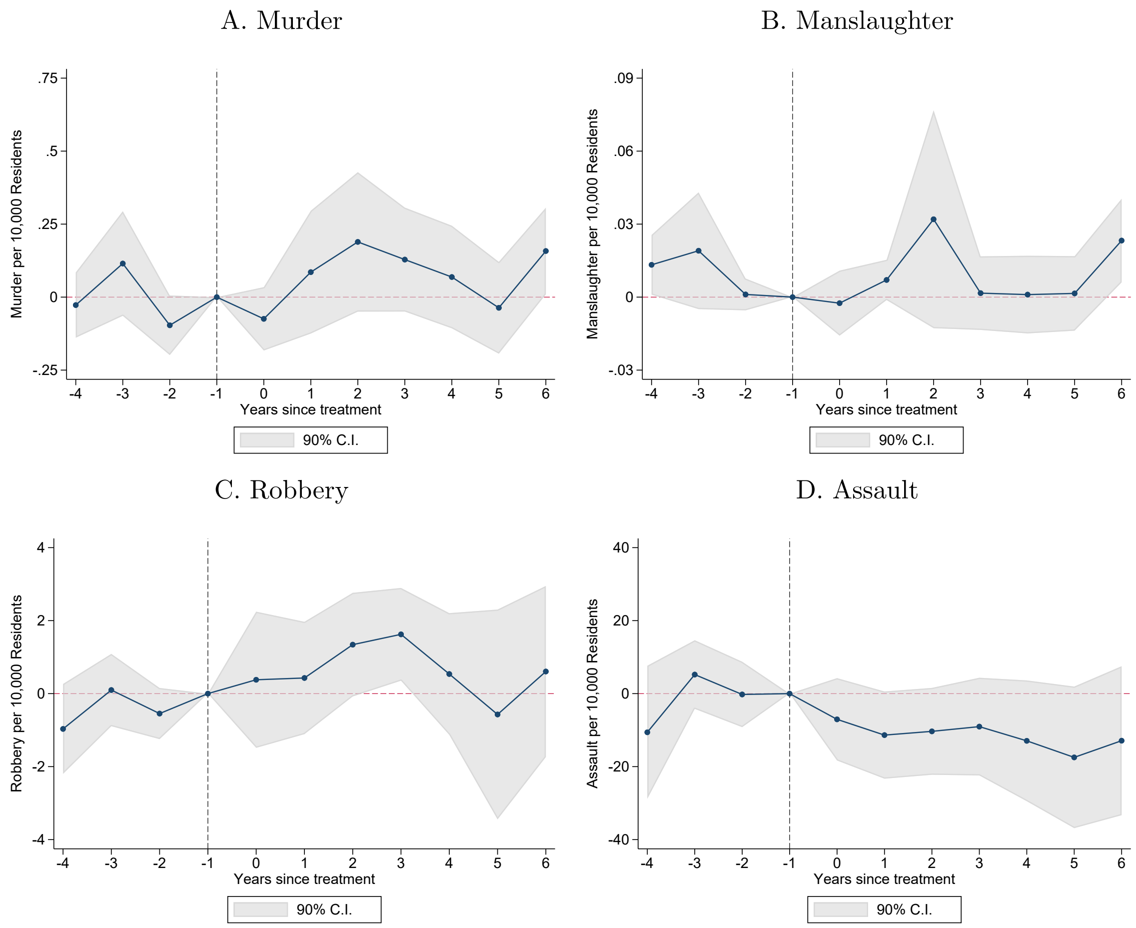
Figure B.4: Timing of Effect on House Price Index



Notes: .

Sources: Federal Housing Finance Agency and Mead et al. (2017).

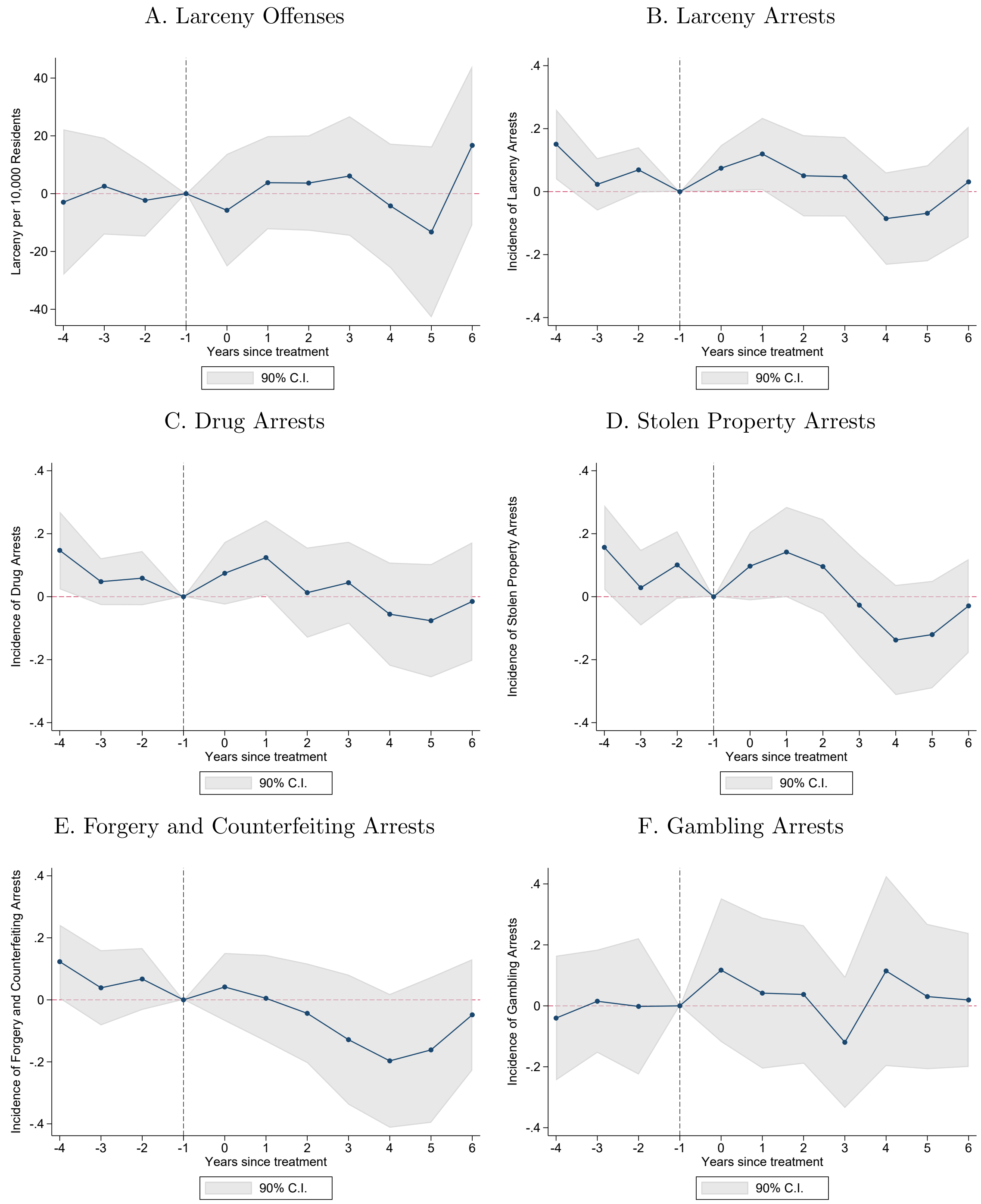
Figure B.5: Placebo Tests on Violent Crime



Notes: Estimates of equation (3). 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 E.2.

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

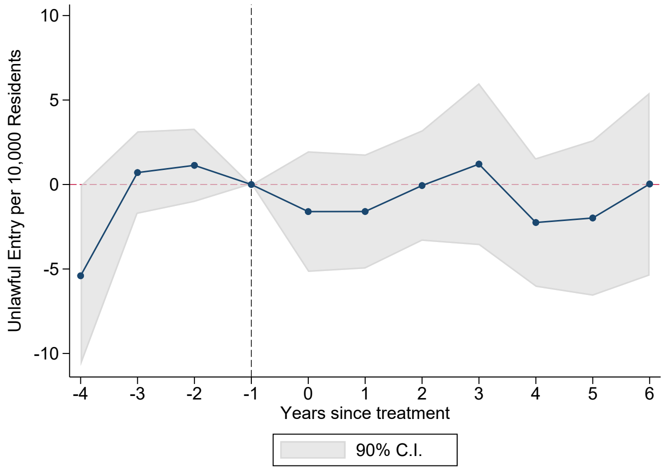
Figure B.6: Placebo Tests on "Income-Generating" Crime



Notes: Estimates of equation (3). 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 E.2.

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

Figure B.7: Timing of Effect on Unlawful Entries without Breaking



Notes: Estimates of equation (3). The dependent variable is the number of burglary offenses without breaking per 10,000 residents.

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

Table B.1: Correlations between Eviction Filings and "Crime over Inhabitable Property"

	Crime over Inhabitable Property	Forcible Entry	Vehicle Theft	Car Theft
	(1)	(2)	(3)	(4)
Evictions	0.096***	0.081***	0.015	0.010
	(0.030)	(0.019)	(0.017)	(0.013)
Observations	2750	2750	2750	2749
Mean DV	52.837	35.231	17.606	14.538
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.859	0.845	0.729	0.717

Notes: Estimates of equation (1). Column 1: the dependent variable is the number of "crime over inhabitable property" offenses (the sum of forcible entry and vehicle theft) per 10,000 residents. Column 2: the dependent variable is the number of forcible entry 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. Eviction Filings: the number of eviction filings per 10,000 residents. Mean DV: average pretreatment dependent variable. Standard errors clustered at the city level are in parenthesis. Significance levels: *** $p < .01$, ** $p < .05$, * $p < .1$.

Sources: crime: FBI's Uniform Crime Reporting Program; evictions: Eviction Lab.

Table B.2: Balance

	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
Evictions	3.325	2.978	0.347	0.178
Crime over Inhabitable Property	58.525	54.652	3.873	0.691
Forcible Entry	33.104	33.136	-0.032	0.996
Vehicle Theft	25.421	21.516	3.905	0.381
Observations	39	207		

Notes: Results from nine separate OLS regressions where the dependent variable is an indicator of nuisance ordinance adoption status at the city level. Explanatory variables are measured as the average pretreatment value in the sample. Robust standard errors in parentheses.

Sources: ACS, FBI and Mead et al. (2017).

Table B.3: Effect of Nuisance Ordinances on Forcible Entry by Residence of Offender

	Forcible Entry Resident	Forcible Entry Non-Resident	Forcible Entry 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 (2). The dependent variables are the number of incidents involving forcible entry as the most serious recorded offense per 10,000 residents. Due to impossibility of distinguishing between missing and zero values, only positive values are used. 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 parenthesis. 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 B.4: Placebo Test on Unfounded "Crime over Inhabitable Property" Offenses

	Unfounded Forcible Entry	Unfounded Vehicle Theft (Total)	Unfounded Car Theft	Unfounded Bus or Truck Theft
	(1)	(2)	(3)	(4)
Treat	-7.307	0.440	0.420	-0.003
	(7.368)	(0.426)	(0.416)	(0.027)
Observations	2692	2700	2699	2681
Mean DV	1.849	0.733	0.657	0.052
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.457	0.381	0.371	0.209

Notes: Estimates of equation (2). Column 1: the dependent variable is the number of unfounded forcible entry offenses per 10,000 residents. Column 2: the dependent variable is the number of unfounded vehicle theft offenses per 10,000 residents. Column 3: the dependent variable is the number of unfounded car theft offenses per 10,000 residents. Column 4: the dependent variable is the number of unfounded bus or truck 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 parenthesis. 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 Robustness

C.1 Alternative Outcome Measures

Table C.5

Panel A: Evictions			
	Evictions (log)	Evictions per 10,000 Tenants	Evictions per Evictions (Pre-Treat.)
	(1)	(2)	(3)
Treat	0.218***	60.212***	0.443***
	(0.069)	(19.599)	(0.108)
Observations	3452	3452	3452
Mean DV	38.215	258.939	1.000
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	No
Adjusted R^2	0.761	0.698	0.282
Panel A: Crime over Inhabitable Property			
	Crime (log)	Crime per 10,000 Tenants	Crime per Crime (Pre-Treat.)
	(4)	(5)	(6)
Treat	0.136	56.501**	0.177**
	(0.090)	(23.102)	(0.072)
Observations	2924	2750	2924
Mean DV	52.676	374.941	1.000
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Adjusted R^2	0.685	0.764	0.070

Notes: Estimates of equation (2). Column 1: the dependent variable is the number of unfounded forcible entry offenses per 10,000 residents. Column 2: the dependent variable is the number of unfounded vehicle theft offenses per 10,000 residents. Column 3: the dependent variable is the number of unfounded car theft offenses per 10,000 residents. Column 4: the dependent variable is the number of unfounded bus or truck 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 parenthesis. 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 Alternative estimator

A growing recent literature has underlined the estimation issues linked to two-way fixed effects estimators with staggered adoption (Borusyak and Jaravel 2017, Callaway and

Sant'Anna 2020, de Chaisemartin and D'Haultfœuille 2020, Sun and Abraham 2020, Athey and Imbens 2021 and Goodman-Bacon 2021). In particular, the coefficient of equation (2) is a weighted average of all the possible 2x2 comparisons of the sample. In the presence of variation in the treatment timing, as in the context of this paper, the comparison between already-treated and not-yet-treated units, where the already-treated units serve as controls in both periods, enters in the estimation with a negative weight because the treatment effect in the second period is differenced out by the difference-in-difference. 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 therefore possible that the estimated coefficients in Section 5 have an opposite sign to the true average treatment effect (de Chaisemartin and D'Haultfœuille 2020).

In the setting of this paper, the issues discussed in the new literature on staggered difference-in-difference are not particularly problematic because a large share of cities in my sample are never-treated units. In fact, when estimating the weights attached to each of the average treatment effects on the treated (ATTs) in equation (2) applied to the eviction rate, I find that the coefficient is obtained as a weighted average of 371 ATTs, of which none receive a negative weight.[61] When focusing on forced entry offenses, estimates are similar: 215 ATTs, of which 204 ATTs receive a positive weight and 11 a negative one, summing to only -.002.

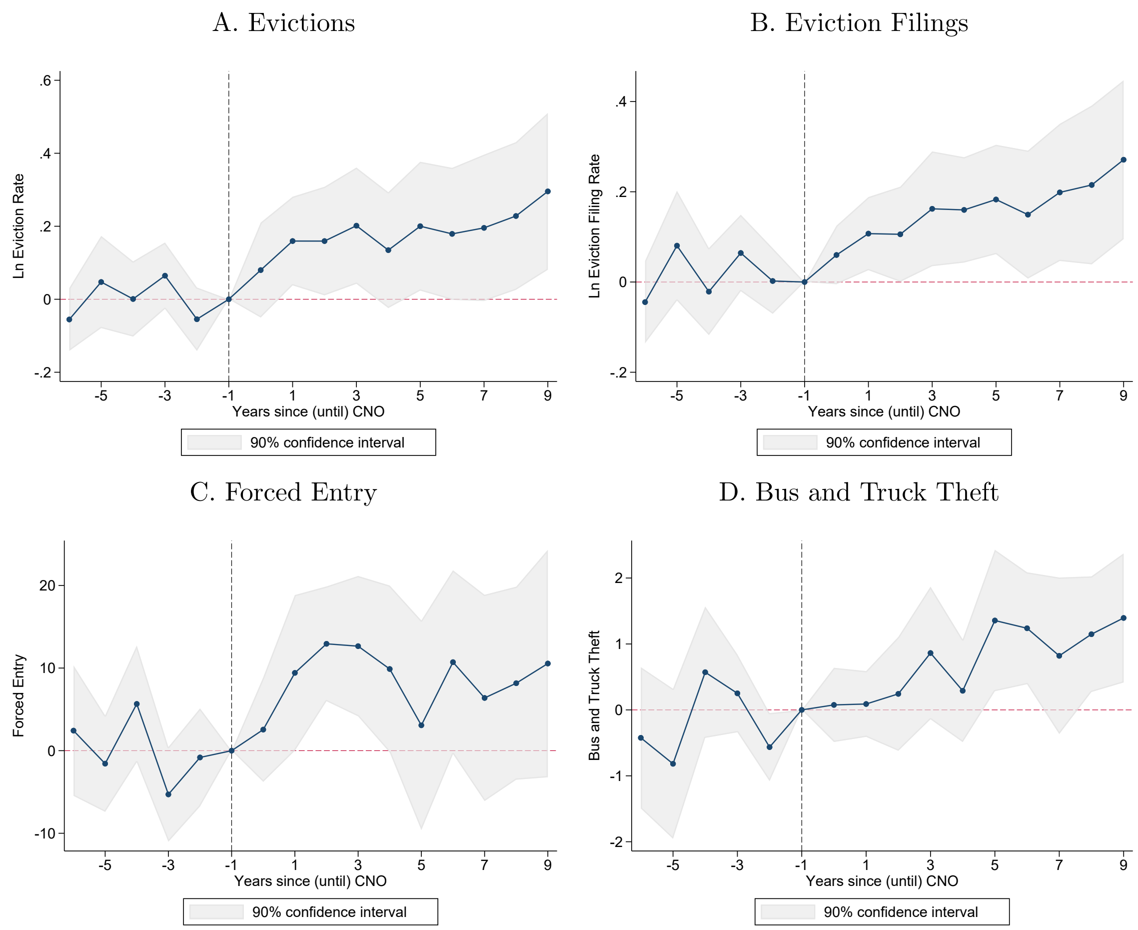
To further inquire these results, I assess the robustness of my coefficients of interest to treatment effect heterogeneity. To do so, I compute the ratio between the coefficient and the standard deviation of the weights serving as a measure of the heterogeneity in ATEs across cities and time periods. Reassuringly, I find that this ratio for the eviction rate is 1.17, almost the double of the coefficient in Table 2, column 1 implying that "the coefficient and the ATT can only be of opposite signs under a very large and implausible amount of treatment heterogeneity" (de Chaisemartin and D'Haultfœuille 2020).[62]

As a further robustness, I estimate the effect of adopting nuisance ordinances on the main outcome variables using the alternative estimator proposed by de Chaisemartin and D'Haultfœuille (2020). Coefficients are displayed in Online Appendix Figure C.8. Results look similar to the ones using the baseline estimation method.

[61]To compute these numbers, I use the Stata command *twowayfeweights* developed by de Chaisemartin and D'Haultfœuille.

[62]For forced entry offenses, the ratio is 12.97, largely higher than the coefficient in Table 2, column 1 (8.1).

Figure C.8: Timing of Effect on Evictions and “Crime over Inhabitable Property,” de Chaisemartin and D’Haultfœuille estimator



Notes: Estimates of equation (3) 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 to take into account the zero values. Panel B: the dependent variable is the log number of eviction filings per capita transformed using the inverse hyperbolic sine to take into account the zero values. Panel C: the dependent variable is the number of forcible entry offenses per 10,000 residents. Panel D: the dependent variable is the number of vehicle theft offenses per 10,000 residents.

D Other Potential Mechanisms

D.1 General Economic Conditions

Unemployment, Income and Poverty.—suggesting that economic conditions not directly related to housing do not mediate the effect of evictions on crime.

"Income-Generating" Crime.—Evictions may lead to crime by increasing financial hardship (Desmond and Kimbro 2015; Gottlieb and Moose 2018). After an eviction, families' belongings are often lost or not easily accessible because stored by moving companies (Desmond 2012). To secure new shelter, households also need to endure extra-expenses, such as those linked to the trial and transitional housing, forcing them to forgo basic needs. In addition, evictions damage credit's rating affecting consumption (Greiner, Pattanayak, and Hennessy 2012; Humphries, Mader, Tannenbaum, and Van Dijk 2019), and lead to employment loss due to the difficulties in transitioning from one residence to another Desmond and Gershenson 2016). Figure B.6 finds no effect on "income-generating" charges (Deshpande and Mueller-Smith 2022) not directly related to housing.

D.2 Criminal Organizations

The evidence gathered thus far also goes against the hypothesis that evicted individuals decide to supply their labor to criminal organizations. This may happen due to the lower opportunity cost of criminal activity or because, by moving into lower quality neighborhoods, evicted individuals have a higher chance to interact with criminals and match their labor demand (Desmond and Shollenberger 2015). If this hypothesis was true, then *any* type of crime should increase, not only crime directly related to housing. Online Appendix Figures B.5 and B.6 show that the number of violent offenses and "income-generating" charges did not change after the adoption of the nuisance ordinances, weakening the plausibility of this mechanism.

D.3 Community Policing

A complementary explanation of the increase in "crime over inhabitable property" due to evictions is lower community policing (Tobón 2021). In fact, evictions may involve tenants that participate to the community policing (Semenza, Stansfield, Grosholz, and Link 2021).

If changes in community policing is a mechanism than *any* type of crime should increase, not only crime directly related to housing. Online Appendix Figures B.5 and B.6 show that the number of violent offenses and "income-generating" crime is unaffected by the adoption of nuisance ordinances.

D.4 Retaliation Against Evicting Landlords

One possible interpretation of the results on forcible entry is that evicted households break into one's own ex-rental units and cause property damage to retaliate against evicting landlords. Although difficult to test, focusing on unlawful entry offenses without breaking can be helpful if we are ready to assume that evicted individuals can have more easily access without the use force into their ex-units.[63] Online Appendix Figure B.7 shows no effect of nuisance ordinances on unlawful entry offenses without breaking. This result, coupled with findings on vehicle theft, public drunkenness arrests and the several heterogeneous effects discussed in Section 5.3.2, suggest that retaliation is not a plausible explanation of why evictions lead to "crime over inhabitable property."

[63]For example, this may be due to the fact that evicted households may dispose of copies of keys, knowledge of alarm systems, neighborhood's community behavior and policing schedule.

E Data

E.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 most US cities, including all those in Ohio, 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 US. 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. 2018a). More information on how this dataset is created and relative sources of information can be found in Desmond et al. (2018a).

E.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. Crime 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 crime offenses that have been "closed," usually by arrest of the offender.[64] In the US, the share of property crimes cleared by arrests or exceptional means is substantially lower than the one for violent crime.[65] 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).[66] I measure "crime over inhabitable property" aggregating forcible entry and vehicle theft offenses. All cities in Ohio have reported at least one forcible entry 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.[67]

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 forcible entry, burglary without breaking, and attempted burglary. Burglary with forcible entry involves the use of force (breaking) to enter the premises, while unlawful entry refers to burglary without the use of force. Around 62 percent of the 1,047,132 completed burglaries in Ohio occurred with the use of force during the period of this study. Since this dataset excludes civil cases, information on burglary does not overlap with "forcible entry" lawsuits linked to evictions. I also focus on two subcategories of the 372,933 completed motor vehicle theft offenses in Ohio from 2000 to 2014: car theft and bus or truck theft—respectively 86 percent and 7 percent of the total.[68]

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

[64]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.

[65]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).

[66]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.

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

[68]The rest is theft of other motor vehicle (6 percent)—sport utility vehicles, motorcycles, motor scooters, all-terrain vehicles, snowmobiles, etc.—and unknown (1 percent).

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 the breaking into private property is recorded as forcible entry, a more serious offense than vehicle theft. Thus, I expect the former to be a more precise measure of "crime over inhabitable property" than the latter.

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 forcible entry 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, property, offender and victim involved in each incident. Due to the impossibility of distinguishing between missing and zero values, I only focus on the intensive margin. Details on crime data are in Online Appendix E.2.

The Uniform Crime Reporting (UCR) Program divides offenses into two groups, Part I and Part II crimes. Each month, participating law enforcement agencies submit information on the number of Part I offenses that become known to them; those offenses cleared by arrest or exceptional means; and the age, sex, and race of persons arrested for each of the offenses. Contributors provide only arrest data for Part II offenses.

E.2.1 Part I

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

Burglary (breaking and entering).—The unlawful entry of a structure to commit a felony or a theft.

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

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.

E.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.

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

NIBRS provides details on each crime incident including information on victims, offenders, arrestees, and property involved.

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

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

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

E.3 Nuisance Ordinances

Table E.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 the nuisance ordinance in the 2000-2014 period and corresponding adoption year.
Source: Mead et al. (2017).