Gentrification & Crime: Empirical Investigation Across American Cities

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2023

Abstract

This paper examines the impact of gentrification on criminal activity in urban neighborhoods to determine whether this process has a detrimental effect on communities. The study utilizes a newly-built unique data set of geo-referenced crime reports from 14 major American cities matched with Census data, to identify gentrified areas in the 2010s. To causally evaulate the impact of gentrification on crime I adopt state of the art event study models to causally evaluate the effects of gentrification, taking into account variations in the timing of this process across different cities and neighborhoods. The analysis reveals that gentrified areas experienced a statistically significant increase in crime ranging from 11 to 17%. The findings suggest that gentrification has a negative impact on neighborhoods, with property crimes showing the most significant increases. Overall, the study suggests that gentrification may have a criminogenic effect on neighborhoods, highlighting the need for further research and policy attention to this issue.

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1 Introduction

In recent decades, among the most relevant changes and challenges that cities have faced stands gentrification. Glass (1964) was the first to put a name to it and described it as a permanent migration of upper- and middle-class professionals with high education to historically low- and working-class neighbourhoods, leading to a substantial change in the social fabric of the neighbourhood and the displacement of incumbent inhabitants. This global phenomenon has implications for shaping better policies for the urban fabric, as new investments can increase pressure on rents and prices, leading to niche services that cater more to the relatively new residents than the incumbent ones (Semi, 2015), resulting in forced outflows of local inhabitants. While gentrification can lead to a more glamorous and commercial zone, it also has adverse effects on vulnerable people, particularly those living in rented houses and without stable occupations. Among the most evident effect of gentrification, there is an increase in house prices (Guerrieri, 2013) which usually lead to the displacement of the existing population (Perez, 2004; Richardson et al, 2019, 2020) who cannot bear the new housing costs. Many interventions that aim to redevelop neighbourhoods and communities can be seen and analysed mainly as gentrification since they are usually more concerned with the transformation of the neighbourhood into a more attractive zone rather than trying to intervene on the socioeconomic reasons behind decay and poverty. However, part of the literature on gentrification indeed focuses on the beneficial effect of this phenomenon in reducing the degradation of the neighbourhood. The influx of wealthy and educated residents could, in this, save the neighbourhoods from decay. In this view, it is crucial to understand deeply this complex transformation process in order to understand and learn how to manage urban transformations. In this paper, we focus on low-income neighbourhoods undergoing economic transitions and analyse the criminal activity in those areas to test the effect of gentrification on the number of committed crimes. The literature has tested the positive effect of unequal cities on crime(Glaeser, 2009) and Lee (2010), Bogges and Hipp (2016) analyze gentrified areas of Los Angeles and their results show an increasing crime rate in treated neighbourhoods. Similarly, Porreca (2023) demonstrates the positive linkage between gentrification and gun violence. The underlying hypothesis is that gentrification tears apart the social and economic fabric of the neighbourhood, exposing the incumbent resident to greater economic distress (Kern, 2022). These could reduce the economic cost of crime for some people forced into troubles. Moreover, the influx of richer inhabitants increases the value of houses, shops, and consumption goods, hence increasing the target for possible crimes. In order to test these predictions, a unique dataset was created that tracks the universe of neighbourhoods in 14 metro areas for the 2015-2019 period, with information regarding both criminal activity and socio-economic indicators that can capture the gentrification process, such as the shares of college graduates, housing values, and per capita income. This paper is one of the few works that try to analyse gentrification in a broader panel of cities over a decade. So far vast part of the literature concentrated its analysis on a single city or a particular part of it, devoting particular attention to the refurbishment or transformation of peculiar areas. Focusing on site-specific transformation, such as public housing demolition, the construction of new railway stations or local housing reform, the risk to capture very local and specific trends is concrete. With this data set I exploit the staggered gentrification of different neighbourhoods in different cities and apply a generalized Difference-in-

Differences (DiD) methodology to identify the impact of gentrification on criminal dynamics. This approach allows me to causally identify the effect of this transformation on criminal activity in the area. To do so I adopt a new class of models for generalized DiD with multiple time periods, as Callaway and Sant'Anna (2020). The estimated results suggest that gentrified neighbourhoods experience a meaningful increase of 11-17% in the number of crimes committed in the area. This increase is largely due to the dynamics of property crimes such as auto theft and burglary, which show a greater and significant increase. Moreover, this study points toward a localized effect of gentrification, since the analysis of the criminal activity of adjacent neighbourhoods do not provide shreds of evidence. The paper proceeds in the following way. Section 2 summarizes the literature to date. Section 3 describes the data for the analysis and Section 4 the empirical strategy. Section 5 presents the results from the analysis. Finally, Section 6 concludes and discusses its implications.

2 Literature Review

2.1 Intra-city Migration and Gentrification

Metropolitan areas now account for the majority of the population in modern economies, with 83% of the US population now classified as urban (Worldbank Data). The distribution of incumbent and new residents within cities has followed different trends over time. From the 1960s to the 1990s, most US cities experienced large population movements from city centers to the suburbs, consistent with the "white flight" phenomenon. The white middle class, due to improved connectivity and reduced commuting times (Baum-Snow, 2007), tended to locate in the suburbs in response to large black migration from rural areas and high levels of racial segregation in post-war America (Boustan, 2010). The increase in violent crime in central areas up to 1991 (Curci, Masera, 2023) also contributed to this exodus. However, from the 2000s onwards, this trend has slowed down and even reversed in many large US cities (Boustan, 2019), with rapid growth in the young and college-educated population near the city center. This urban revival is driven by changing tastes for proximity to highly urbanized non-tradable service amenities (Glaeser et al., 2008; Behrens et al., 2019; Couture, Handbury, 2020), as well as by the increased participation of women in the labor market. Kern (2021) shows how the increase of women that go to work daily has increased the commuting cost of living in the suburbs in order to maintain a work/life balance, which has led to an influx of younger, educated women and couples into new neighborhoods in the central cities This recent surge of the young, educated, and affluent into cities has reversed decades of suburban flight, but in many neighborhoods, it has resulted in gentrification. Florida (2017) has shown how gentrification and inequality are the direct outgrowths of the re-colonization of the city by the affluent and the advantaged. The displacement of incumbent residents and the resulting disruption of the neighborhood's social and economic fabric could lead to worse conditions for the inhabitants.

2.2 Theoretical Predictions

The influx of new inhabitants can cause a great shock to the neighborhood. Criminological research has primarily examined the effects of gentrification using the social disorganization theory, which assumes that crime results from neighborhood social conditions rather than any individual characteristic of neighborhood residents, and that crime will be highest in neighborhoods characterized by high levels of concentrated disadvantage, residential instability, and ethnic heterogeneity (Shaw McKay, 1942). Gentrification typically leads to residential turnover, instability, and displacement (Guerrieri, 2013; Richardson, 2019; Kern, 2022) that disrupt social networks and social control processes, which can increase crime rates. These disruptions are a byproduct of the high levels of residential mobility associated with gentrification as long-term residents are replaced with new residents. As such, economic disparities may increase the social distance between incumbent and new inhabitants, reducing social interactions (Blum, 1985; Hipp Perrin, 2009) and limiting the possibility of creating the necessary social ties. Richer inhabitants may have different perspectives and interests due to their expectations for the future, and they may become less sensitive to common goods and less willing to contribute to local welfare (Boitani, 2021). Saez and Zucman (2016) have also shown that rising income inequality in the USA is responsible for creating greater class divides into urban spaces where enclaves of rich and poor live side-by-side. In addition, the presence of higher-income households in the neighborhood results in an increase in the price of both housing and consumption goods. The process of gentrification can exacerbate the relative deprivation of those with fewer economic resources, leading to increased crime rates in response to these conditions. Studies have found that neighborhoods with more economic inequality have higher crime rates (Hipp, 2007), and Glaeser et al. (2009) have shown that more unequal cities face higher crime rates due to differences in the opportunities available to their inhabitants. On the other hand, the "rational offender" perspective suggests that gentrification can increase criminal activity by increasing both the number and attractiveness of potential targets. According to Cornish and Clarke (1986), potential criminals are sensitive to the array of potential targets, and residents moving into the neighborhood likely have more economic resources and material possessions of greater value, thus increasing the number of suitable targets. The focus of the rational offender theory is indeed on crimes of gain ("rational crimes") and hence predicts a linkage between the gentrification process and a subsequent increase in burglary, robbery, and larceny.

2.3 Empirical Evidences

The literature has not reached a clear consensus on the consequences of gentrification on criminal behavior in the neighborhood. The demographic and economic shifts induced by the gentrification process may either enhance or reduce the likelihood of committing a crime. For instance, Kirk and Laub (2010) reviewed a large set of research on the relationship between crime rates and gentrification for the 1970-90 period and found evidence that neighborhood change, whether in the form of socioeconomic improvements or population loss, results in short-term destabilizing effects that produce more crime in the near term. Similarly, Covington and Taylor (1989) found that gentrifying neighborhoods in Baltimora experienced an increase in so-called "rational crimes", such as robbery and larceny. Because gentrification is accompanied by residential turnover and heterogeneity, in treated neighbourhoods this process leads to the ideal conditions for an increase in crime. Bogges and Hipp (2016) found that neighborhoods with higher socioeconomic status increases are associated with an increase in the crime rate in Los Angeles during the 1990s. Again, they explained that because gentrifying neighborhoods have more suitable crime targets, this can increase the amount

of crime in the area. Lee (2010) uses the 1994 earthquake that hit the Northridge section of Los Angeles as a natural experiment to examine the effect of gentrification on neighborhood crime. Property owners in Northridge were provided low-interest loans to rebuild homes after the earthquake. The low-interest loans spurred a rise in the purchase of homes by upper-income households in low- and moderate-income neighborhoods in Northridge. These neighborhoods subsequently experienced a small increase in robbery, assault, and auto theft. Porreca (2023) used a two-way fixed effect DiD estimator to validate the relationship between the gentrification of one block and levels of gun violence across neighborhoods in Philadelphia. He demonstrated that, on average, gentrification increases levels of gun violence, with 21% of the city's shootings across the ten-year study window being attributed to spillover effects from gentrification.
However, some scholars suggest that gentrification could reduce crime by spurring economic development, reducing urban blight, increasing economic opportunities for the poor, and de-concentrating poverty (Economist, 2018); since the extant inhabitants that are more susceptible to being displaced are probably those in the worst socioeconomic condition and then more at risk of committing crimes (Baumer et al, 2014;, 2017) this could lead to a crime reduction. Autor et al. (2019) evaluated the influence of gentrification on crime by relying on the abrogation of rent control in Cambridge, MA, in 1995. They found that working-class neighborhoods in Cambridge experienced a rise in rents, a spike in new construction, and an influx of more affluent residents after the lifting of rent control. Blocks with more rent-control units experienced a steeper drop in crime than other blocks. The reduction in crime occurred within one year of the elimination of rent control and remained persistently lower thereafter. However, the peculiarity of Cambridge, a relatively small city (113k inhabitants) home to two leading universities (Harvard University and MIT), must be emphasized. Aliprantis and Hartley (2015) examined trends in homicides and police calls for service by census block from 1999 to 2011 in Chicago before and after the closing and demolition of public housing projects. They found that closing high-rise public housing was associated with a significant drop in crimes in blocks where they were located and in the blocks within a half mile and there was no evidence of the displacement of crime into adjacent census blocks.

As pointed out by MacDonald and Stokes (2020), the major part of the existing literature focuses on single-city studies, particularly on site-specific interventions such as new railway stations and public housing dismissions, as sources of gentrification. However, unobservable city-specific characteristics can interfere with estimations on a single-city data-set. To contribute profitably to the literature and address this issue, I built a cross-cities data-set that allows me to control for different cities' unique trends, resulting in more precise estimations of the effects of gentrification on crime. Furthermore, I contribute to the literature by adopting an approach that identifies gentrification based on observable demographic characteristics, as opposed to the most widespread gentrification-inducing interventions. This approach is more directly linked to the actual phenomenon under study and can be easily measured in different contexts, hence increasing the external validity of the findings. Lastly, to the best of my knowledge, this is the first work that estimates the effect of gentrification by taking advantage of the different timing of the phenomenon across neighborhoods and cities. The adoption of state-of-the-art staggered DiD models (Callaway and Sant'Anna (2020), Borusyak et al (2022), De Chaisemartin and D'haultfœuille (2017), Sun and Abraham (2020)) enhances the causal interpretation of the results. Finally, with the adoption of these models, I am among the few researchers (Vannutelli, 2020; Henkel et al, 2022;) who have applied this new literature on staggered DiD in an empirical framework.

3 Data

I extracted a sample of neighborhoods in 14 major American cities[1], and collected from various sources. To measure neighborhood boundaries consistently, I adopted the Census Tract, which is a widely-used measure in the literature (Guerrieri, Hartley, Hurst, (2013); Lester, Hartley, (2014), Ding, Hwang, Divringi, (2016), Meltzer, Ghorbani, (2017)) that identifies homogeneous areas with an average of about 4,000 residents. This allows for harmonized data between different sources and provides an area large enough to analyze crime trends that could not be captured at a smaller scale. The sample consists of 3,611 neighborhoods/tracts observed over the period from 2015 to 2019.

The dependent variable in this study is the number of occurred Part I crimes, which are serious crimes likely to be reported to the police and occur with regularity in all areas of the country (FBI, 2004). These crimes are categorized as either violent (aggravated assault, murder, rape, robbery) or property-related (arson, automobile/vehicle theft, burglary, theft/larceny). Data on these crimes were collected from the police department sites of each city, where precise information on each crime committed is recorded and made available to the public. Each crime is recorded with its location (latitude and longitude), enabling precise crime localization (adopting Picard's geoinpoly (2015)). Additionally, the category of crime is described adhering to standard definitions from the FBI. This information allows for the precise count of each crime and the construction of a data set that collects crime data across different cities and years.

To capture the gentrification process, economic and demographic data were collected from the U.S Census Data and in particular from The National Historical Geographic Information System (NHGIS) from the University of Minnesota (Manson et al, 2021). This source provides access to time series data for all levels of U.S. census geography, which was used to gather data from the American Community Survey (US CENSUS - ACS). The data collected for this study include population characteristics, such as racial composition, education level, and income, as well as the state of the housing stock and market, such as building age, house value, and median rent. Descriptive statistics, including mean, standard deviations, and 25th-75th percentiles, for both the dependent and independent variables collected, are reported in Table 1. Crime data and census data are consistently harmonised between the different sources, regarding both the temporal and spatial dimension.

Figure 2 from the Appendix displays both which neighbourhood gentrified within the observational window and the average crime rate. The blue shades represent the intensity of delinquency measured as the average number of crimes committed over the entire period of my study (2015 -

[1] Austin, Boston, Chicago, Los Angeles, Milwaukee, Minneapolis, New Orleans, Philadelphia, Pittsburgh, Portland, San Francisco, Seattle, Tucson, Washington

2019), the darker the color higher the crime rate. The red dots instead pinpoint all that neighbourhood that have been identified as gentrified all over the period, and so taking into account all the five different cohorts of gentrified neighbourhood. From a first visual inspection, it can be deduced that some correlation between neighbourhood with the higher crime number and gentrification does exist. In fact, gentrified neighbours tend to overlap with those with major number of crimes. This first piece of evidence puts the bases for the analysis that follows.

4 Empirical Strategy

4.1 Identification of gentrifying neighborhoods

As pointed out by Glaeser (2018), gentrification is a complex phenomenon that can be better understood by analyzing it beyond economic indicators. To classify gentrified neighborhoods, I consider both the transformation in the housing market and the economic and educational attainment of the local population. I collected the necessary data from the American Community Survey (ACS), and based on existing literature (Freeman, 2005; Federal Reserve Bank of Philadelphia, 2016; Richardson et al., 2019, 2020), I define a neighborhood (n) as gentrified over the period [T - T+1] if it meets the following criteria: (i) it has a starting population of at least 500 inhabitants to exclude abrupt increases in formerly unpopulated areas, (ii) it has a median income lower than the median for that metropolitan area (MSA) at the beginning of the period [T], (iii) it has a proportion of newly built houses below the median for the respective MSA, (iv) it has a percentage increase in educational attainment greater than the median increase in educational attainment for that MSA during the period, and (v) it has an increase in real housing prices/rents during the period. To operationalize the gentrification definition, I looked at different periods, consistently with the extant literature (Glaeser, 2018, 2020; Florida, 2017), resulting in five different cohorts depending on the year in which the Census Tract results gentrified. Once a neighborhood is classified as gentrified, it is assumed to remain so throughout the entire analysis period. Given the nature of the dependent variable of interest, an event study forms the basis of my analysis. This approach uses a difference-in-differences (DiD) design in which a set of units in the panel receives treatment at different points in time, and once a unit is treated, it is considered treated in all subsequent periods.

4.2 Baseline Model

The baseline specification would be the following:

$$Crime_{it} = \alpha + \beta_1(Gentrification_{nt}) + \tau_t + \eta_n + \zeta_c * \tau_t + \beta X_i + \epsilon_{it} \tag{1}$$

where the dependent variable is the inverse hyperbolic sine transformation (IHS) of the number of crimes occurred in neighbourhood [n] in year [t]. Inverse Hyperbolic Since transformation approximates the natural logarithm of a variable and allows retaining zero-valued observations (*Bellemare*, 2019); when the dependent variable is a dummy the coefficient of IHS transformation the coefficient of interest can be read as a percentage increase/decrease[2]. The variable Gentrification identifies

[2]More precisely the resulting approximation of a percentage change in y due to a discrete change in a dummy dependent variable= $exp(\beta - 1)$

treated neighbourhood [i] at time [t][3]; the vector X include controls at the 2010 baseline value interacted with time fixed effect; τ are the time fixed effects; η are neighbourhood fixed effects; ζ are city fixed effects interacted with time fixed effects,ε is an error term. In all regressions, standard errors are clustered at the neighbourhood level to allow for flexible error correlation structure within units; the coefficient of interest is β_1, which captures the causal effect of gentrification on crime.
In order to causally interpret the coefficient β_1, it has to be true that treated and control units are effectively comparable. Specifically it must holds the assumption that in absence of gentrification, the crime trends would have been alike in the two groups of neighbourhoods. To deal with this issue, since my setting involves multiple treatment groups and time periods I include neighbourhood and time fixed effects. Thus, panel and time fixed effects control for fixed differences between treated and control units and for aggregate fluctuations. Moreover, the inclusion of city fixed effects interacted with year dummies allows me to control also for possible city trend that can bias the estimations. Lastly, the matrix of interactions between the vector of control variables [4] and allows me to mitigate issue related to the existence of differential trends across municipalities related to these characteristics. Moreover it allows for differential trends by initial characteristics; for example this accounts for the fact the less populated areas are less likely to gentrify or have an high number of crimes.

4.3 DiD with dynamic treatment effects

However, naively applying specification (1) would pose a set of empirical challenges that have been recently highlighted by a growing literature on the pitfalls of two-way fixed effects estimators with staggered adoption (de Chaisemartin and D'Haultfoeuille (2019), Goodman-Bacon (2021)). In particular, the β from equation 1 is a weighted average of all the possible 2x2 comparisons in my sample. With treatment roll-out, these weights can be negative because already-treated units act as controls, at the very least harming identification and potentially leading to average treatment effects or average treatment on the treated of opposite sign. Therefore, it is also estimated using comparisons among already-treated units and not-yet-treated units, where the already-treated units serve as controls. This induces a bias in presence of heterogeneous treatment effects across groups experiencing gentrification at different points in time. Since research highlighted these challenges, many papers proposed alternative estimators, hence I implement these kind of estimator to strengthen my results and compare among different specifications. I consider five different cohorts [c] and once a neighbourhood become treated, hence gentrified, it remains treated for all the period of the study; since the time span it is relatively small, it is realistic to assume that gentrified neighbourhoods do not change their status over 5 years. To investigate pre-trends, as well as the dynamic evolution of the treatment effect, I estimate the following specification:

$$Crime_{nt} = \alpha + \Sigma\gamma_k * D_k * Gentrification_{nc} + \tau_t + \eta_n + \zeta_c * \tau_t + \beta X_i + \epsilon_{it} \quad (2)$$

Where $Gentrification_{ic}$ is a dummy that takes the value of 1 if the neighbourhood i is treated in the cohort [c]. D_k are a set of relative event-time dummies, that take the value of 1 if year t is k

[3] it is similar to the canonical DiD [Treat x Post] variable
[4] population, %female, %young, %wht, Gini index

periods after (or before) the treatment. The coefficients of interest are the γ_k, measuring the change in outcomes of treated municipalities k years after treatment, relative to the pre-treatment year, compared to the change in outcomes of control municipalities, that can be both not-yet-treated units or never-treated-units.

4.4 Threats to Identification

The key identifying assumption in my research design is that there are no differential trends between neighborhoods experiencing gentrification at different points in time. This means that the timing of the occurrence, and hence the timing of treatment, should not be correlated with the evolution of outcomes over time. To check the plausibility of this assumption, in Figure 1 I examine whether outcomes exhibit parallel trends in the pre-treatment period. This provides positive evidence in favor of the comparability of outcomes and, in turn, the reliability of the estimations. This observation is consistent across all models used, as shown in Figure 4 from the Appendix. In addition to this, I conduct a regression analysis to see whether any observable characteristics of municipalities predict the timing of gentrification. The results, as shown in Table 4, indicate that there is no particular variable that has consistent predictive power for different cohorts, except for the share of white population. Therefore, I control for differential trends by white population size by including white population-by-year fixed effects in my regressions, as mentioned above. These analyses provide further support for the validity of this research design and the reliability of the results of this analysis.

5 Estimation Results

5.1 Baseline Model

The results for the estimation of Eq(1) are reported in Table 1. The table includes three columns, each with an increasing number of fixed effects and controls, and the results are similar in direction and significance across all specifications. The coefficient for the number of crimes increases between 8% and 17%, and is statistically significant across all specifications. The most significant reduction in the magnitude of the coefficient occurs when including city-specific trends (column 3), highlighting the importance of controlling for different city dynamics and unobservable characteristics. This underscores the importance of conducting a multi-city analysis to obtain a precise estimation of gentrification effects. In contrast, the inclusion of controls does not substantially alter the results. These findings suggest a criminogenic effect of gentrification, providing evidence of a disruptive dynamic in gentrified neighborhoods.

5.2 Event Study Analysis

The validity and unbiasedness of the staggered treatment timing difference-in-differences estimator used in this study rely on the assumption of parallel trends between the control and treatment groups before the treatment occurred. I have provided evidence in the form of non-significant pre-treatment coefficients in Figure 1, which reports the dynamic coefficients for the estimation

Table 1: The impact of gentrification on crime

Dependent Variable: IHS Tot Crime			
	(1)	(2)	(3)
Gentrification	0.17***	0.09**	0.08**
	(0.04)	(0.04)	(0.03)
Observations	18,055	18,055	18,055
census tract FE	YES	YES	YES
year FE	YES	YES	YES
City#year	NO	YES	YES
$\text{Controls}_{2010}\#year$	NO	NO	YES

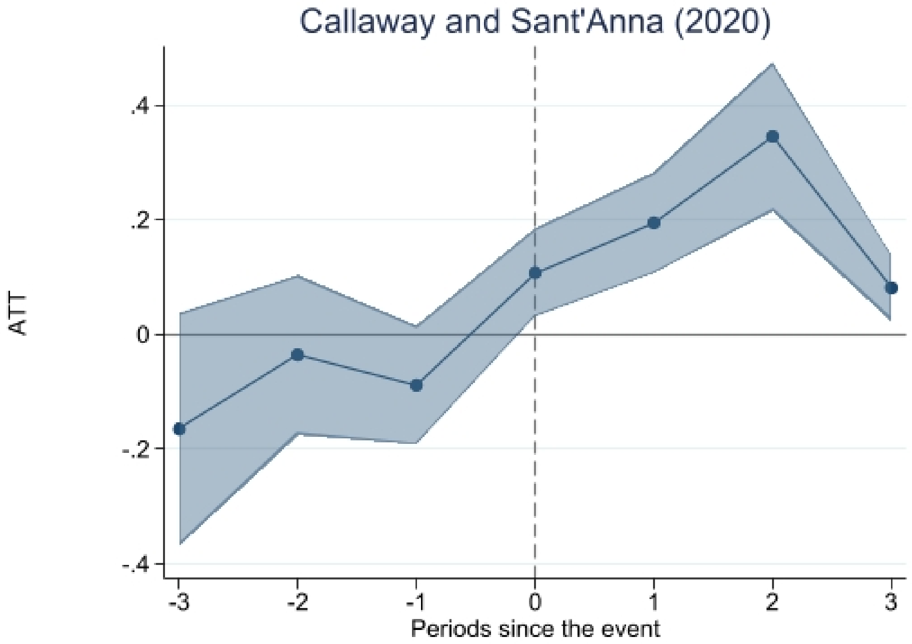
This table report results for estimation of Eq(1). The dependent variable is the IHS tranformation of the number crimes committed the neighbourhoods. All specifications include census tract and year fixed effects. Column 2 include also MSA-by-year FE. SE in brackets clustered at the panel level. *** p<0.01, ** p<0.05, * p<0.1

of Eq(2). The assumption of common trends is not violated, since no one of the pre-treatment coefficients is significant at the 95% confidence level. The dynamic results show that the effect of gentrification on criminal activity decreases over time. The estimated ATT following Callaway and Sant'anna are reported in Table 3 from the Appendix and is consistent with the baseline findings, indicating an increase of approximately 11-17% of crimes in gentrified neighborhoods. Callaway and Sant'anna model allows to include different control groups, and I have also tested the robustness of results by including different control groups. I adopt not yet treated units as control (colums 1-3), hence those neighbourhood that are gentrified in a different, successive period, and never treated units as control (column 4) and the coefficients estimated in all cases point toward a similar increase of 12% in the number of crimes committed.

5.3 Different Type of Crimes

The key identifying assumption in my research design is that there are no differential trends between neighborhoods experiencing gentrification at different points in time. This means that the timing of the occurrence, and To gain a better understanding of the actual consequences of gentrification and to identify possible channels for the criminogenic effect, I estimated Equation (2) for each kind of Part I crime. The results are reported in Table 5 and Figure 3 in the Appendix. This analysis allows me to disentangle the effect of gentrification on different types of crimes. Table 5

Figure 1: Event Study Plot of Gentrification Effect on Crime



Note: Estimated treatment effects from the gentrification of a neighbourhood on ihs number of all crimes committed, following Callaway and Sant'anna, 2020; The blue area show the estimated 95% confidence intervals, based on standard errors clustered on census tracts; all the models include all kind of FE and city trends; horizontal ax shows the treatment year, so that positive values correspond to post-treatment years

presents the coefficients estimated using the Callaway and Sant'anna model. Figure 10 provides dynamic coefficients for all types of crimes, estimated using different event study models to test the robustness of the results to different specifications. The magnitude and significance of the coefficients hold across all the models. Regarding violent crimes, only robbery showed a statistically significant increase, while the coefficient for assault was only slightly significant. However, when considering Figure 3 to control for pre-treatment trends, it appears that assault and robbery do not satisfy the parallel trend assumption, so the interpretation of their coefficients may not be reliable. For property crimes, there were statistically significant increases across the board. Auto theft (GTA), burglary, robbery, and theft showed the steepest increases, at around 16% each. By looking at the pre-treatment coefficient from Figure 3, it is apparent that there were no observable differences in the dynamics of property crime before gentrification occurred. This is evidence in favor of the parallel trend assumption holding, which enhances the causal interpretation of the coefficients. The increase in auto theft supports the idea that the crime increase is not due to misreporting. GTA is the property crime that is least prone to misreporting to the police. This can be explained by a couple of reasons. Firstly, motor vehicles are registered under specific people's names, meaning that any ticket or fine arising from a specific vehicle will be addressed to the owner.

Additionally, the owner may also be held responsible if the vehicle is involved in other criminal activities. This creates a strong incentive to report the theft to the police as soon as possible to avoid legal consequences later. Secondly, it is more common to have insurance against motor vehicle theft than any other personal goods. To collect the insurance premium, it is necessary to report the crime to the police, significantly reducing misreporting. The harsher economic conditions that the poorer former inhabitants face following the increase in house values and rents (Guerrieri, 2013; Glaeser, 2017, Desmond, 2016 are paired with additional potential drivers for criminal activity. On one hand, the influx of richer inhabitants leads to an increase in the number and quality of potential property crime targets. The new people introduce new lifestyles and all the commodities associated with them, thus increasing the value of goods and amenities in their possession, as well as in their homes (Kern, 2022).

5.4 Robustness tests

To further validate the robustness of the previous results, various models were used for the staggered Difference in Differences (DiD) analysis. Figure 4 presents the estimated dynamic coefficients for equation (2) using models developed by Callaway and Sant'Anna (2020), Borusyak et al (2022), De Chaisemartin and D'haultfŒuille (2017), and Sun and Abraham (2020). These models provide alternative instruments to address issues related to event studies with standard Two-way Fixed Effects (TWFE) models, and their results show a positive and statistically significant effect of gentrification, consistent with the findings of the baseline model. Moreover, also the magnitude of the coefficients is similar among all the estimations, thus corroborating the validity of the results.

The stable unit treatment value assumption (SUTVA) is crucial for identification in difference-in-differences; it requires that the gentrification of one tract does not have an effect that extends beyond the neighborhood itself. If gentrification has the effect in inducing shifts in criminal activity in surrounding neighborhoods, this would introduce a bias into the treatment effect estimator. Hence, I conducted a placebo test to verify whether SUTVA holds and to assess the validity of the results. The dependent variable was constructed using adjacent non-treated neighborhoods and their crime rates: I) for all the units in my sample I have identified their adjacent neighbourhoods; II) I take into account only non-treated adjacent neighbourhood; III) for each unit I computed the average number of crime committed in adjacent neighbourhood that did not gentrify. The results of the placebo test, presented in Table 6 in the Appendix, show that the coefficient for gentrification is only slightly positive and not statistically significant in any specification. This indicates that the main results of the study are not driven solely by dynamics common to adjacent neighborhoods, but by the actual effects of gentrification on the neighborhood in question. Moreover, these results suggest that gentrification does not displace criminals into adjacent neighborhoods nor have a spillover effect on non-gentrified neighborhoods. The criminogenic effect of gentrification appears to be highly localized, in line with previous findings that posit how crime tends to happen close to the offender's residence. The findings from Langella et al (2022) suggest that the high cost of distance for criminals has a significant deterrence effect, which supports the results presented in Table 6.

Lastly, I show that my results do not rely on a specific city's presence in the sample. In Table 7 in the Appendix, I estimate Eq (2) by removing from the sample the city specified in each column. I find that the estimated coefficients are quite stable and statistically significant, excluding the possibility that our estimates depend on one outlier city. Overall, the results of this study suggest that gentrification harms the social fabric of the neighborhood and can lead to an increase in criminal activity.

6 Conclusion

In conclusion, the findings of this study suggest that gentrification has a detrimental effect on criminal activity in the neighborhood. The results estimated adopting an event-study Difference in Difference point towards a detrimental effect of gentrification since it is the cause of an increase of crimes in the neighbourhood where it occurs. Therefore, it is essential to consider the health and safety of the urban fabric as a whole when implementing urban interventions. Further research is needed to assess the long-term effects of gentrification on crime rates and to identify policies that can mitigate its negative consequences. The use of a unique cross-city dataset enhances the external validity of these results, making them more applicable to other cities around the world. However, it's important to note that the results are limited to a short-term analysis, as uniform crime data are not yet widely available. Therefore, it would be valuable to conduct a follow-up study once more data becomes available, to take into account longer-term effects and any potential different dynamics that may arise. In light of these findings, urban policymakers and planners need to consider the health and safety of the urban fabric as a whole when designing and implementing urban interventions. As gentrification continues to spread around the world, it's crucial to carefully evaluate its potential impacts on the social and economic fabric of neighborhoods, in order to ensure that any urban interventions are both effective and equitable.

7 References

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8 Appendix

Table 2: Descriptive statistics

	(mean)	(s.d.)	(25th pct)	(75th pct)
Tot.Crime	148.07	192.45	57	180
Arson	.62	1.37	0	1
Assault	11.38	19.17	1	13
Auto Theft	14.05	16.30	3	19
Burglary	22.15	23.82	8	29
Murder	.55	1.30	0	1
Rape	1.37	2.61	0	2
Robbery	10.89	14.89	2	15
Theft	87.03	152.03	23	94
Population	3765	1836	2497	4792
Female %	.51	.05	.48	.53
Black Population %	.25	.32	.02	.39
White Population %	.52	.29	.26	.79
College Graduate %	.43	.24	.21	.65
Young People (under 34) %	.50	.11	.42	.56
Old People (over 65) %	.12	.06	.07	.15
Median Household Income	58156	34595	33423	74643
New buildings (20 year) %	.12	.16	.02	.16
Median Rent	1146	449	871	1335
Median House Value	350178	312466	139100	463000
Gini Index	.45	.08	.40	.49
# observations	18,055			

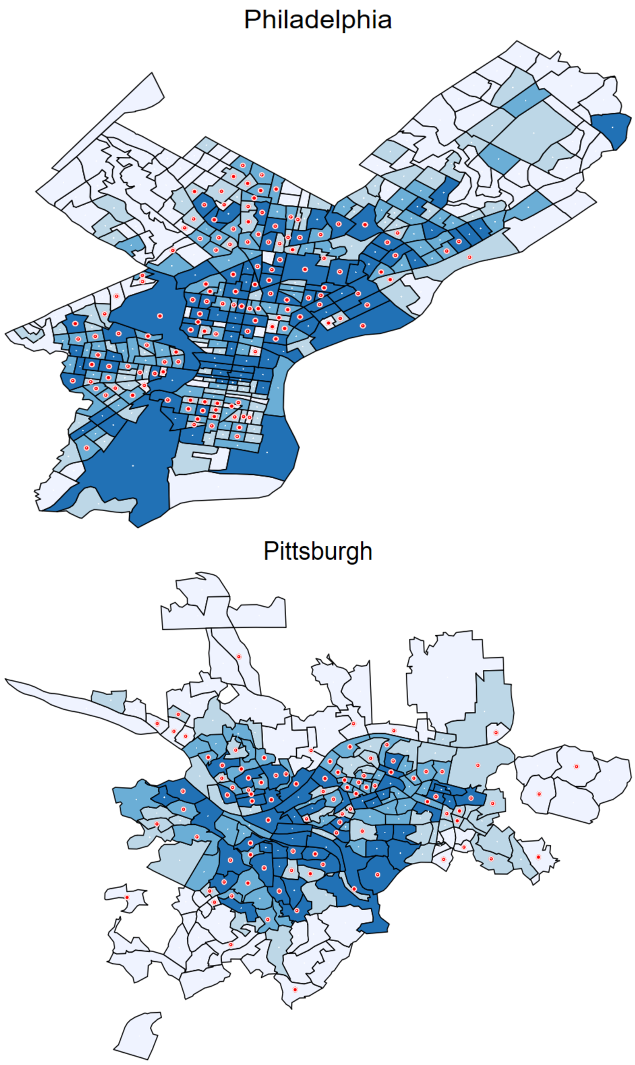
The table show the mean, the standard deviation and 25th and 75h percentiles for all variables. Descriptive statistics are on the full sample of census tract from Austin, Boston, Chicago, Los Angeles, Milwaukee, Minneapolis, New Orleans, Philadelphia, Pittsburgh, Portland, San Francisco, Seattle, Tucson, Washington. The sample is a panel of neighbourhoods over years. Panel A: number of crimes committed. Panel B: tract characteristics adopted as controls.

Table 3: Estimation of Callaway and Sant'anna

Dependent Variable: IHS Tot Crime				
	(1)	(2)	(3)	(4)
Gentrification	0.178***	0.18***	0.123***	0.11**
	(0.04)	(0.04)	(0.03)	(0.03)
Observations	16,600	16,600	16,600	16,600
census tract FE	YES	YES	YES	YES
year FE	YES	YES	YES	YES
City#year	NO	YES	YES	YES
$\text{Controls}_{2010}\#year$	NO	NO	YES	YES
Control group	not yet	not yet	not yet	never

This table report results for estimation of Eq(2) following Callaway and Sant'anna (2020). The dependent variable is the IHS tranformation of the number crimes committed the neighbourhoods. All specifications include census tract and year fixed effects. The first three columns report the estimation adopting not yet treated units as control group, the fourth column adopt nevere treated units as control group. SE in brackets clustered at the panel level.
*** p<0.01, ** p<0.05, * p<0.1

Figure 2: Gentrification and crime across Philadelphia and Pittsburgh



Note: Blue shaded area represent the number of crime; the darker the area, the greater the number of committed crimes in that neighbourhood. Red dots identify which neighbourhood gentrified over the entire period of the study

Table 4: Characteristics that Predict Treatment Timing

	(2015)	(2016)	(2017)	(2018)	(2019)
Population	-0.0001	-3.20e-06	0.00002	-0.00001	-.00002*
	(0.0001)	(8.77e-06)	(0.00001)	(0.00001)	(.00001)
Share female	-0.00005*	-3.56e-06	-0.00004*	7.65e-06	.00003
	(0.00002)	(0.00001)	(0.00002)	(0.00001)	(0.00001)
Share young	0.00003	6.61e-06	0.00001	0.00003	0.00001
	(0.00009)	(8.82e-06)	(9.43e-06)	(0.03)	(9.07e-06)
Share white	-0.081***	-0.033**	-0.094***	-0.07	-0.087**
	(0.014)	(0.01)	(0.014)	(0.01)	(0.01)
Gini index	0.23***	0.07	-0.01	-0.04	-0.044
	(0.04)	(0.04)	(0.04)	(0.039)	(0.039)
Observations	3611	3611	3611	3611	3611
R-sq	0.02	0.003	0.0136	0.0128	0.0151

: The table displays results from 5 separate OLS regressions where the dependent variables are indicators for gentrification occurring in 2015, 2016, 2017, 2018, 2019. The explanatory variables are measured in 2010. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5: The impact of gentrification on different kind of crimes

	Arson	*Assault*	*GTA*	*Burglary*	*Murder*	*Rape*	*Robbery*	*Theft*
Gentrification	0.030	0.085*	0.137***	0.164***	0.010	-0.028	0.164**	0.166***
	(.021)	(.032)	(.034)	(.035)	(.021)	(.025)	(.032)	(.033)
Observations	16,600	16,600	16,600	16,600	16,600	16,600	16,600	16,600
census tract FE	YES	YES	YES	YES	YES	YES	YES	YES
year FE	YES	YES	YES	YES	YES	YES	YES	YES
City#year	YES	YES	YES	YES	YES	YES	YES	YES
$\text{Controls}_{2010}\ \#year$	YES	YES	YES	YES	YES	YES	YES	YES

The dependent variable is the IHS tranformation of the number of each kind of crime listed in each column. Results obtained following Callaway and Sant'Anna (2021) All specifications include census tract, year and MSA-by-year FE. SE in brackets clustered at the panel level. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Placebo Test

Dependent Variable: Avg. Neighbouring Tract's Crime

	(1)	(2)	(3)
Gentrification	0.001	0.0003	0.002
	(.010)	(.010)	(.010)
Observations	16,600	16,600	16,600
census tract FE	YES	YES	YES
year FE	YES	YES	YES
City#year	NO	YES	YES
$\text{Controls}_{2010}\#year$	NO	NO	YES

The dependent variable is the IHS tranformation of the number crimes committed in adjacent not-gentrified neighbourhoods. Results obtained following Callaway and Sant'Anna (2021). All specifications include census tract and year fixed effects. Column 2 include also MSA-by-year FE. SE in brackets clustered at the panel level. *** p<0.01, ** p<0.05, * p<0.1

Figure 3: Event Study analysis for all kinds of Part I Crimes

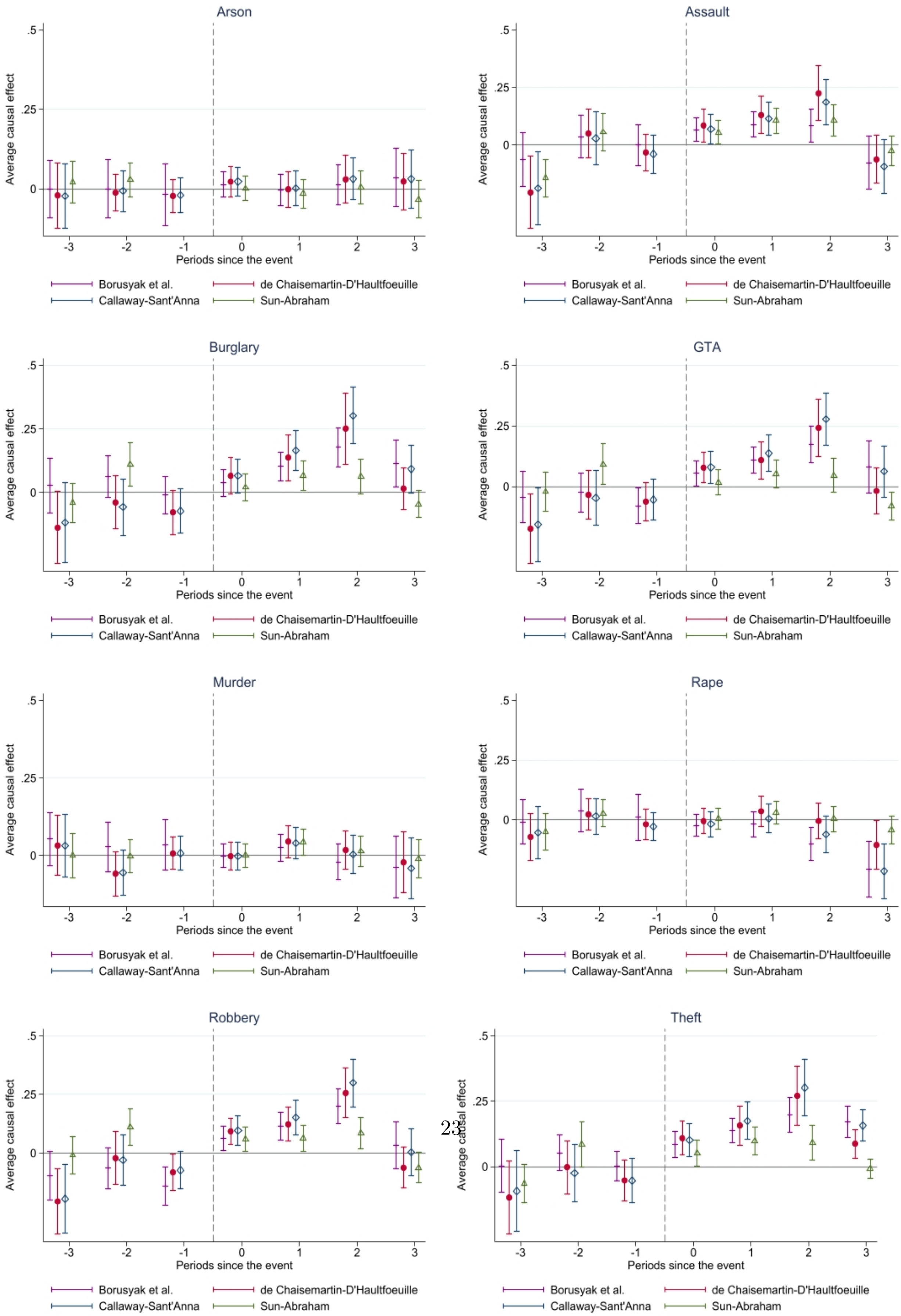
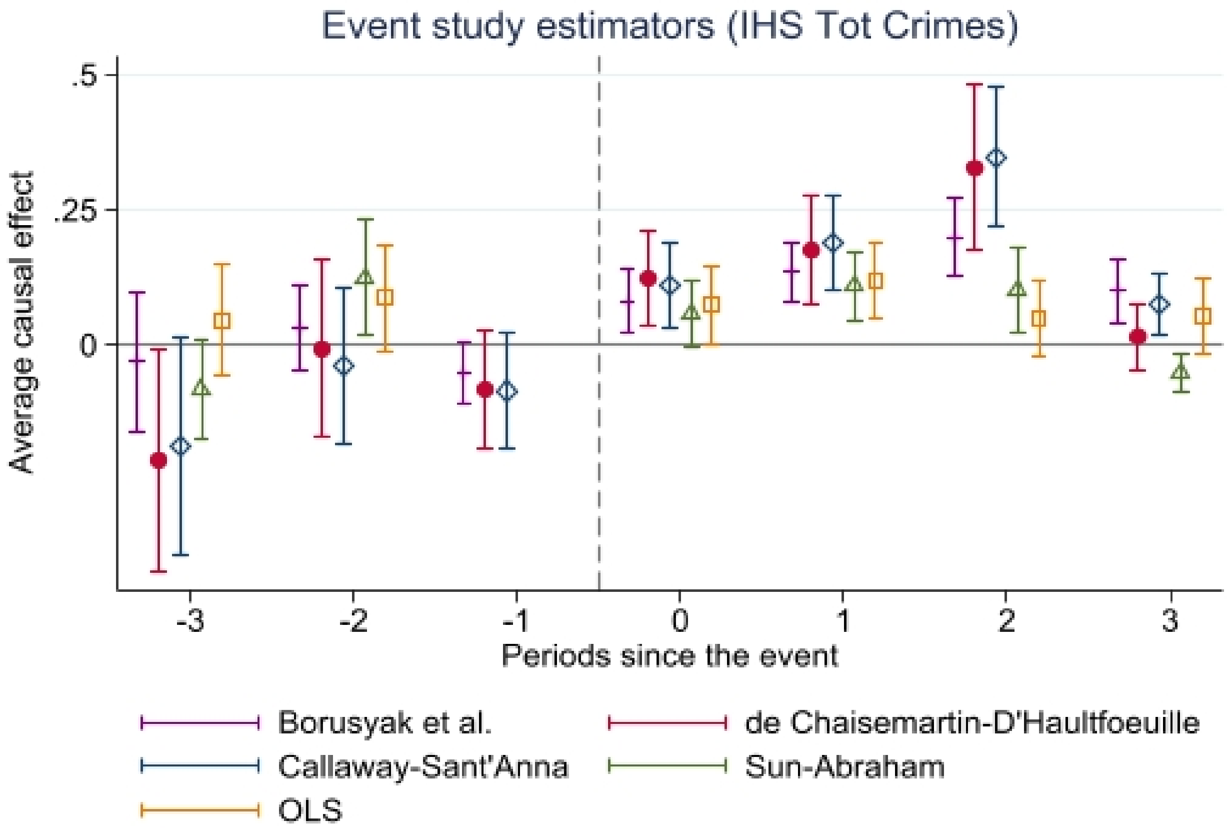


Figure 4: Treatment effects with event studies using a range of methods



Note: Estimated treatment effects from the gentrification of a neighbourhood on ihs number of all crimes committed; the vertical lines show the estimated 95% confidence intervals, based on standard errors clustered on census tracts; all the models include all kind of FE and city trends; in all three panels, the horizontal axis shows the treatment year t, so that positive values of t correspond to post-treatment years

Table 7: The impact of gentrification on crime - subsamples

	Austin	Boston	Chicago	Los Angeles	Milwaukee	Minneapolis	New Orleans
Gentrification	0.19***	0.17***	0.18***	0.2*	0.16***	0.19***	0.19**
	(0.04)	(0.04)	(0.04)	(0.01)	(0.04)	(0.04)	(0.04)
	Philadelphia	**Pittsburgh**	**Portland**	**San Francisco**	**Seattle**	**Tucson**	**Washington**
Gentrification	0.18***	0.20***	0.17***	0.19***	0.18***	0.18***	0.19***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
census tract FE	YES	YES	YES	YES	YES	YES	YES
year FE	YES	YES	YES	YES	YES	YES	YES
City#year	YES	YES	YES	YES	YES	YES	YES
Controls_{2010} *#year*	YES	YES	YES	YES	YES	YES	YES

The dependent variable is the IHS tranformation of the number of total crimes. Each column report results from the estimation of Eq. 1, for different sub-samples of observations from which the city specified in the column has been removed. Results obtained following Callaway and Sant'Anna (2021). All specifications include census tract and year fixed effects. Column 2 include also MSA-by-year FE. SE in brackets clustered at the panel level.
*** p<0.01, ** p<0.05, * p<0.1