GTA: Gentry City.
Gentrification and Crime across American Metropolis

Alessandro Corvasce *

July 25, 2023

Abstract

This study investigates the effects of gentrification on criminal behavior in urban neighborhoods to assess whether or not this phenomenon is destructive to communities. To identify gentrified neighborhoods in the 2010s, the study employs a newly constructed, unique data set of geo-referenced crime records from 14 major American cities paired with Census data. To examine the effect of gentrification on crime, I employ state-of-the-art event study models to evaluate the consequences of gentrification, accounting for variations in the timing of this process between cities and neighbourhoods. The results shows that gentrified neighborhoods faced a statistically significant increase in crimes estimated between 11 to 17 percent, with property crimes showing the most significant increases. Overall, the study indicates that gentrification may have a criminalizing influence on areas, underlining the need for additional policy consideration of this issue by urban planners and scholars.

Keywords: Gentrification, Property Crime, Rational Offender Theory
JEL Classification: R11, K42

*Department of Economics, Management and Quantitative Methods - DEMM @ University of Milan
Ph.D. School in Economics and Finance – DEFAP @ Catholic University of the Sacred Heart, Milan

1 Introduction

Gentrification has been one of the major shifts and challenges cities have experienced in recent decades. This term, coined by Glass (1964), refers to the permanent movement of upper- and middle-class professionals with advanced degrees to formerly low-income and working-class neighbourhoods. The distribution of population in American cities has indeed seen substantial shifts throughout the years. Until the 1990s, there was a trend of population movements from city centers to suburbs known as "white flight," which was largely caused by the white middle class relocating to suburbs favored by the diffusion of new highways (Baum-Snow (2007)) and in response to racial segregation (Boustan (2010)) and the increase in violent crime in central areas until 1991 (Curci and Masera (2023)). Since the 2000s, however, this trend has slowed and even reversed in many large U.S. cities (Boustan et al. (2019)), with an increasing number of young, educated people moving closer to the city center, enticed by non-tradable service amenities (Glaeser et al. (2018); Couture and Handbury (2020)) and pushed by the increased participation of women in the labor market (Kern (2021)). This trend has led to gentrification in several neighborhoods as a direct result of the rich and privileged re-colonization of the city (Florida (2017)). Many interventions that aim to redevelop neighborhoods and communities can be assessed largely as gentrification because they are typically more concerned with the transformation of the neighborhood into a more attractive zone for the retail and real estate markets (Semi (2015)) than with addressing the socioeconomic causes of deterioration and poverty.

Gentrification causes a significant disruption of the neighborhood's socioeconomic fabric, as long as the forced relocation of existing inhabitants. New residents stimulate housing demand and attract investments, both of which increase pressure on rents and house prices (Freeman (2005); Guerrieri et al. (2013)), which frequently results in the displacement of the existing population (Perez (2004); Richardson et al. (2019), Richardson et al. (2020)), particularly those living in rented housing and without stable employment. Coupled with deteriorated affordability, gentrification spurs an increase of amenities in the neighbourhood as new, richer inhabitants enter the area with their more valuable belongings, like better cars. In light of the rational offender theory, the cost opportunity of committing crimes is reduced do to the greater availability of potential targets. The "reasoning criminal" (Scott (2014)) will then respond to its worst personal conditions and to the increase in targets by committing more (property) crimes.

This study examines the relationship between gentrification and crime in neighborhoods experiencing economic transition. To learn more about this link, I created a unique dataset that monitors neighborhoods in 14 major cities during the 2010s. This dataset contains statistics on both crime and socioeconomic indicators, including the number of college graduates, the value of homes, and the per capita income. I deploy a Difference-in-Differences with dynamic treatment effects model to determine the impact of gentrification on criminal dynamics by analyzing the staggered gentrification of different neighborhoods in different cities using this dataset. According to the results of this analysis, the number of crimes committed in gentrified neighborhoods increases by 11–17%. This increase is driven mostly by property crimes like burglary, theft and grand theft auto (GTA), which show a more significant increase than other categories of crime. In addition, this study demonstrates that the effect of gentrification is localized, as the analysis of criminal behavior in neighboring areas does not reveal a significant increase. This study provides important evidence of gentrification's impact on crime and highlights the necessity for policymakers to address the potential unintended consequences of local developments. On top of that, this paper documents a potential mechanism for this effect, showing that following a block's gentrification the quality and quantity of potential property crime increase. Adopting the number of Electric Vehicle chargers as proxy for better cars, I show that these spread in gentrified neighbourhood. This in turn could reduce the cost opportunity of crime and leads to the increases in GTA documented herein.

As pointed out by MacDonald and Stokes (2020), the majority of the present literature on gentrification and crime is based on single-city studies, which may be problematic due to unobserved city-specific features that may bias the results. In addition, a significant portion of the literature utilizes site-specific interventions to capture the gentrification process, such as public housing demolitions or changes in zoning rules, thereby capturing highly localized effects. These factors may weaken the external validity of the findings. As a result, the literature has not yet reached an agreement on the effect of gentrification on neighborhood criminal behavior. Covington and Taylor (1989) found that rational crimes, like as robbery and theft, increased in gentrifying Baltimore neighborhoods. As highlighted by Bogges and Hipp (2016) in their study on Los Angeles areas with greater socioeconomic status increases over the 1990s, the turnover and heterogeneity that accompany gentrification create ideal conditions for a surge in crime in affected districts. Similarly, Lee (2010) reported a spike in robberies, assaults, and auto thefts in gentrified neighborhoods. He utilized the 1994 Los Angeles earthquake as a natural experiment. Property owners in damaged areas were offered low-interest loans to rebuild after the earthquake; therefore stimulating an increase in the acquisition of homes and resulting in gentrification. In addition, the association between gentrification and gun violence in Philadelphia was validated using a two-way fixed effect DiD estimator. Porreca (2023) demonstrated that, on average, gentrification increases levels of gun violence, with 21% of the city's shootings during the study frame being ascribed as results of gentrification.

Yet, some academics contend that gentrification may reduce crime by promoting economic development, reducing urban blight, providing economic prospects for the poor, and de-concentrating poverty (Economist (2018)). Hence, gentrification may result in a decrease in crime. Smith (2012), regressing gang-related killings on neighborhood demographic characteristics and an indicator for the destruction of public housing, found declines in homicides as signs of gentrification grow more common. Similarly, Aliprantis and Hartley (2015) analyzed trends in killings and police calls for service by census block in Chicago from 1999 to 2011 prior to and following the destruction of public housing units. They discovered that the closure of high-rise public housing was related with a significant decrease in crime in the surrounding blocks. Autor et al. (2019) find that after gentrification, precipitated by the end of rent control in Cambridge, Massachusetts, there had been significant decreases in the overall crime rate. Yet, it should be emphasized that Cambridge is a very small city with two prestigious universities (Harvard University and MIT), as such this is an example of how specific city trends could influence the results.

To address this issue and offer an even more substantive contribution to the field, I created a cross-cities dataset. This consists of over 3,000 neighborhoods observed between 2015 and 2019. This allows me to account for city-specific trends and obtain more precise estimates of how gentrification affects crime. By utilizing a broader and more diversified dataset that encompasses numerous metropolitan areas, I was able to incorporate city-specific trends into my estimated model. In addition, unlike earlier studies, my analysis identifies gentrification based on visible demographic features as opposed to specific interventions. This approach is more tightly linked to the investigated phenomenon and may be assessed in a wider range of settings, hence boosting the external validity of the findings. My work provides a more sophisticated view of the relationship between gentrification and crime by detecting gentrification based on demographic changes and across a panel of diverse cities.

In addition, this is the first study to assess the impact of gentrification by using the phenomenon's varying timing across areas and cities. This method allows for a more

exact assessment of the impact of gentrification on crime, as it accounts for the fact that gentrification might occur at various times and in different locations. To improve the interpretation of the results, I utilized cutting-edge staggered difference-in-differences models, such as Callaway and Sant'Anna (2021). These models provide a more precise examination of the relationship between gentrification and crime.
Lastly, my study contributes to the literature by being one of the few to apply this new literature on staggered difference-in-differences in an empirical framework (Vannutelli (2020); Henkel et al. (2022)) and by providing a more accurate and exhaustive analysis of the effects of gentrification on crime. My work makes a substantial contribution to the literature on gentrification and crime by employing this cutting-edge method and including a vast and diverse dataset.

The paper proceeds in the following way. Section 2 presents the underlying hypothesis. Section 3 describes the data for the analysis and Section 4 the empirical strategy. Section 5 presents the results from the analysis and Section 6 discuss the possible mechanism Finally, Section 7 concludes and discusses its implications.

2 Theoretical Predictions

Criminological research has predominantly examined the effects of gentrification using the social disorganization theory, which assumes that crime results from neighborhood social conditions rather than any individual characteristics of neighborhood residents, and that crime will be highest in neighborhoods with high levels of concentrated disadvantage, residential instability, and ethnic heterogeneity (Shaw and McKay (1942)). Gentrification often results in residential turnover, instability, and displacement (Guerrieri et al. (2013); Richardson et al. (2019); Kern (2022)), which disrupt social networks and social control mechanisms and can lead to an upsurge in crime rates. Gibbons et al. (2020) have shown that in gentrified areas people have a lessened sense of connection to neighbourhood community, resulting in less cooperation and support among inhabitants; this can be manifested as less effort from the community to mitigate and prevent antisocial behaviour. 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 a result, economic inequalities may increase the social distance between incumbents and new residents, diminishing social interactions (Hipp and Perrin 2009) and limiting the chance of establishing the required social relationships. Richer residents may have different perspectives and interests as a result of their future aspirations; they may also become less sensitive to shared goods and less eager to contribute to the local welfare (Boitani (2021)). Saez and Zucman (2016)) have also demonstrated that rising income inequality in the United States is accountable for increasing class divides in metropolitan areas where wealthy and poor pockets coexist. In addition, the presence of higher-income households in an area causes an increase in the cost of housing and consumer items. Gentrification can exacerbate the relative impoverishment of individuals with fewer economic resources, leading to a rise in crime rates as a result of these conditions. Research have indicated that communities with greater economic inequality have higher crime rates (Hipp (2007)), and Glaeser et al. (2009) has demonstrated that disparities in the options available to residents contribute to higher crime rates in more unequal cities.

The "rational offender" perspective provides further insight into the relationship between gentrification and criminal activity. According to scholars such as Cornish and Clarke (2009), Gul (2009), Scott (2014) potential offenders are sensitive to the availability and desirability of targets. In the context of gentrification, the influx of newcomers into a neighborhood often brings increased economic resources and valuable material possessions. This creates a greater pool of eligible targets for crimes of gain, aligning with the rational offender theory. Under the rational offender framework, it is anticipated that gentrification will be associated with an increase in offenses such as burglary, robbery, and larceny. The logic behind this expectation lies in the attractiveness of gentrified areas to potential offenders, who perceive a higher likelihood of finding lucrative targets. The increase in the number and desirability of potential targets due to gentrification may incentivize individuals to engage in property crimes as they assess the benefits of such offenses to outweigh the potential risks. By considering the rational offender theory, we gain a deeper understanding of the underlying motivations and decision-making processes that contribute to the observed correlation between gentrification and an uptick in crimes of gain, such as burglary, tehft, and larceny.

3 Data

The adopted dataset consist of a panel of 14 large cities in the United States (reported in Table A.2) and data are gathered from multiple sources. These cities has been selected across American Metropolis (urban areas with a population greater than 1 million people) and according to police data availability. To measure neighborhood boundaries consistently, I adopted the Census Tract, a widely-used measure in the literature (Guerrieri et al. (2013); Lester and Hartley (2014); Ding et al. (2016); Meltzer and Ghorbani

(2017)) that identifies homogeneous and relatively permanent statistical subdivisions of a county, covering an average of about 4,000 residents. In order to facilitate statistical comparisons from census to census, census tract boundaries are drawn with the goal of being preserved for a long time. This enables for the harmonization of data from many sources and provides a broad enough area to study crime trends. The final sample consists of 3,611 census tracts observed between 2015-2019.

The dependent variable of this study is the number of Part I crimes, which includes significant crimes that are typically reported to the police and occur frequently throughout the country (Federal Bureau of Investigation (2004)). These crimes can be categorized as either violent (aggravated assault, murder, rape, robbery) or property-related (arson, grand theft auto, burglary, theft/larceny). Crime data is obtained from either open data websites or police department websites, and data is collected individually from each city's website; Table A.2 report the sources of the data. To ensure the study's accuracy, I have collected data from various cities across the USA, focusing on cities that provide crime data with sufficient geographic granularity and a time span that aligns with the study's timeframe. In order to accurately determine the number of crimes committed in each census tract, I require datasets that provide precise location information for each criminal event. The reported locations can either be at the census tract level or in the form of geographic coordinates, allowing for exact crime localization (following the approach proposed by Picard (2015)). Furthermore, I am interested in the categorization of crimes based on FBI standards. This information enables an accurate tally of each crime occurrence and facilitates the construction of a dataset that aggregates crime statistics from different cities and years. As a result, I have successfully categorized each crime based on its occurrence date, location, and category. Consequently, the final dataset reports the yearly number of crimes for each census tract. Due to variations in data collection methods across different cities, the availability of crime data has been a crucial criterion for selecting cities for this study.

To capture the gentrification process, economic and demographic data were acquired from the U.S. Census Data, specifically from the University of Minnesota's National Historical Geographic Information System (NHGIS) (Manson et al. (2021)). This source gives access to time series data for all levels of U.S. census geography, and I used it to collect American Community Survey (ACS) data. Population factors, such as racial composition, education level, and income, as well as housing stock and market conditions, such as building age, home value, and median rent, are among the data collected for this study.

In Table A.1, descriptive statistics, including mean, standard deviations, and 25th-75th percentiles, are presented for both the dependent and independent variables gathered. In terms of both the temporal and spatial dimensions, crime statistics and census data are systematically harmonized between the various sources.

4 Empirical Strategy

4.1 Identification of gentrifying neighborhoods

Empirical research on gentrification lacks consensus regarding its definition and measurement methods. In this study, I build on the cornerstone study of Glass (1964), where gentrification was described for the first time and is defined as ”the permanent migration of upper- and middle-class professionals with high education to historically low- and working-class neighbourhoods with a subsequent substantial change in the social fabric of the neighbourhood”. Some studies focus exclusively on income changes to measure gentrification (Ellen and O'Reagan (2011)). However, Owen (2012) highlighted how this approach may not capture neighborhoods experiencing gentrification when the process is driven by residents with relatively lower incomes, such as students, recent graduates, or artists. Hence as pointed out by Glaeser et al. (2018), gentrification can be better understood by analyzing it with a multi-faceted approach. Henceforth, to classify gentrified neighborhoods, I consider both the transformation in the housing market and the shift in the economic and educational attainment of the local population. Following a wide stream of extant literature, I employ a threshold approach to identify neighborhoods that have the potential for gentrification at the start of a specific time period. Subsequently, I analyze and compare the changes that occur within these eligible neighborhoods over the designated time frame (Freeman (2005); Ding et al. (2016); Richardson et al. (2019), Richardson et al. (2020)). Hence, I define a neighborhood (n) as gentrified [1] if it meets the following criteria: **(i)** it has a starting population of at least 500 inhabitants; **(ii)** it has a median income lower than the median for that metropolitan area (MSA) at the beginning of the period; **(iii)** it has a proportion of newly built houses below the median for the respective MSA at the beginning of the period; **(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 house prices/rents during the

[1] I have made comparisons over two subsequent non-overlapping vintages of 5y ACS: 2006/10-2011/15; 2007/11-2012/16; 2008/12-2013/17 and so on

period. Criteria (i) assure that the results are not driven by an abrupt change in a unpopulated area due to just few new inhabitants; criteria (ii) identifies low income area wrt to each city and criteria (iii) ensures that these area were not already interested by any real estate investments; criteria (iv) depicts the influx of new inhabitants and ascertain it to be greater than the specific city dynamics; criteria (v) secures that the process is involving also the housing market of the neighborhood. To construct this gentrification indicator, I looked at different waves of ACS, consistently with the extant literature (Glaeser et al. (2018); Glaeser et al. (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 that the period is relatively short, it is realistic to assume that gentrified neighbourhoods do not change their status over the course of this study. In the following Robustness subsection, I also employ two different measures of gentrification in order to validate my assumptions.

Figure A.1 depicts both the gentrified neighborhoods as well as the average number of crimes committed within the observation window. The level of delinquency, as defined by the average number of crimes committed over the full period of my study, is represented by the varying hues of blue; the deeper the color, the higher the crime rate. The red dots indicate all of the neighborhoods that have been designated as gentrified during the span of the study, therefore accounting for all five distinct cohorts of gentrified neighborhoods. A visual examination demonstrates a correlation between gentrification and an increase in the neighborhood's crime rate. In fact, gentrified areas tend to coincide with those that have the greatest crime rates. This first piece of evidence establishes the foundation for the subsequent analysis.

4.2 Estimation Model

The baseline specification to identify the relationship between gentrification and criminal activity would be a two-way fixed effect differences-in-differences model. City tracts gentrify independently of one another across time and cities. Exploiting this variation provides an ideal setting from which to estimate gentrification's impact on crime. The estimated equation would be:

$$Crime_{it} = \alpha + \beta_1(\mathit{Gentrification}_{nt}) + \tau_t + \eta_n + \epsilon_{it} \tag{1}$$

where the variable Gentrification identifies treated neighbourhood [n] at time [t][2] and in the estimation are included both time fixed effects (τ) and neighbourhood fixed effects (η).

However, the application of Specification (1) without considering the empirical problems highlighted by recent literature on two-way fixed effects estimators with staggered adoption, such as De Chaisemartin and D'Haultfœuille (2017) and Goodman-Bacon (2021), can introduce several issues. One crucial concern is related to the weights assigned to the treated and control units in the estimation of β in Equation 1. In the case of treatment roll-out, some units in the sample have already been treated, and they now serve as controls for the remaining untreated units. However, these weights can potentially be negative, which can harm the identification strategy and introduce biases. This situation arises because the treated units may exhibit treatment effects that are different from the average treatment effect or the treatment effect on the treated.

This bias can arise due to the presence of heterogeneous treatment effects across the units in the sample. Ignoring this heterogeneity and solely relying on the two-way fixed effects estimators can lead to misleading results. Therefore, it is crucial to consider alternative methods or strategies that account for this potential bias and provide more robust and accurate estimates.

The growing literature on this topic has proposed various approaches to address the challenges posed by staggered adoption and heterogeneous treatment effects; hence I implement the model proposed by Callaway and Sant'Anna (2021) to strengthen my results. To do so, I estimate the following event study specification:

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

The dependent variable is the Inverse Hyperbolic Sine transformation of the number of committed crimes, adopted to be able to interpret the treatment effect as an elasticity and to deal with the large right tale of crime data (Bellemare and Wichman (2020))[3]. $Gentrification_{nc}$ is a dummy that takes the value of 1 if the neighborhood [n] 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 periods after (or before) the treatment. The coefficients of interest are the γ_k, measuring the change in outcomes of treated neighbourhood k years after treatment, compared with the change in outcomes of control neighbourhood. To figure out what the coefficient means in terms of causality, it has to be true that the treated and control units

[2]it is similar to the canonical DiD [Treat x Post] variable

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

are basically comparable. Specifically, it must hold 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 periods, I include neighbourhood (η) and time (τ) fixed effects. Thus, the inclusion of FEs control for fixed differences between treated and control units and for aggregate fluctuations. Moreover, the inclusion of city fixed effects (ζ) interacted with year dummies, allows me to control also for possible city trends that can bias the estimations. Lastly, the matrix X_i of interactions between the vector of control variables [4] at their 2010 value and year dummies allows me to mitigate issue related to the existence of differential trends related to these characteristics. Moreover, it allows for differential trends by initial characteristics.

4.3 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 gentrification 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 A.2 I examine whether outcomes exhibit parallel trends in the pre-treatment period. It can be observed that the estimated effects for the periods before treatment are not statistically significant; this is in favour of the presence of parallel pre-trend, thus corroborating the common trend assumption. The depicted estimated coefficients provide positive evidence in favor of the comparability of outcomes and, in turn, the reliability of the estimations. 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 A.3, indicate that there is no particular variable that has consistent predictive power among different cohorts, except for the share of the white population. Therefore, I control for differential trends by initial characteristics by including baseline (measured in 2010) characteristics-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 estimates. Moreover, another possible concern is that there are other processes happening at the same time of gentrification than can mislead my results. In order to take into account this issue, in a specification of my estimates I have also included linear neighbourhood trend[5]. This strategy allows me to take into account unobserved transformations occurring at the neighbourhood level and

[4] population, %female, %young, %wht, Gini index

[5] namely [$census\ tract_n$] * [$time_t$]

so to disentangle the effect of eventual contemporaneous processes.

5 Estimation Results

The results of the estimation of Equation (2) are obtained by adopting Callaway and Sant'Anna (2021) model and are reported in Figure A.2 and in Table A.4. The estimated coefficients report an increase ranging between 11% and 17% of crimes in gentrified neighborhoods. The most significant reduction in the coefficient's magnitude occurs in column 3 of Table A.4, when city-specific trends are included in the analysis. This result highlights the importance of controlling for different city dynamics and unobservable characteristics in the analysis, further emphasizing the need for a multi-city analysis to obtain a precise estimation of gentrification effects. In contrast, the inclusion of controls does not significantly alter the results. On top of that, the Callaway and Sant'anna model allows to include different control groups, and so I have tested the robustness of results by adopting not yet treated units as controls in columns 1 to 4, hence only those neighbourhood that gentrified in a different, successive period, and never treated units as controls in column 5; results are similar and show an increase of 11% of the number of crimes. In column 4 I have included also linear neighbourhood trends, to deal with the possibility of other unobserved processes occurring at the same time; the estimated coefficient is stable e mantains its significance. The dynamic results show that the effect of gentrification on criminal activity decreases over time. The staggered treatment timing difference-in-differences estimator used in this study is based on the idea that the control and treatment groups were moving in the same direction before the treatment. I have provided evidence in the form of non-significant pre-treatment coefficients in Figure A.2. The assumption of common pre-trends is not violated, since none of the pre-treatment coefficients is significant at the 95% confidence level; this is an evidence in favour of the common trend assumption. Given the main dependent variable is the inverse hyperbolic sine transformation of crime is important to study whether the overall population is increasing. The main concern here is that gentrification may lead to an increase in the number of people living in a neighborhood and this would mechanically increase the number of crimes. In order to verify that this is not the case, I estimated Equation (2) with the tract population as dependent variable and in Table A.5 results are reported. It is possible to notice how the change in population is really small and not statistically significant. These are evidences that the tract's population is not subject to abrupt change; hence the increase in criminal activity is not due to a greater number of people.

5.1 Robustness tests

To validate the robustness of the previous results, various models were used for the staggered Difference in Differences analysis. Figure A.3 presents and compares the estimated dynamic coefficients for Equation (2) using models developed by Callaway and Sant'Anna (2021), Borusyak et al. (2022), De Chaisemartin and D'Haultfœuille (2020), Sun and Abraham (2020). These models provide alternative instruments to address issues related to event studies with standard Two-way Fixed Effects models, and all their results show a positive and statistically significant effect of gentrification, consistent with the baseline findings. Moreover, also the magnitude of the coefficients is similar among all the estimations, thus corroborating the validity of the results.

Also, the results of the estimation of Equation (1) are presented in Table A.6 from the Appendix, with the three columns reflecting an increasing number of fixed effects and controls. The outcomes demonstrate a uniform magnitude and significance across all specifications. The increase in crime rates ranges from 8% to 17% and is statistically significant under all settings. The magnitude of the coefficients estimated by OLS TWFE is smaller than the baseline results, in line with Goodman-Bacon (2021). This is because the bias created by dynamic treatment effects pushes the estimates closer to zero away from the true parameter; thus meaning not only is TWFE biased, but it's biased towards zero. In addition, I demonstrate that my findings are independent of the presence of any particular city in the sample. In Table A.7, I estimate Eq. (2) by eliminating the city indicated in each column from the sample. I find the predicted coefficients to be extremely steady and statistically significant, ruling out the notion that our findings are dependent on a single outlier city. Henceforth, I can assure that my results are not driven by particular model specification nor by specific sample issues thus strengthening the validity of the findings.

The stable unit treatment value assumption (SUTVA) is essential for the identification in the difference-in-differences framework; it requires that the gentrification of a single tract has no influence outside the neighbourhood itself. If gentrification had the impact of fostering shifts in criminal behaviour in adjacent areas, the treatment effect estimator would be biased. I conduct a placebo test to determine the validity of SUTVA and the trustworthiness of the results. The dependent variable was built using crime rates in neighbouring non-treated neighbourhoods: i) I identified the surrounding neighbourhoods for each tract in my sample; ii) I only included non-treated adjacent neighbourhoods; and iii) for each tract, I calculated the average number of crimes committed in adjacent neighbourhoods that did not undergo gentrification. The findings of the placebo test, which are shown in Table A.8 in the Appendix, indicate that the coefficient for gentrification is marginally positive and not statistically significant under any specification. These findings indicate that gentrification neither displaces criminals into surrounding communities nor has an effect on non-gentrified areas. The criminogenic effect of gentrification appears to be extremely localised, consistent with other research indicating that crime typically occurs near the offender's house. The findings from Kirchmaier et al. (2022) indicate that the high cost of travel has a substantial deterrent effect on offenders, which is consistent with the conclusions reported in Table A.8.

Moreover, it is worth analysing the effect of gentrification adopting a continuous measure in order to verify whether the results are not driven only by the extensive margin of the main specification, as developed by Glaeser et al. (2023) and Porreca (2023) . Hence, I build this index in order to model the fact that the greater influx of new educated inhabitants in poorer tract results in higher measure of gentrification.

$$Gentrification\ index = (median\ income\ rank) * (\%\ graduate\ increase) \tag{3}$$

Where the median income rank is the inverse percentile (100 - pct)[6] of median income at the beginning of the period and it is multiplied by the percentage increase in the share of college graduates. This index is increasing in both its component, hence gentrification is stronger whether there is a greater influx of new more educated residents in former poorer neighbourhood. To estimate the effect of gentrification on crime adopting this index I adopted a standard OLS fixed effects model, whose results are reported in the first three columns of Table A.9. Gentrification still has a positive and statistically significant impact on tract's crimes. Lastly, I constructed an alternative binary indicator that differs from the one adopted in the baseline. To build it, I adopt the same 5 criteria from section 4.1 but criteria (i) - (iii) are not rolling and always measured in 2010. Hereafter, I replicate my baseline estimation model and columns (4) and (5) of Table A.9 displays the results.

5.2 Different Type of Crimes

In order to acquire a better knowledge of the real effects of gentrification and to discover potential mechanisms for the criminogenic effect, I computed Equation (2) for each type of Part I crime. This methodology enables me to separate the impact of gentrification on various types of crime.

Table A.10 displays the estimated coefficients using the Callaway and Sant'anna model.

[6]this means that a tract whose median income is in the 20th pct of its city will have a rank of 100-20=80, meaning that is below the 80% of all the other tract of the city

Figure A.4 and Figure A.5 show dynamic coefficients for violent and property crimes respectively. The coefficients' magnitude and significance are consistent across all models. For violent crimes, only robbery exhibited a statistically significant increase, whilst the assault coefficient is just marginally significant. When controlling for pre-treatment from Figure A.4, the presence of paralell pre-trends is evidence in support of the common trend assumption. On the other hand, there were statistically significant increases in property offences across the board. Grand theft auto (GTA), burglary, and theft exhibited the steepest increases, ranging from 14 to 16 percent. By examining the pre-treatment coefficient from Figure A.5, it is evident that there were no discernible differences in the dynamics of property crimes prior to the occurrence of gentrification. This provides support for the parallel trend assumption, hence enhancing the causal interpretation of the coefficients. These increases in property crime points support the rational offender viewpoint. The in-movers introduce new lifestyles and all the related items, hence enhancing the value of their possessions and dwellings (Kern (2022)). Hence, the influx of new residents increases the quantity and quality of prospective property crime targets.

A possible treat is that only reported offences can be counted when working with crime statistics, and these might not correctly reflect the true crime rate in a specific location. To overcome this issue, I limited my analysis to Part I crimes, which are far less likely to be underreported than other types of crimes. In addition, the fact that there has been an increase in auto theft bears to the argument that the rise in crime is not attributable to underreporting. GTA is the most unlikely case of a property crime remaining unreported to the authorities (Bureau of Justice Statistics). This is due to two factors: first, motor vehicles are registered under their respective owners' names, making them accountable for any tickets or fines, as well as any criminal activity involving the vehicle. Hence, the owners have a compelling reason to report the theft to the authorities as soon as possible in order to avoid any legal consequences that may follow from the crime. Second, as opposed to any other sort of personal property, it is more common practise to insure a motor vehicle against loss or theft. In order to collect the insurance payment, the crime must be reported to the police, which dramatically reduces the frequency of underreporting. Since the rise in the number of other crimes is comparable to that of auto theft, underreporting may also be a minor source of bias in these data. Nonetheless, the 14 percent increase in GTA might be interpreted as gentrification's minimum effect on crime. McCollister et al. (2010) asses the financial impact that individual criminal activities have on American society as a whole, and determined Grand Theft Auto to be the property crime that causes the most economic harm, with an estimated loss of over $10,000 for every episode. Even taking into account the rise in GTA alone, there are significant consequences and costs for the entire population of the neighbourhood; this highlights the importance of these results in order to comprehend and manage the neighbourhood transformations.

6 Mechanism

The analysis reveals a positive association between gentrification and criminal activity in neighborhoods, particularly regarding property crimes. This finding suggests that offenses such as theft, burglary, and vandalism contribute significantly to the observed increase in crime. The implications of this result align with the rational offender theory, which posits that individuals engage in criminal behavior after carefully considering the potential benefits and costs. According to this theory, if the perceived benefits of committing a crime outweigh the expected costs, individuals are more likely to engage in criminal activities. In the context of gentrification, as neighborhoods undergo revitalization and experience an increase in property values, there is a corresponding rise in the number of attractive targets for property crimes. Offenders may find the benefits of such offenses outweigh the perceived risks or costs. Since grand theft auto (GTA) is among the least under-reported crimes and the estimated results are highly reliable, I focused on this kind of property crime to depict the possible mechanism that drives the increase in criminal activity. To examine this mechanism, I constructed a proxy measure for the increase in the quality and quantity of potential targets for GTA. I leveraged the evidence that electric vehicles (EVs) are typically more expensive than traditional vehicles, with an average price premium of almost 25% (The New York Times (2023)). Moreover, the price distribution of EV is more skewed towards higher prices; thus it is more common to observe higher value EV than traditional cars. Additionally, the used market for EVs is less developed and widespread. Thus, an increase in the number of EVs can be considered an indicator of more valuable targets for GTA. Although I do not have precise data on the exact number of EVs in a specific neighborhood, I used the number of EV chargers in each census tract as a proxy. I have followed anecdotical evidences and knowledge (Walling (2023), Forbes (2021), The Washington Post (2021)) that highlight how EV and their chargers are less widespread in low income and black areas, thoroughly becoming sign of gentrification. To gather data on EV chargers, I utilized the U.S. Department of Energy's Alternative Fuels Data Center, which provides comprehensive information on the precise locations of chargers, including latitude and longitude.

Hence, I estimated Equation 2 with the logged number of EV chargers per 10,000 adult individuals as the dependent variable. The results are shown in Table A.11 and demonstrate a positive relationship between gentrification and the presence of EV chargers in a given census tract. This provides suggestive evidence that, as a consequence of gentrification, there is an increase in the value and density of vehicles in the area. This, in turn, likely makes these targets more appealing for criminal activities, particularly those related to property crimes such as GTA. By recognizing the rational offender theory as the driving force behind these results, I gain insight into the underlying mechanisms that contribute to the observed increase in criminal activity during the process of gentrification.

7 Conclusion

Since the gloomy days of the 1970s and 1980s, several metropolitan centres have undergone remarkable resurgences. This turnaround has reintroduced economic growth to areas in which it was absent for a while. It has also posed challenges for people who could not afford the rising rents and costs of living that typically accompany gentrification, leading to economic hardship and a weakening of social bonds. This paper examines whether a rise in criminal behaviour is occurring in communities undergoing this change. To do so I built an unique cross-city dataset to improves the external validity of the findings, making them more applicable to other cities . Using a DiD with dynamic treatment effects, these results are robust to varying model assumptions. In particular, local criminality increases by up to 12 percent (about 18 more crimes in the typical census tract). This increase is centred in property crimes; in fact, GTA and burglary exhibit the greatest increase, approximately 16 percent. There are indications that the rise in crime does not spread to adjacent, non-gentrifying neighbourhoods. The dynamic estimation indicates that the criminogenic effect is decreasing. It is crucial to emphasise, however, that the results are confined to a short-term examination, as standardised crime data are not yet publicly accessible. In light of this, it would be beneficial to undertake a follow-up study once further data becomes available in order to account for longer-term effects and any potential shifts in dynamics. In light of these findings, urban policymakers and planners must develop and implement urban interventions with the health and safety of the entire urban fabric in mind. As gentrification continues to expand across the globe, it is essential to analyse its possible effects on the social and economic fabric of areas to ensure that urban solutions are successful and equitable.

References

Aliprantis, D. and D. Hartley (2015). Blowing it up and knocking it down: The local and city-wide effects of demolishing high concentration public housing on crime. *Journal of Urban Economics*.

Autor, D. H., C. J. Palmer, and P. A. Pathak (2019). Ending rent control reduced crime in cambridge. *AEA Pap. Proc.*

Baum-Snow, N. (2007). Did highways cause suburbanization? *The Quarterly Journal of Economics*.

Bellemare, M. F. and C. J. Wichman (2020). Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*.

Bogges, L. N. and J. R. Hipp (2016). The spatial dimensions of gentrification and the consequences for neighborhood crime. *Justice Quarterly*.

Boitani, A. (2021). *L'illusione liberista*. Laterza.

Borusyak, K., X. Jaravel, and J. Spiess (2022). Revisiting event study designs: Robust and efficient estimation. *CEPR Discussion Papers*.

Boustan, L. P. (2010). Was postwar suburbanization "white flight"? evidence from the black migration. *The Quarterly Journal of Economics*.

Boustan, L. P., R. A. Margo, M. Miller, J. Reeves, and J. Steil (2019). Does condominium development lead to gentrification?

Callaway, B. and P. H. Sant'Anna (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*.

Cornish, D. and R. Clarke (2009). Understanding crime displacement: an application of rational choice theory.

Couture, V. and J. Handbury (2020). Urban revival in america, 2000 to 2010. *Journal of Urban Economics*.

Covington, J. and R. B. Taylor (1989). Gentrification and crime: Robbery and larceny changes in appreciating baltimore neighborhoods during the 1970s. *Urban Affairs Review 25*.

Curci, F. and F. Masera (2023). Flight from urban blight: Lead poisoning, crime, and suburbanization. *The Review of Economics and Statistics*. Accepted.

De Chaisemartin, C. and X. D'Haultfœuille (2017). Fuzzy differences-in-differences. *Review of Economic Studies*.

De Chaisemartin, C. and X. D'Haultfœuille (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*.

Ding, L., J. Hwang, and E. Divringi (2016). Gentrification and residential mobility in Philadelphia. *Regional Science and Urban Economics 61*(C), 38–51.

Economist (2018). In praise of gentrification. *The Economist*.

Ellen, I. G. and K. O'Reagan (2011). Who gentrifies low-income neighborhoods? *Regional Science and Urban Economics 41*, 89–97.

Federal Bureau of Investigation (2004). Crime in the united states - uniform crime reports.

Florida, R. (2017). *The New Urban Crisis*. Basic Books.

Forbes (2021). Communities and governments want fair playing field in ev charging.

Freeman, L. (2005). Displacement or succession? residential mobility in gentrifying neighborhoods. *Urban Affair Reviews*.

Gibbons, J., M. S. Barton, and T. T. Reling (2020). Do gentrifying neighbourhoods have less community? evidence from philadelphia. *Urban Studies 57*(6), 1143–1163.

Glaeser, E. L., H. Kim, and M. Luca (2018). Nowcasting gentrification: Using yelp data to quantify neighborhood change. In *AEA Papers and Proceedings*, Volume 108, pp. 77–82.

Glaeser, E. L., M. Luca, and E. Moszkowski (2020). Gentrification and neighborhood change: Evidence from yelp. Working Paper w28271, National Bureau of Economic Research.

Glaeser, E. L., M. Luca, and E. Moszkowski (2023). Gentrification and retail churn: Theory and evidence. Working paper, National Bureau of Economic Research.

Glaeser, E. L., M. Resseger, and K. Tobio (2009). Inequality in cities. *J. Regional Sci. 49*.

Glass, R. L. (1964). *London: Aspects of Change*. MacGibbon & Kee.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics 225*, 254–277.

Guerrieri, V., D. Hartley, and E. Hurst (2013). Endogenous gentrification and housing-price dynamics. Working Paper 13-05, Federal Reserve Bank of Cleveland.

Gul, S. (2009). An evaluation of rational choice theory in criminology.

Henkel, M., E. Kwon, and P. Magontier (2022). The unintended consequences of post-disaster policies for spatial sorting. Technical report, MIT Working Paper Series.

Hipp, J. (2007). Income inequality, race, and place: Does the distribution of race and class within neighborhoods affect crime rates?

Kern, L. (2021). *Feminist City: Claiming Space in a Man-made World*. Verso.

Kern, L. (2022). *Gentrification Is Inevitable and Other Lies*. BTL Books.

Kirchmaier, T., M. Langella, and A. Manning (2022). Commuting for crime. *R&R at The Economic Journal*.

Lee, Y. (2010). Gentrification and crime: Identification using the 1994 northridge earthquake in los angeles. *Journal of Urban Affairs 32*, 49–61.

Lester, T. W. and D. Hartley (2014). The long term employment impacts of gentrification in the 1990s. *Regional Science and Urban Economics 46*, 79–93.

MacDonald, J. M. and R. J. Stokes (2020). Gentrification, land use, and crime. *Annual Review of Criminology 3*, 195–214.

Manson, S., J. Schroeder, D. Van Riper, T. Kugler, and S. Ruggles (2021). *IPUMS National Historical Geographic Information System: Version 16.0*. Minneapolis, MN: IPUMS.

McCollister, K. E., M. T. French, and H. Fang (2010). The cost of crime to society: new crime-specific estimates for policy and program evaluation. *Drug and alcohol dependence 108*.

Meltzer, R. and P. Ghorbani (2017). Does gentrification increase employment opportunities in low-income neighborhoods? *Regional Science and Urban Economics 63*, 13–25.

Owen, A. (2012). Neighborhoods on the rise: A typology of neighborhoods experiencing socioeconomic ascent. *City Community 11*, 345–369.

Perez, G. (2004). *The near northwest side story: Migration, displacement and Puerto Rican families*. Berkeley, CA: University of California Press.

Picard, R. (2015). Geoinpoly: Stata module to match geographic locations to shapefile polygons.

Porreca, Z. (2023). Gentrification, gun violence, and drug markets. *Journal of Economic Behavior and Organization*.

Richardson, J., B. Mitchel, and J. Franco (2019). *Shiftings Neighbourhood: Gentrification and cultural displacement in American cities*. NCRC.

Richardson, J., B. Mitchel, and J. Franco (2020). *Gentrification and Disinvestments*. NCRC.

Saez, E. and G. Zucman (2016). Wealth inequality in the united states since 1913: evidence from capitalized income tax data. *Q. J. Economics*.

Scott, M. (2014). *The Reasoning Criminal: Rational Choice Perspectives on Offending*. Routledge.

Semi, G. (2015). *Gentrification*. Il Mulino.

Shaw, C. R. and H. D. McKay (1942). *Juvenile delinquency and urban areas*. University of Chicago Presss.

Smith, C. M. (2012). The influence of gentrification on gang homicides in chicago neighborhoods, 1994 to 2005. *Crime Delinquency*.

Sun, L. and S. Abraham (2020). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*.

The New York Times (2023, February). Electric vehicle prices expected to decrease according to New York Times article. *The New York Times*.

The Washington Post (2021, December). Ev charging deserts leave black communities unconnected. *The Washington Post*.

Vannutelli, S. (2020). From lapdogs to watchdogs: Random auditor assignment and municipal fiscal performance in italy. *Review of Economics and Statistics*.

Walling, M. (2023). Ev charging stations multiply, but are often out of reach for disadvantaged populations. *& the West, Stanford University*.

Appendix

A Tables and Figures

Table A.1: 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
Adult Population	2594	1320	1675	3311
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			

Note: The table reports the mean, the standard deviation and 25th and 75h percentiles for all variables. Descriptive statistics are on the full sample of census tracts. The sample is a panel of neighbourhoods over years. Panel A: number of crimes committed. Panel B: tract characteristics adopted as controls.

Table A.2: Crime Data Sources

City	Website
Austin	*https://data.austintexas.gov/Public-Safety/Crime-Reports/*
Boston	*https://data.boston.gov/dataset/crime-incident-reports*
Chicago	*https://www.chicago.gov/city/en/dataset/crime.html*
Los Angeles	*https://data.lacity.org/Public-Safety/Crime-Data*
Milwaukee	*https://data.milwaukee.gov/dataset/wibr*
Minneapolis	*https://opendata.minneapolismn.gov/datasets/cityoflakes::crime-data*
New Orleans	*https://nopdnews.com/transparency/policing-data/*
Philadelphia	*https://data.phila.gov/visualizations/crime-incidents*
Pittsburgh	*https://pittsburghpa.gov/publicsafety/crime-data*
Portland	*https://www.portland.gov/police/open-data/crime-statistics*
San Francisco	*https://www.sanfranciscopolice.org/stay-safe/crime-data/crime-reports*
Seattle	*https://data.seattle.gov/Public-Safety/SPD-Crime-Data*
Tucson	*https://policeanalysis.tucsonaz.gov/*
Washington	*https://opendata.dc.gov/datasets/DCGIS::crime-incidents*

Note: The table reports the source of crime data for each city in the dataset. Crime data are collected by each police department and are usually shared through official website Open Data portals or directly on the PD website.

Table A.3: 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

Note: 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 A.4: Estimation of Callaway and Sant'anna

Dependent Variable: IHS Tot Crime

	(1)	(2)	(3)	(4)	(5)
Gentrification	0.178***	0.18***	0.123***	0.16***	0.11**
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Observations	16,600	16,600	16,600	16,600	16,600
census tract FE	YES	YES	YES	YES	YES
year FE	YES	YES	YES	YES	YES
City#year	NO	YES	YES	YES	YES
Controls$_{2010}\#year$	NO	NO	YES	YES	YES
Neighbourhood trend	NO	NO	NO	YES	NO
Control group	not yet	not yet	not yet	not yet	never

Note: The table reports 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. In the first column are included in the estimation census tract and year fixed effects; in the second column also city-by-year are included; in the third also initial characteristics times year; in the fourth colum are included also linear neighbourhood trend. The first four columns report the estimation adopting not yet treated units as control group, the fourth column adopt never treated units as control group. SE in brackets clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1

Table A.5: The impact of gentrification on neighbourhood adult population

Dependent Variable: Tract adult population

	(1)	(2)	(3)
Gentrification	6.73	5.09	3.48
	(7.41)	(7.47)	(7.93)
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

Note: The dependent variable is the neighbourhood's population. In the first column are included in the estimation census tract and year fixed effects; in the second column also city-by-year are included; in the third also initial characteristics times year. SE in brackets clustered at the tract level.
** p<0.01, ** p<0.05, * p<0.1

Table A.6: The impact of gentrification on crime - Eq(1)

Dependent Variable: IHS Tot Crime

	(1)	(2)	(3)	(4)
Gentrification	0.17***	0.09**	0.08**	0.07*
	(0.04)	(0.04)	(0.03)	(0.04)
Observations	18,055	18,055	18,055	18,055
census tract FE	YES	YES	YES	YES
year FE	YES	YES	YES	YES
City#year	NO	YES	YES	YES
Controls$_{2010}\#year$	NO	NO	YES	YES
Neighbourhood trend	NO	NO	NO	YES

Note: This table reports results for estimation of Eq(1). The dependent variable is the IHS transformation of the number crimes committed the neighbourhoods. In the first column are included in the estimation census tract and year fixed effects; in the second column also city-by-year are included; in the third also initial characteristics times year. SE in brackets clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1

Table A.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
$\text{Controls}_{2010}\ \#year$	YES	YES	YES	YES	YES	YES	YES

Note: This table reports the estimation results of Eq(2) and the dependent variable is the IHS tranformation of the number of total crimes. Each column report results 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 as long as city-by-year FE and initial charactaristic times year interactions. Ronust SE in brackets clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1

Table A.8: 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

Note: The table reports the estimation adopting as dependent variable the IHS tranformation of the number crimes committed in adjacent not-gentrified neighbourhoods. Results obtained following Callaway and Sant'Anna (2021). In the first column are included in the estimation census tract and year fixed effects; in the second column also city-by-year are included; in the third also initial characteristics times year.. SE in brackets clustered at the tract level. *** p<0.01,** p<0.05,* p<0.1

Table A.9: Alternative measures of gentrification's effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	IHS(crime)					n° crimes	
	0.015**	0.012**	0.0002**	0.06*	0.08**	7.64***	9.65***
	(0.006)	(0.005)	(0.0001)	(0.03)	(0.03)	(2.28)	(2.40)
Observations	17,699	17,687	17,687	16,600	16,600	16,600	16,600
continuous gentri	YES	YES	YES	NO	NO	NO	NO
fix gentri	NO	NO	NO	YES	YES	NO	NO
baseline gentri	NO	NO	NO	NO	NO	YES	YES
census tract FE	YES	YES	YES	YES	YES	YES	YES
year FE	YES	YES	YES	YES	YES	YES	YES
City#year	NO	YES	YES	YES	YES	NO	YES
$\text{Controls}_{2010}\#year$	NO	YES	YES	NO	YES	NO	YES
Population Control	NO	NO	NO	NO	NO	YES	YES

Note: The table reports the estimated results adopting alternative gentrification measures and crime measurement. Columns (1) - (3) displays estimations of an OLS TWFE regression where the explanatory variable is a continuous measure of gentrification; in the first two columns the continuous indicator has been standardized (*mean*: 2.32e-10; *std. dev.*: 1); in the third column the continous measure is adopted as is (*mean*: 10.7; *std. dev.*: 41.2). Columns (4) and (5) report the estimates of Eq(2) with a binary indicator measured with a fixed vintage of ACS. Column (6) and (7) reports the estimate of Eq(2) adopting as dependent variable the actual count of crime instead of the IHS transformation and including the tract population as control. SE in brackets clustered at the tract level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.10: The impact of gentrification on different kind of crimes

Dependent Variable:	*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

Note: This table reports the results of estimation on Eq(2) adopting as dependent variable the IHS tranformation of the number of each kind of crime; columns heading distinguish which crime is considered in the estimation. Results obtained following Callaway and Sant'Anna (2021). All specifications include census tract, year and city-by-year FE, as long as initial characteristic times year interactions. Robust SE in brackets clustered at the tract level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

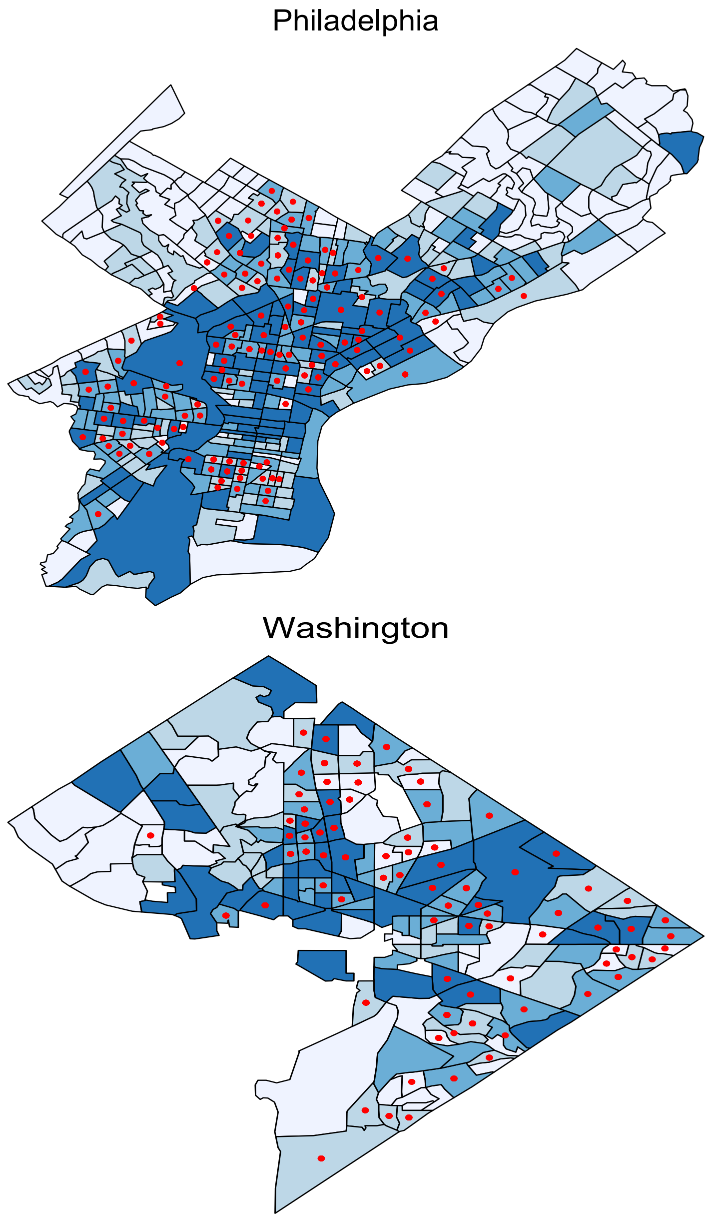
Table A.11: The impact of gentrification on EV

Dependent Variable: EV charger

	(1)	(2)	(3)
Gentrification	0.0024**	0.0025**	0.0021**
	(0.001)	(0.001)	(0.00)
Mean	.2749	.2749	.2749
Observations	16,484	16,484	16,484
census tract FE	YES	YES	YES
year FE	YES	YES	YES
City#year	NO	YES	YES
Controls$_{2010}\#year$	NO	NO	YES

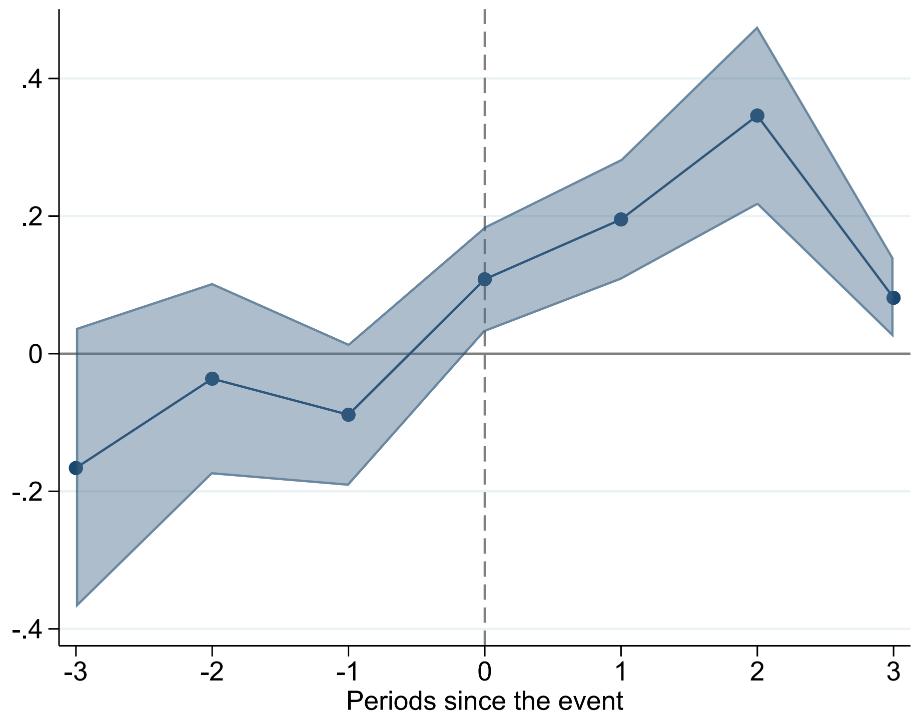
Note: The dependent variable is the logged number of EV Charger per 10,000 people. In the first column are included in the estimation census tract and year fixed effects; in the second column also city-by-year are included; in the third also initial characteristics times year. SE in brackets clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1

Figure A.1: Gentrification and crime across Philadelphia and Washington



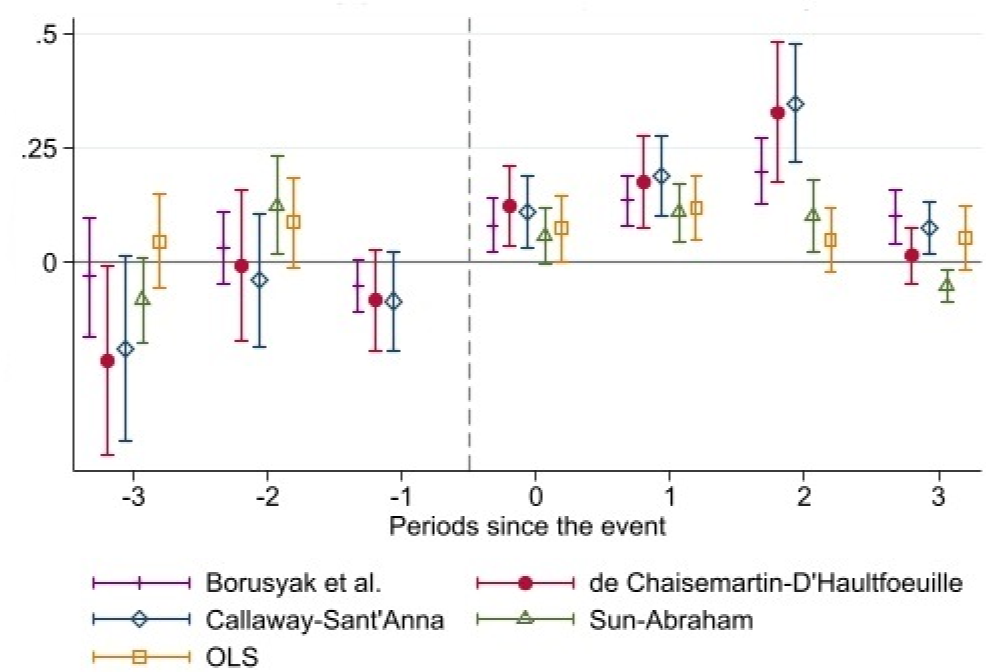
Note: The figure shows the geographical distribution of criminal activity and gentrification across Philadelphia and Pittsburg. Blue shaded areas represent the number of crime; the darker the area, the greater the number of committed crimes in that neighbourhood. Red dots identify which neighbourhood gentrified over the entire period of the study.

Figure A.2: Event Study Plot of Gentrification Effect on Crime



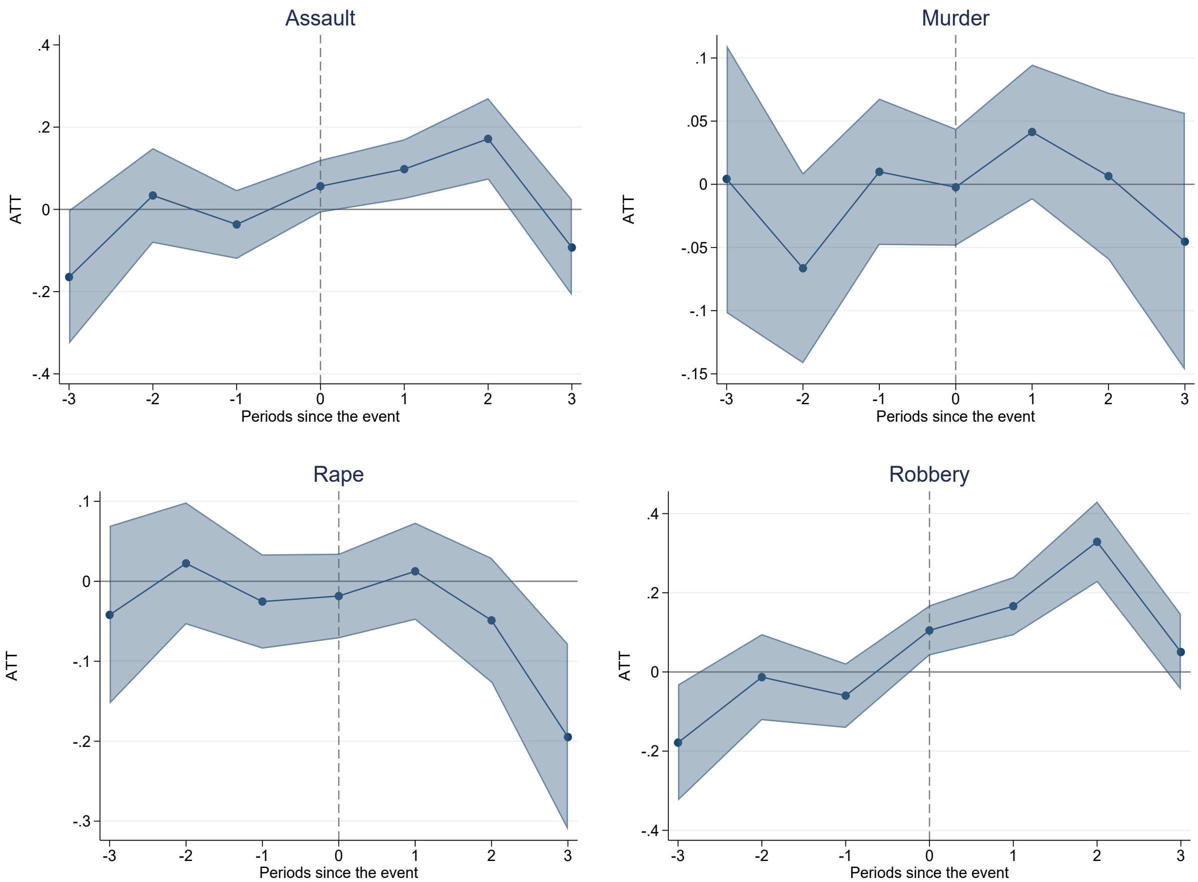
Note: The figure shows estimated treatment effects from the gentrification of a tract on ihs number of all crimes committed, employing Callaway and Sant'Anna (2021); The blue area show the estimated 95% confidence intervals, based on standard errors clustered on census tracts; the model include all kind of FE and city trends; horizontal ax shows the treatment timing, so that t=0 correspond to the first period in which a tract results gentrified and positive values correspond to post-treatment periods. In Callaway and Sant'Anna model there is no explicit base line or omitted category since it estimates the effects is using all good 2x2 designs; hence for periods after treatment, the effect is: E(DY|t)-E(DY|g-1) (eg. the last period before first treatment); for periods before treatment: E(DY|t)-E(DY|t-1).

Figure A.3: Comparison of Event Study Plot



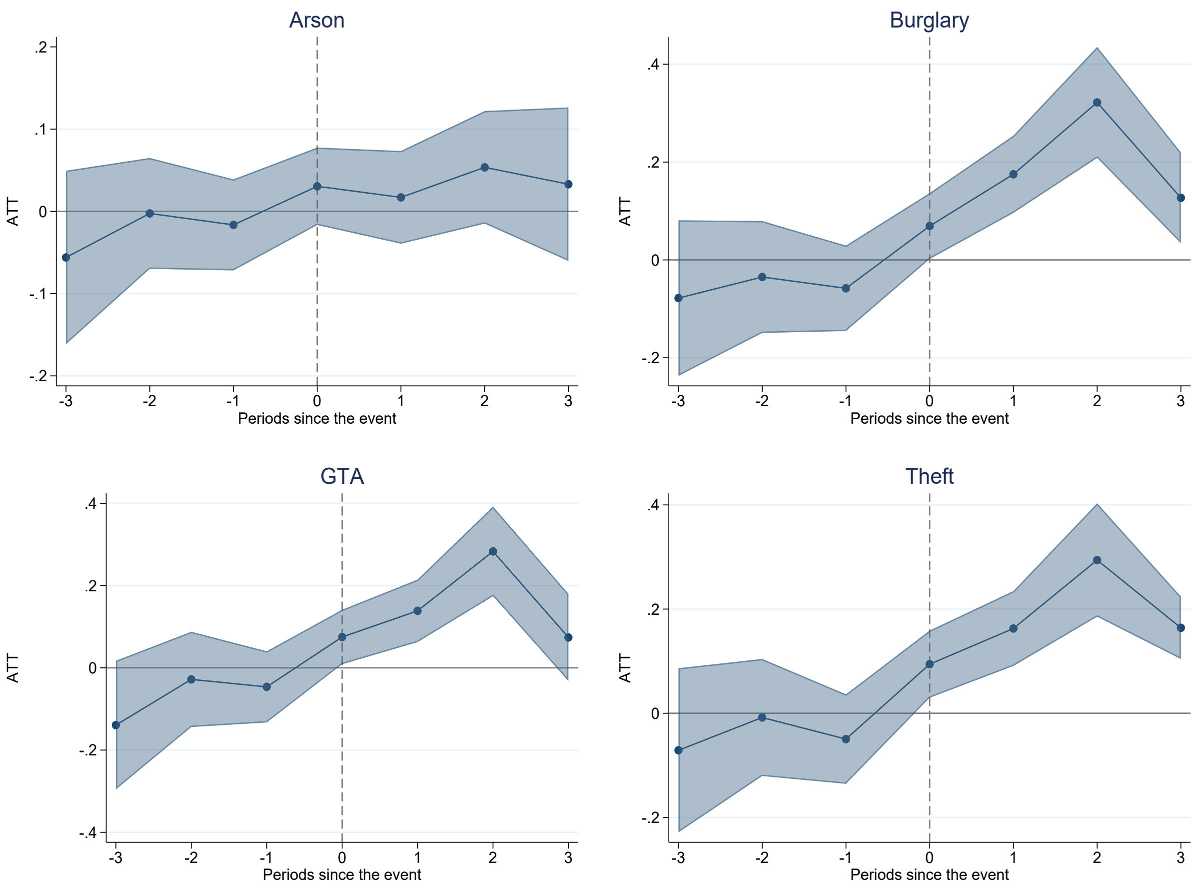
Note: The figure shows estimated treatment effects from the gentrification of a neighbourhood on ihs number of all crimes committed adopting different event study models; the vertical lines show the estimated 95% confidence intervals, based on standard errors clustered on census tracts; all the models 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.

Figure A.4: Event Study analysis for Violent Part I Crimes



Note: The figure shows estimated treatment effects from the gentrification of a neighbourhood on IHS number of violent crimes committed employing Callaway and Sant'Anna (2021); 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.

Figure A.5: Event Study analysis for Property Part I Crimes



Note: The figure shows estimated treatment effects from the gentrification of a neighbourhood on IHS number of property crimes committed employing Callaway and Sant'Anna (2021); 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.