NYU Furman Center

Has Falling Crime Invited Gentrification?

Ingrid Gould Ellen, Keren Mertens Horn, and David Reed
July 2019

This work was supported by the Annie E. Casey Foundation and the Open Society Foundations.

furmancenter.org

Has Falling Crime Invited Gentrification?

Ingrid Gould Ellen [a]
Keren Mertens Horn [b]
Davin Reed [c]

July 2019

[a] Wagner Graduate School of Public Service, New York University, The Puck Building, 295 Lafayette St., New York, NY 10012, USA

[b] Department of Economics, University of Massachusetts Boston, 100 Morrissey Blvd, Boston, MA 02125, USA

[c] Federal Reserve Bank of Philadelphia, Community Development and Regional Outreach Department, 10 N Independence Mall, Philadelphia, PA 19106, USA

Email addresses: ingrid.ellen@nyu.edu (I.G. Ellen), keren.horn@umb.edu (K. M. Horn), davin.reed@phil.frb.org (D. Reed)

The research in this paper was conducted while the authors were Special Sworn Status researchers of the U.S. Census Bureau at the New York Census Research Data Center. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau, the Federal Reserve Bank of Philadelphia, or the Federal Reserve System. All results have been reviewed to ensure that no confidential information is disclosed. This work was supported by the Annie E. Casey Foundation and the Open Society Foundations.

Abstract

Since the early 1990s, central city crime has fallen dramatically in the United States. We explore the extent to which this trend may have contributed to gentrification. Using confidential census microdata we show that reductions in central city violent crime are associated with increases in the probability that high-income and college-educated households move into central city neighborhoods, including low-income neighborhoods, instead of the suburbs. We then use neighborhood-level crime and home purchase data for five major U.S. cities and find that falling neighborhood crime is associated with increasing numbers and shares of high-income movers to low-income central city neighborhoods.

Keywords: crime, gentrification, neighborhood choice

JEL codes: R11, R22, R23

1. Introduction

Violent crime has fallen dramatically in the United States. From 1991 to 2012, the national violent crime rate fell by 49 percent, and it fell even more in central cities and low-income, urban neighborhoods in particular (Ellen and O'Regan, 2009; Sharkey 2018). The latter part of this time period also saw growing proportions of high-income, college-educated, and white households moving into central city neighborhoods, a process referred to as gentrification (Couture and Handbury 2017, Baum-Snow and Hartley 2017). Understanding whether falling crime has invited gentrification is important for understanding the long-term implications of enhancing public safety for segregation, city finances, and housing prices. If falling central city violent crime has helped unleash demand among higher income households for central cities that was previously masked by aversion to violent crime, then American cities could grow to look more like Paris and less like Detroit (Brueckner, Thisse, and Zenou 1999).

We empirically examine the relationship between falling crime and gentrification using three complementary approaches that leverage geographically precise neighborhood choice data. For the first two approaches, we use confidential, geocoded individual microdata from the 2000 Decennial Censuses and the 2010-2012 ACS for residents of the 200 largest metropolitan areas in the U.S. We restrict the sample to household heads who moved within the past year.[1] For each individual in each survey year, we observe his or her block of residence as well as demographic characteristics such as income, race, education level, and tenure status. We merge these individual data with the time-varying demographic, housing, and economic characteristics of the central city and suburbs of their metropolitan area (Core-Based Statistical Area, or CBSA).[2]

[1] The decisions of recent in-movers should be more sensitive to current crime. Further, research on neighborhood change shows that changes are driven by in-movers (Ellen 2000).
[2] We map all geographies to consistent 2010 boundaries using the Longitudinal Tract Database (LTDB).

Finally, we add central city and suburban violent crime rates from the Uniform Crime Reports (UCR) that the Federal Bureau of Investigation (FBI) makes public.

Using these data, we first examine how falling rates of violent crime in central cities affect the composition of households choosing to live in those cities. Estimating linear probability models that control for metropolitan area fixed effects as well as time-varying individual and metropolitan area characteristics, we find that from 2000 to 2010-2012, larger declines in central city violent crime are associated with larger increases in the probability that gentrifiers (high-income, college-educated, and white households) choose the central city over the suburbs. While the association is modest, it is significant and robust. Importantly, falling city crime is not associated with changes in the probability that low-income, less-educated, or non-white households move to the central city, suggesting that falling central city violent crime may have affected the *mix* of the types of individual choosing the central city over the suburbs.

To test whether falling city crime has contributed to the gentrification of *low-income* central city neighborhoods in particular, we estimate multinomial logit models that distinguish among moves to the suburbs, to high-income central city neighborhoods, and to low-income central city neighborhoods. We again find that falling city crime is associated with compositional shifts: while greater reductions in central city violent crime are linked to larger increases in the probability that higher income, college educated, or white households choose low-income central city neighborhoods instead of the suburbs, we find no such relationship for lower-income, non-college educated, or minority movers.

Finally, we consider the implications of changes in *neighborhood*-level violence on neighborhood choices in five major U.S. cities (Austin, Chicago, Philadelphia, Seattle, and

Washington, D.C.) for the years 1998 to 2010.[3] We use Home Mortgage Disclosure Act (HMDA) data to capture neighborhood choices. We aggregate home purchases to create tract-level changes in the number of high- and low-income homebuyers from 2000 to 2010, which we merge with tract-level changes in violent crime for the same period. Regressions again suggest that falling neighborhood violent crime is associated with increases in the number of high-income homebuyers, and that these relationships are stronger for high-income buyers than for low-income buyers.

In sum, across multiple geographies and datasets, we find robust associations between falling levels of violence and the mix of households opting for cities and for low-income city neighborhoods in particular. While we cannot pinpoint the direction of causality, several mechanisms could explain why reductions in violence would contribute to a changing composition of residents. First, safety itself is an amenity, so improvements in safety make cities more attractive. If high-status individuals value safety more than lower-status individuals, this will contribute to an increase in the share of movers to safer areas who are high-status. O'Sullivan (2005) describes a monocentric model with these features. Second, the reduction in central city violent crime could affect residential choices by "revealing" central city amenities that were there all along (Albouy et al., 2018). If these amenities are more valued by higher-status individuals, this will also create an increase in the share of movers who are high-income. This mechanism is consistent with the monocentric model with amenities developed by Brueckner et al. (1999). Finally, the reduction in violent crime could initially attract some higher status individuals to the central city, which then leads to an endogenous increase in amenities enjoyed by these households, further attracting higher status households (Diamond 2016;

[3] The cities were selected based on availability of crime data (described below) and concern about gentrification.

Couture and Handbury 2017; Su 2018). While the reduction in violent crime plays more of a supporting role in these latter stories, it provides the initial impetus.

2. Background and Theoretical Framework

Our study builds on a large and growing body of literature examining what drives gentrification. As far back as 1981, Kern argued that renewed interest in central city living was in part driven by a growth in a segment of the population that has a strong preference for central city goods and cultural amenities, particularly young, unmarried adults and childless couples. He found support for this argument in data from New York City in the 1970s.

Many theories have since been offered to explain why more high-status households are choosing to live in downtown areas, such as an aging housing stock that is ripe for renovation (Brueckner and Rosenthal, 2009), increasing importance of knowledge in the economy leading to a growth in high-skilled employment in central cities (Glaeser and Gottlieb 2006; Baum-Snow and Hartley 2017), increasing preferences for urban amenities (Glaeser, Kolko and Saiz 2001; Glaeser and Gottlieb 2006; Couture and Handbury 2017; Baum-Snow and Hartley 2017), declining leisure time among higher income workers (Edlund et al. 2015; Su 2018), and reductions in crime (Glaeser and Gottlieb 2006).[4] Our analysis centers on this last hypothesis. We focus on high-status households who are making a residential move and then examine whether they are more likely to choose a central city location within the metropolitan area when crime has declined, controlling for a series of household, city, and CBSA characteristics.

We also draw on the literature examining the causes of gentrification defined more specifically as moves by higher-status households into *lower-status*, urban neighborhoods. This

[4] In a related literature Lee and Lin (2017) emphasize the importance of natural amenities in shielding high-income neighborhoods from change.

literature focuses less on why higher-income households are making these choices, though Ellen, Horn and O'Regan (2013) emphasize the importance of city-wide demand and price shocks. Guerrieri, Hartley, and Hurst (2013) and Su (2018) underscore that the entry of a few higher-income households into low-income urban neighborhoods can attract additional high-income neighbors, through endogenous amenities. We build on these studies by exploring whether reductions in violence are a part of the gentrification story.

A number of prior studies have examined the extent to which crime shapes residential location decisions more generally.[5] Researchers have mostly explored whether *increases* in crime drive households out of neighborhoods or cities and/or discourage people from entering specific neighborhoods or cities. The results typically show that increases in crime rates are followed by population losses (Frey, 1979; Morenoff and Sampson, 1997; Nechyba and Strauss, 1997; Cullen and Levitt, 1999; Bayoh, Irwin and Haab, 2006). In one of the most cited works in this literature, Cullen and Levitt (1999) find that a 10 percent rise in central city crime corresponds to a 1 percent decline in central city population.

There is a smaller literature exploring whether *reductions* in crime can attract households to the central city. Ellen and O'Regan (2010) examine this question and find little evidence that reductions in central city crime during the 1990s attracted households to move into cities during the same time period. They do, however, find support for a retention effect: lower levels of city crime are associated with lower levels of exodus to the suburbs. In contrast to this paper, our interest is exploring the link between reductions in crime and changes in the *composition* of households choosing neighborhoods. We also examine a later time period.

[5] For a complete review of the literature on crime and neighborhood change see Kirk and Laub (2010). For the purpose of this paper, we focus on a subset of studies that examine the relationship between crime and population changes.

To motivate our analysis of residential choices, we begin with a static neighborhood choice model along the lines of McFadden (1973, 1978) and Bayer et al. (2004). We also draw on Brueckner et al. (1999) and O'Sullivan (2005), who incorporate amenities and crime, respectively, into the monocentric model. The model highlights the way different mechanisms can lead to falling crime contributing to gentrification. We consider each metropolitan area as containing two areas, the central city and the suburbs. In the initial period, crime is high in the central city and low in the suburbs, reflecting a low amenity value in the central city and a high amenity value in the suburbs. In the second time period, crime rates in the central city decline, and the greater safety may increase the willingness to pay of higher-status households for city homes, pulling them towards the central city. Alternatively, lower crime rates may enhance the ability of higher status households to consume the urban amenities they enjoy. Work by Rosenthal and Ross (2010) supports this theory, as they observe that services targeted towards higher-income households (such as high-end restaurants) are less likely to operate in areas with high levels of violent crime than are those targeting a lower-income clientele, suggesting restaurant owners adjust choices in ways that are consistent with higher-income households' being more sensitive to violent crime. Finally, it is also possible that reductions in crime help to attract some higher status households, and the presence of these initial households then furthers the endogenous growth of the urban amenities they enjoy (Guerrieri, Hartley and Hurst, 2013; Diamond 2016; Couture and Handbury 2017; Su 2018). Modeling these dynamics is beyond the scope of this paper, but they are nevertheless consistent with our results.

We assume that the indirect utility an individual receives from living in a location depends on their individual characteristics X, location characteristics W, and violent crime. The probability that an individual chooses a given location, such as the central city, is the probability

that the location maximizes their utility among all possible locations. Following McFadden (1973, 1978), this can be written as a linear probability model:

$$\Pr(\text{choose } CC^{H}_{ijt}) = \beta_0^{H} + \beta_1^{H}X_{it} + \beta_2^{H}W_{jt} + \beta_3^{H}\text{crime}_{jt} + \beta_4^{H}\kappa_j + \varepsilon^{H}_{iit} \quad (1)$$

$$\Pr(\text{choose } CC^{L}_{ijt}) = \beta_0^{L} + \beta_1^{L}X_{it} + \beta_2^{L}W_{jt} + \beta_3^{L}\text{crime}_{jt} + \beta_4^{L}\kappa_j + \varepsilon^{L}_{iit} \quad (2)$$

X_{it} is a vector of individual characteristics such as age and household structure. W_{jt} is a vector of time-varying central city and suburban characteristics such as housing costs, education levels, and share minority. Crime_{jt} is violent crime level in the central city relative to the suburbs.[6] κ is a vector of metropolitan area fixed effects. *H* and *L* correspond to higher- and lower-status individuals, respectively.[7]

Equation 1 shows how falling violence can contribute to the patterns of gentrification we observe. First, assuming that crime is a disamenity ($\beta_3^{H} < 0$), a fall in central city crime from 2000 to 2010 relative to the suburbs, which we document empirically, will increase the probability that high-status individuals move to the central city instead of the suburbs. Moreover, if the aversion to violent crime is stronger for high status households than for low status households ($\beta_3^{H} < \beta_3^{L} < 0$), then the probability will increase more for high status households, changing the composition of movers to the central city to be more high status. We find empirical support for both of these propositions. Finally, if falling crime also induces changes that increase the quantity or quality of central city amenities in W_{jt}, this could contribute to further

[6] Both a relative decline in central city crime (relative to the suburbs) and an absolute decline in central city crime (regardless of what happens in the suburbs) could contribute to gentrification of the central city. In our city-level regression models we include a relative decline but results are qualitatively similar when using an absolute decline.
[7] Through fully stratifying by individual status, we effectively interact status with all variables in the model. Our interest is specifically in the interaction of status with crime: does falling crime affect move probabilities more for higher-status than for lower-status individuals.

gentrification. We cannot test this endogenous mechanism with our approach, but Su (2018) provides evidence of how small initial shocks to the number of high-status individuals living in the central city can spur endogenous amenity change and gentrification.[8]

Of course, it is also possible that the direction of causality runs in reverse. Rising numbers of higher-status households could invite a reduction in violence as higher-income residents invest in private security systems, attract more police presence, and invite more restaurants and retailers who offer eyes on the street. The empirical evidence on the effects of gentrification on violent crime is mixed (Covington and Taylor, 1985; Papachristos et al, 2011). Most recently, Autor, Palmer and Pathak (2019) find that crime falls in gentrifying areas, though their results are stronger for property crime.[9]

3. CBSA-Level Models

To study the implications of city-level crime changes, we use the restricted access version of the confidential, geocoded versions of the 2000 Decennial Census and the 2010, 2011, and 2012 American Community Survey (ACS). We focus on this decade because research shows gentrification trends accelerated after 2000 (Baum-Snow and Hartley 2017, Couture and Handbury 2017, Edlund et al. 2015). The data allow us to observe a rich set of household characteristics, including whether they have moved in the past year, and their census tract of residence. This level of geographic detail on individual household location is far greater than that

[8] Specifically, he shows that exogenous shocks to high skilled individuals' value of time increases the probability that they locate downtown. While this change itself contributes only slightly to gentrification, endogenous amenity responses to the initial shock fuel further gentrification.

[9] Many economists have studied why crime has declined over the past few decades. Some of the most prominent theories presented include increased police numbers, increased incarceration, aging population and growth in income (Levitt, 2004; Roeder, et al, 2015). Some additional theories include the decline in lead exposure (Reyes, 2007; Aizer and Currie, 2019), a growth in local non-profits (Sharkey, Torrats-Espinosa, Takyar, 2017) and decreased alcohol consumption (Roeder et al.,,2015). For a recent review of the literature, see Roeder et al., (2015).

provided in public use versions of these datasets, which only identify household location at the level of the Public Use Microdata Area (PUMA), a geographic area of approximately 100,000 people. Our sample includes the 227 Core Based Statistical Areas (CBSAs) that had a population greater than 100,000 in 1990 and for which we can construct measures of suburban crime.[10] We identify central cities as the largest principal city within the CBSA. We create consistent geographic boundaries over time by cross-walking CBSAs and tracts to 2010 boundaries using the Longitudinal Tract Data Base.[11] Following past literature, we define low-income neighborhoods as census tracts with median household incomes below that of the CBSA, based on 2000 data.

Tables 1 and 2 show violent crime trends in our sample of 227 CBSAs, drawing on three-year average crime rates from the FBI Uniform Crime Reports (UCR).[12] This table shows that on average both violent crime and homicides declined in our sample of cities between the 1996-1998 time-period and the 2006-2008 time-period. On average, violent crime declined by 105 counts per 100,000 people in the central cities and 51 counts per 100,000 people in the suburbs.

It is worth noting that we are not studying the period of time when crime declined the most in the U.S. Nationally, violent crime peaked in 1991, declined rapidly through 1999, and then fell more slowly, though steadily, through 2013. Nevertheless, we see significant declines in violent crime during our time period, and more importantly, we see significant variation. As shown in Table 2, the median city in our sample experienced a decline in violent crime of 21 percent between 1988 and 2008, but more than ten percent experienced declines greater than 70

[10] 244 CBSAs meet the population criterion. States have made reporting to the Uniform Crime Report (UCR) mandatory in different years and therefore precincts began reporting at different times. For 17 of the 244 CBSAs in our sample, the UCR data do not include crime data for at least one jurisdiction in the years used in our city-level analysis. We therefore drop these 17 CBSAs, yielding 227 in our final sample.
[11] http://www.s4.brown.edu/us2010/Researcher/Bridging.htm
[12] We calculate suburban crime by summing all violent crimes reported in the remainder of the police precincts in that CBSA, and creating three year averages to reduce noise in the measure.

percent, and, at the other extreme, more than ten percent experienced *increases* of over 20 percent. Further, we see significant variation in the magnitude of the reductions in violent crime in cities relative to their surrounding suburbs, with some cities seeing smaller declines (at least in percentage terms) than their suburban counterparts.

We limit our analysis to households who moved into a new home in the past year and identify three household types who are typically considered potential gentrifiers: high-income households (household income above CBSA median household income), college-educated households (head of household has a college degree), and white households (head of household identifies as non-Hispanic white).[13] Table 3 shows trends in the distribution of destinations for each of these types of recent mover households. As shown, the share of all three types of households moving into low-income and high-income central city tracts increased on average between 2000 and 2010 in our sample of CBSAs.

Table 4 describes the characteristics of the recent movers in the 227 CBSA sample. We observe approximately 2.4 million mover households over the two periods: 39 percent are high-income, 65 percent are white, and 30 percent are headed by someone with a bachelor's degree or more. Given our focus on households who have moved in the last year, the sample is also quite young, with 49 percent headed by someone less than 35 years old.

4 City-Level Models

4.1 Moves to Any Central City Neighborhood

[13] See Freeman (2005) and McKinnish, Walsh, and White (2010) for examples of studies that use these definitions. We also explored heterogeneity for more detailed individual types consisting of all unique combinations of income level by education level and by race/ethnicity. Results for these sub-types did not reveal additional heterogeneity beyond that revealed by the three broad types alone.

To consider the link between crime and moves into a central city home, we estimate a fully interacted version of model (1) which we express as follows:

$$Y_{ict} = \alpha + \beta_1 CRIME_{ct-1} + \beta_2 CRIME_{ct-1}*HHType_{ict} + \lambda_1 X_{ict} + \lambda_2 X_{ict}*HHType_{ict} + \delta_1 W_{ct} + \delta_2 W_{ct}*HHType_{ict} + \kappa_c + \kappa_c*HHType_{ict} + \tau_t + \tau_t*HHType_{ict} + \varepsilon_{ict} \quad (3)$$

i indexes the household, *c* the CBSA and *t* the time period. Y is a binary variable that takes value 1 if a household moves into a home in the largest central city in the CBSA and value 0 if it moves elsewhere in the CBSA.[14] CRIME represents the difference between the violent crime rate in the largest central city and that in its surrounding suburbs.[15] We use the average of the crime rate in the three previous years (1996, 1997, 1998 and 2006, 2007, 2008) to reflect information movers had at the time they made their residential choice.[16] We also estimate the models using the simple reduction in central city violent crime rates since this decline may be most salient to households. We obtain similar results.

X represents a set of household characteristics that theory and empirical research suggest shape residential choices, including family type (married, single mother, single father, and other), presence of children under 18, household income, householder race/ethnicity, householder foreign born status and linguistic isolation, employment status, age and householder education level (shown in Table 4).

[14] While most CBSAs only have one principal city, we include here CBSAs that have multiple principal cities and define the central city as the biggest of those cities. Results are robust to estimating models for only the CBSAs with one principal city.
[15] We specify as the difference between log central city and log suburban violent crime per capita. Our results are broadly similar when using the absolute difference in central city and suburban violent crime per capita.
[16] Averaging the three previous years helps reduce noise and improves precision. When instead using one year of crime data (lagged one, two, or three years from the year of the move), our results are very similar.

W represents a set of central city and suburban characteristics. These capture changes in other differences between central cities and suburbs that might be correlated with crime and also affect household moves. The full set of city and suburban characteristics includes median gross rent; the median value of owner occupied housing; median household income; poverty rate; share of households who are non-white; share of households who are foreign born; share of housing units built before 1940; share of housing units built in the past 10 years; and share of CBSA employment that is in the central city. Shares are included as differences between central city and suburban shares, and all other control variables are specified as the log of the central city attribute minus the log of the suburban attribute.

Finally, κ represents a set of CBSA fixed effects and τ represents year fixed effects. We interact all independent variables with HHType, an indicator for whether the head of household is high-income, college-educated, or white. We cluster standard errors at the CBSA level.

The key coefficient of interest is β_2. Because we include CBSA fixed effects, it is identified from variation in crime and patterns of residential moves within CBSAs over time. Thus, negative values are interpreted as evidence that falling crime in a city is associated with an increase in the probability that households of a particular type choose to move into that central city instead of its surrounding suburbs.

Identifying causality is challenging. We lag crime to help to address reverse causality. We control for omitted time-invariant CBSA attributes with CBSA fixed effects, and we control for omitted trends that are common across CBSAs with year effects. While we cannot fully address the threat of changes in other time-varying unobserved city variables, we conduct several tests of robustness (as detailed below) and obtain similar results.[17]

[17] We would ideally use an instrument for city crime that 1) affects residential decisions only through its effect on crime, 2) is exogenous, and 3) is sufficiently strong in predicting crime. We experimented with many instruments,

Table 5 presents the estimated coefficients on key crime variables from the linear probability models described by equation 3. We separately estimate three types of models, in which each type of model is fully interacted with a given household type (high-income, college-educated, and white). Columns 1 through 3 present results for interactions with our high-income household indicator, Columns 4 through 6 show interactions with college-educated, and Columns 7 through 9, interactions with white. For each of these three types of models, we present three specifications. The first includes all household level controls. The second adds a subset of time-varying, contemporaneous characteristics describing the central city relative to its surrounding suburbs. The third adds the full set of central city/suburban characteristics, lagged one full decade.

Our results suggest that declines in violent crime are associated with an increased probability that higher-status households choose to move to the central city. For example, Column 1 shows that a 10-point decline in the log ratio of central city to suburban violent crime (which is just above the mean) is associated with a 0.28 percentage point increase in the probability that a high-income household chooses a central city home instead of a suburban one. This magnitude is fairly modest given that the share of high income households choosing a home in the central city rather than the suburbs increased by 4.7 percentage points over this same period, but it's significant, and violent crime rates meanwhile have no association with the

including state prison admittances and releases (Cullen and Levitt 1999), lead exposure (Reyes 2007), and police grants (Evans and Owens 2007). These are plausibly exogenous but unfortunately are also very weak in our setting, with first stage F statistics far below the standard threshold of 10. We believe these are stronger in their original settings because those use annual panels, whereas our setting is a two-period panel of metropolitan areas. Additionally, it is less obvious that the exclusion restriction would hold in our setting. For example, it is easy to imagine that grants to increase the number of police officers in a central city could affect households' decisions to move to the central city through channels other than crime declines. Other channels might include perceptions of safety, rather than actual crime declines, or making available more city budget dollars for investment in central city infrastructure or amenities.

prevalence of moves into central city homes by low-income, non-college-educated, or non-white households.

For high-income households, the inclusion of controls reduces the magnitude of our key coefficient by half, to -0.14, though it remains statistically significant. For college-educated households the magnitude also falls by half with the inclusion of contemporaneous controls, though it remains unchanged when using lagged controls instead of contemporaneous controls. For white households, we only see a significant association with crime when the full set of lagged controls are included in the model.

4.2 Moves to Low-Income Central City Neighborhoods

We next test whether falling central city violent crime is linked to an increase in the probability that high-income, college-educated, and white movers choose to settle not only in central cities but in *low-income* neighborhoods within central cities. To do so, we estimate multinomial logit models that are identical to equation 3 but with Y redefined to take a value of 1 if a household moves into a home in a low-income central city neighborhood (first column), 2 if it moves into a home in a high-income central city neighborhood, (second column), and 3 if it moves into a suburban home, (omitted reference group). We then run three versions of these models, each with a different set of controls as described in Section 4.1.

Table 6 presents key coefficients. It shows that falling violent crime in a central city relative to its surrounding suburbs is associated with an increase in the odds that high-income households (but not low-income households) opt for a low-income central city neighborhood rather than the surrounding suburbs. Specifically, the coefficient on moves into low-income central city tracts (instead of suburban tracts) for high-income households is -0.20 (presented in

column 1 of Panel A), suggesting that a 10-point decline in the log ratio of central city to suburban violent crime is linked to a 2 percent increase in the relative odds of moving to a low-income central city tract instead of the suburbs.[18] Violent crime rate declines of 43 percent (the 90th percentile of declines in our sample) would correspond to a 12 percent increase in the relative odds of moving into homes in low-income central city tracts.[19] We again find qualitatively similar results across specifications, though coefficients decline in magnitude with the inclusion of additional controls. Interestingly, we find no evidence that reductions in violent crime in a city attract higher income households to *high*-income neighborhoods within that city (compared to its surrounding suburbs).

We see similar results in Panel B, which shows models that interact crime and other area characteristics with a dummy variable indicating if a household is college-educated. As shown, the association between falling central city crime and moves to low-income central city neighborhoods is only statistically significant for households with college-graduates, and not significant for those without. What is more, we again find no evidence that such declines are associated with moves by college-educated households into *high*-income central city neighborhoods. While results in Panel C for white interactions are somewhat less robust to the controls included, they provide evidence of similar patterns.

Overall, the multinomial logit results suggest that when violent crime in a central city falls, higher income, college-educated, and white households are more likely to settle in that city's low-income neighborhoods. Significantly, we do not find any similar associations for lower-status households, suggesting a shift in the composition of households moving to low-income central city neighborhoods. We also find no associations between crime reductions and

[18] exp(-0.2 * ln(0.90)) = 1.02, a 2% increase in the odds ratio from a base of 1.
[19] exp(-0.2 * ln(0.53)) = 1.12, a 12% increase in the odds ratio from a base of 1.

moves by higher-status households into high-income neighborhoods, which may reflect the fact that high-income neighborhoods were already perceived to be safe or that central city crime declined most in low-income neighborhoods (Ellen and O'Regan, 2009). We examine this possibility further in Section 5 by estimating a set of neighborhood-level crime models.

4.3 Robustness Checks

We conduct a series of robustness checks using alternative measures of crime, time periods and geographies. First, we estimate each specification in Tables 5 and 6 using homicide rates rather than violent crime, both because homicides are measured with less error than other crimes and because households are more likely to know about homicides, given their salience. Results for homicides are qualitatively similar and are available upon request.

We also estimate these models for three decades, the 1990s, 2000s and 2010s, and again find similar results, although results for white households, which are also weaker in our main specifications, are not robust over these additional decades.

In a final series of checks, we find that our results are broadly similar when we specify the city-suburban difference in crime and other characteristics as absolute differences instead of differences in logs. Results are also similar when we estimate models with absolute rates of city violent crime (rather than rates of violence in cities relative to the suburbs).

5 Neighborhood-Level Models

Thus far, our focus has been on the links between citywide reductions in violent crime and residential choices. But another key question is whether a reduction in violent crime in a *neighborhood* is associated with an increased tendency of high-income households to choose that

neighborhood. To examine this question, we obtain point-specific crime data for the years 1999 to 2009 for five major cities: Austin, Chicago, Philadelphia, Seattle, and Washington, D.C. We assign each crime to a consistent 2010 tract using latitude and longitude and aggregate these into tract-level violent crime counts. We construct two-year averages of neighborhood violent crime rates, 1999-2000 and 2009-2010, to reduce noise.[20]

To measure tract-level neighborhood choices, we use data on the near-universe of home purchases from 2001 and 2011 Home Mortgage Disclosure Act (HMDA). Covering the near universe of home purchases, these data include the year of purchase, the census tract of the purchase, and applicant income. We aggregate the number of purchases in each year and tract, distinguishing between high- and low-income households using income data provided in the HMDA data.[21] As before, we define households as high income if their income is above the CBSA median. The race/ethnicity indicator for Hispanic is not consistent in the 2001 and 2011 HMDA waves, and the data set provides no information about education in either year, so we focus on income to identify potential gentrifiers. We supplement these data with tract characteristics from the Census Bureau and from Lee and Lin (2017).

Figure 1 shows variation in neighborhood-level violent crime per capita in our five cities. There is substantial variation in these changes both within and across cities. Figure 2 maps declines in violent crime per capita alongside increases in the number and share of homebuyers who are high-income. It makes clear that the neighborhoods experiencing the largest crime declines also experienced the most positive changes in the number of high-income buyers and in the share of all buyers who are high-income.[22] Moreover, many of these changes occurred in

[20] We do not have 1998 crime data for all of our cities and so cannot estimate three-year average crime rates.
[21] As before, we define households as high income if their income is above the CBSA median.
[22] Note that numbers of buyers declined in absolute terms from 2000 to 2010 because of the housing bust. Our interest is in variation within cities across neighborhoods, controlling for these and other common trends.

central neighborhoods where gentrification has been a concern. Figure 3 shows binned scatterplots of the same data points in Chicago, again suggesting a relationship between declining crime and gentrification.

To more formally test whether changes in neighborhood-level violent crime per capita are associated with changes in the number and share of high-income homebuyers choosing that neighborhood, we estimate versions of the following regression:

$$\Delta Buyers_{cj} = \alpha + \beta_1 \Delta CRIME_{cj} + \lambda X_{cj} + \kappa_c + \varepsilon_{cj} \quad (4)$$

$\Delta Buyers_{cj}$ is, alternatively, the percent change in the number of high-income buyers, number of low-income buyers, or share of all buyers who are high-income in city *c* and census tract *j* from 2001 to 2011. $\Delta CRIME_{cj}$ is the percent change in violent crime per capita in a census tract over the decade between 1999-2000 and 2009-2010. β_1 is the coefficient of interest: the elasticity of home purchases in a neighborhood with respect to violent crime. X_{cj} is a set of fixed neighborhood characteristics measured in 2000, including many standard neighborhood demographics along with characteristics found in previous research to be correlated with gentrification: share college educated, share minority, poverty rate, median household income, share of housing units built before 1940, share of housing units built in past 10 years, an indicator for whether the tract is a low-income tract, the distance in miles to the nearest high-income census tract, the distance in miles to the metropolitan area's central business district, the distance in miles to an ocean or Great Lake, the tract population density, and the average age of the housing stock in a tract. κ_c is a set of fixed effects for the five cities, and ε_{cj} is the error term.

Table 7, Panel A shows results for the full sample of all central city neighborhoods in the five cities. A 10 percent decrease in violent crime is associated with a 3 percent increase in the number of high-income homeowners buying homes in that tract. This finding is robust to our inclusion of a large set of neighborhood controls, though the coefficient is halved to -0.167. Columns 3 and 4 show that, consistent with city-wide crime models, the association is smaller for low-income buyers and loses significance when we include neighborhood controls. Putting these two together, Columns 5 and 6 of Panel A show that falling violence is associated with an increase in the share of all homebuyers who are high-income, or a change in the composition of households choosing a neighborhood.

Table 7, Panel B shows that falling neighborhood crime is also associated with increasing numbers and shares of high-income households buying homes in low-income central city neighborhoods. Indeed, the coefficients on change in violent crime are somewhat larger in the sub-sample of initially low-income neighborhoods, though they are not statistically different from those in Panel A.[23]

6. Conclusion

Gentrification and falling violent crime rates are two of the most salient trends affecting American cities over the previous few decades. This research provides support for the notion that these trends are connected: reductions in central city violent crime are associated with more high-income, college-educated, and white households choosing to move into homes in central cities, and more specifically to low-income, central city neighborhoods. These crime reductions are not associated with changes in residential patterns of lower status households, suggesting that

[23] As before, neighborhoods are defined as low-income if their median household income is below the CBSA median household income in 2000.

increases in safety may be changing the mix of households moving to central city neighborhoods. The results hold when studying crime and mobility at the city level and the neighborhood level and are robust to various alternative specifications.

These results are consistent with a simple monocentric model in which violent crime declines in the city center lead higher status households to differentially adjust their location decisions to access the central city. The specific mechanisms could be differential sensitivities to violent crime, differential valuation of central city amenities that are now more accessible when crime is lower, and/or endogenous increases in central city amenities that are initiated by the crime declines (O'Sullivan 2005, Brueckner et al. 1999, Couture and Handbury 2015, Su 2018).

We caution that our city-level model estimates are quantitatively small and somewhat sensitive to the inclusion of different sets of control variables. However, our neighborhood-level estimates suggest that falling crime might have played a more meaningful role in the gentrification of lower-income central city neighborhoods. None of these results prove a causal relationship, nor do they rule out alternative or complementary factors explaining recent gentrification trends. Recent work by Couture and Handbury (2017) and Baum-Snow and Hartley (2017) finds evidence that the growing preferences of young, college-educated adults for urban amenities drove much of the increase in moves by this group into downtown areas from 2000 to 2010. Of course, crime may be part of their story too, as reduced crime might contribute to shifting preferences as people are better able to enjoy urban amenities when violence levels fall. Further, knowledge that cities in general have become safer may encourage college-educated adults to choose cities across the country, regardless of city-specific crime changes.

Taken together, our results suggest that the dramatic decrease in violent crime experienced by central cities in recent years may have contributed to changes in the composition

of households in central city neighborhoods, including those that are initially low-income, with implications for longer-term city trends of gentrification, neighborhood change, economic integration, and house prices.

References

Aizer, A. and J. Currie (2019). Lead and Juvenile Delinquency: New Evidence from Linked Birth, School, and Juvenile Detention Records. *The Review of Economics and Statistics*, forthcoming. https://doi.org/10.1162/rest_a_00814

Albouy, D., Christensen, P., and I. Sarmiento-Barbieri (2018). Unlocking Amenities: Estimating Public Good Complementarity. NBER Working Paper No. 25107

Autor, D H, C J Palmer, and P A Pathak (2019). Gentrification and the Amenity Value of Crime Reductions: Evidence from Rent Deregulation. AEA Papers and Proceedings, 109 : 381-84.

Baum-Snow, N. and D. Hartley (2017). Accounting for Central Neighborhood Change, 1980-2010. Working Paper.

Bayer, P., McMillan, R., and K. Rueben (2004). An Equilibrium Model of Sorting in an Urban Housing Market. NBER Working Paper 10865.

Bayoh, I., Irwin, E.G., and T. Haab (2006). Determinants of Residential Location Choice: How Important Are Local Public Goods in Attracting Homeowners to Central City Locations? *Journal of Regional Science* 46(1):97-120.

Brueckner, J. and S. Rosenthal (2009). Gentrification and Neighborhood Housing Cycles: Will America's Future Downtowns Be Rich? *The Review of Economics and Statistics* 91(4):725-743.

Brueckner, J., Thisse, J.-F., and Y. Zenou (1999). Why is Central Paris Rich and Downtown Detroit Poor? An Amenity-Based Theory. *European Economic Review* 43:91–107.

Couture, V. and J. Handbury (2017). Urban Revival in America, 2000 to 2010. NBER Working Paper 24084.

Covington, J., and R. Taylor. (1985). Gentrification and Crime: Robbery and Larceny Changes in Appreciating Baltimore Neighborhoods During the 1970s. *Urban Affairs Quarterly* 25 (1): 142-172.

Cullen, J. and S. Levitt (1999). Crime, Urban Flight, and the Consequences for Cities. *The Review of Economics and Statistics* 81(2):159–169.

Diamond, R. (2016) The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000. *American Economic Review* 106(3): 479-524.

Edlund, L., Machado, C. and M. M. Sviatschi (2015). Bright Minds, Big Rent: Gentrification and the Rising Returns to Skill. NBER Working Paper 21729.

Ellen, I.G., Horn, K.M. and K. O'Regan (2013). Why do higher-income households choose low-income neighborhoods? Pioneering or Thrift? *Urban Studies* *50*(12), 2478–2495.

Ellen, I.G. and K. O'Regan (2010). Crime and Urban Flight Revisited: The effect of the 1990s drop in crime on cities. *Journal of Urban Economics* 68: 247-259.

Ellen, I. G., and K. O'Regan (2009). Crime and U.S. Cities: Recent Patterns and Implications. *The ANNALS of the American Academy of Political and Social Science* 626(1): 22–38.

Evans, W. and E. Owens (2007). COPS and Crime. *Journal of Public Economics* 91(1-2): 181-201.

Frey, W. (1979). Central City White Flight: Racial and Nonracial Factors. *American Sociological Review* 44(3):425–448.

Freeman, L. (2005). Displacement of Succession? Residential Mobility in Gentrifying Neighborhoods. *Urban Affairs Review* 40(4):463-491.

Glaeser, E. and J. Gottlieb (2006). Urban Resurgence and the Consumer City. *Urban Studies* 43(8):1275-1299.

Glaeser, E., J. Kolko, and A. Saiz (2001). Consumer City. *Journal of Economic Geography* 1:27-50.

Guerrieri, V., D. Hartley, and E. Hurst (2013). Endogenous gentrification and housing price dynamics. *Journal of Public Economics* 100: 45.

Kirk, D. and J. Laub (2010). Neighborhood Change and Crime in the Modern Metropolis. *Crime and Justice* 39(1):441-502.

Kern, C. (1981). Upper-Income Renaissance in the City: Its Sources and Implications for the City's Future. *Journal of Urban Economics* 9:106–124.

Lee, S. and J. Lin (2017). Natural Amenities, Neighborhood Dynamics, and Persistence in the Spatial Distribution of Income. *The Review of Economic Studies* 85(1): 663-694.

Levitt, S. (2004). Understanding Why Crime Fell in the 1990s: Four Factors that Explain the Decline and Six that Do Not. *Journal of Economic Perspectives* 18(1): 163-190.

McFadden, D. (1973). Conditional Logit Analysis of Qualitative Choice Behavior, in P. Zarembka (ed.), Frontiers in Econometrics, pp. 105-142, Academic Press: New York.

McFadden, D. (1978). Modelling the Choice of Residential Location. Spatial Interaction Theory and Planning Models, Amsterdam: North Holland, pp. 75–96.

McKinnish, T., Walsh, R. and T. White (2010). Who Gentrifies Low-Income Neighborhoods? *Journal of Urban Economics* 67:180-193.

Morenoff, J.D. and R. J. Sampson (1997). Violent Crime and the Spatial Dynamics of Neighborhood Transition: Chicago, 1970-2000. *Social Forces* 76(1): 31-64.

Nechyba, T. and R. P. Strauss (1997). Community Choice and Local Public Services: A Discrete Choice Approach. *Regional Science and Urban Economics* 28:51–73.

O'Sullivan, A. (2005). Gentrification and Crime. *Journal of Urban Economics* 57:73-85.

Papachristos, A V, C M Smith, M L Scherer, and M A Fugiero (2011). More Coffee, Less Crime? The Relationship between Gentrification and Neighborhood Crime Rates in Chicago, 1991 to 2005., *City & Community* 10(3): 215–240.

Reyes, J. W. (2007). Environmental Policy as Social Policy? The Impact of Childhood Lead Exposure on Crime. *The B.E. Journal of Economic Analysis and Policy* 7(1) article 51.

Roeder, O., L. Eisen, and J. Bowling. 2015. What Caused the Crime Decline? Brennan Center for Justice (https://www.brennancenter.org/ publication/what-caused-crime-decline).

Rosenblatt, P. and S. DeLuca (2012). We Don't Live Outside, We Live in Here: Neighborhood and Residential Mobility Decisions Among Low-Income Families. *City and Community* 11(3): 254-284.

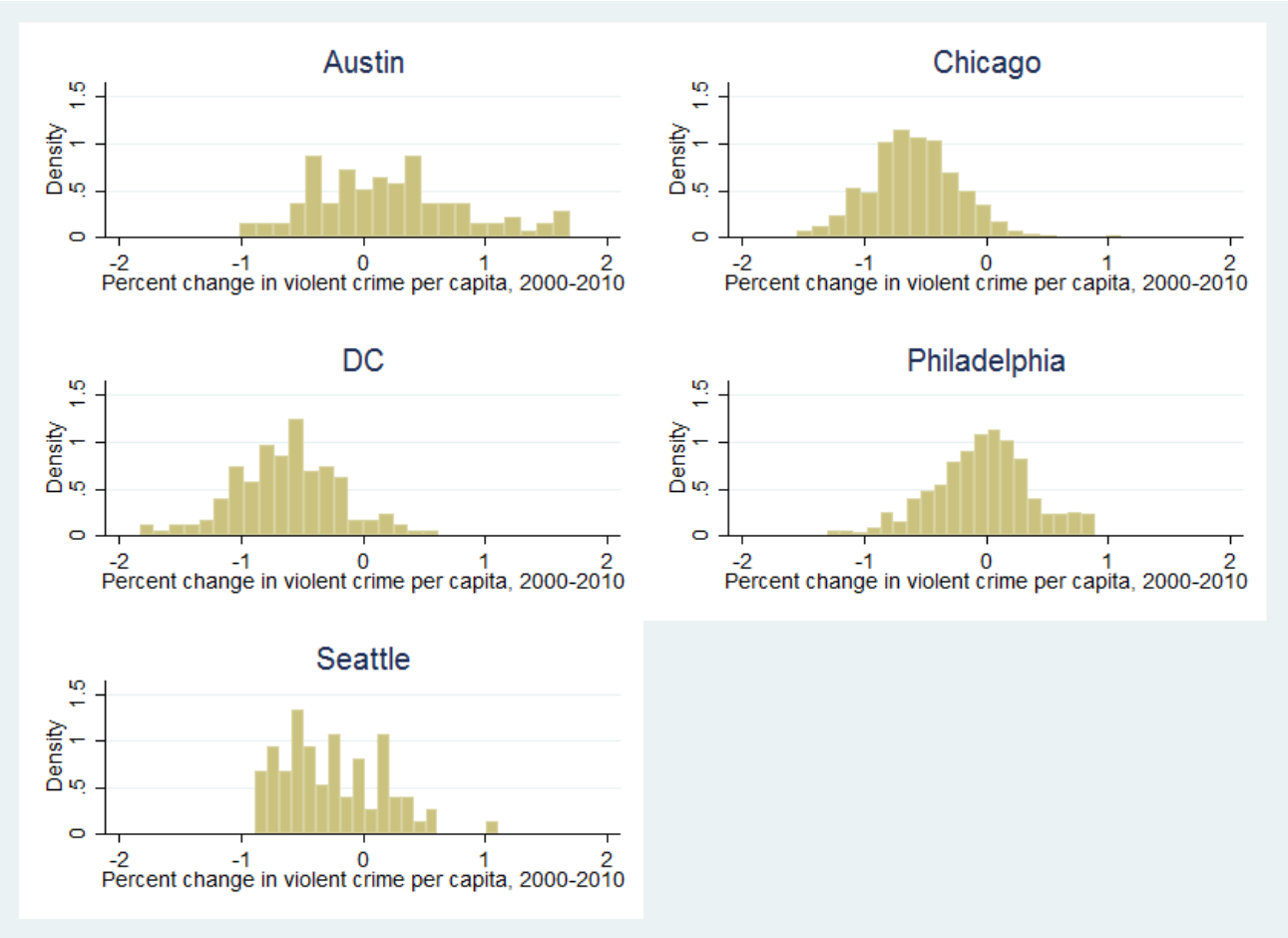
Rosenthal, S. and A. Ross (2010). Violent Crime, Entrepreneurship and Cities. *Journal of Urban Economics* 67(1): 135-149.

Sharkey, P. (2018). *Uneasy Peace: The Great Crime Decline, the Renewal of City Life, and the Next War on Violence*. WW Norton & Company.

Sharkey, P., G. Torrats-Espinosa and D. Takyar (2017). Community and the Crime Decline: The Causal Effect of Local Nonprofits on Violent Crime. *American Sociological Review* 82(6): 1214-1240.

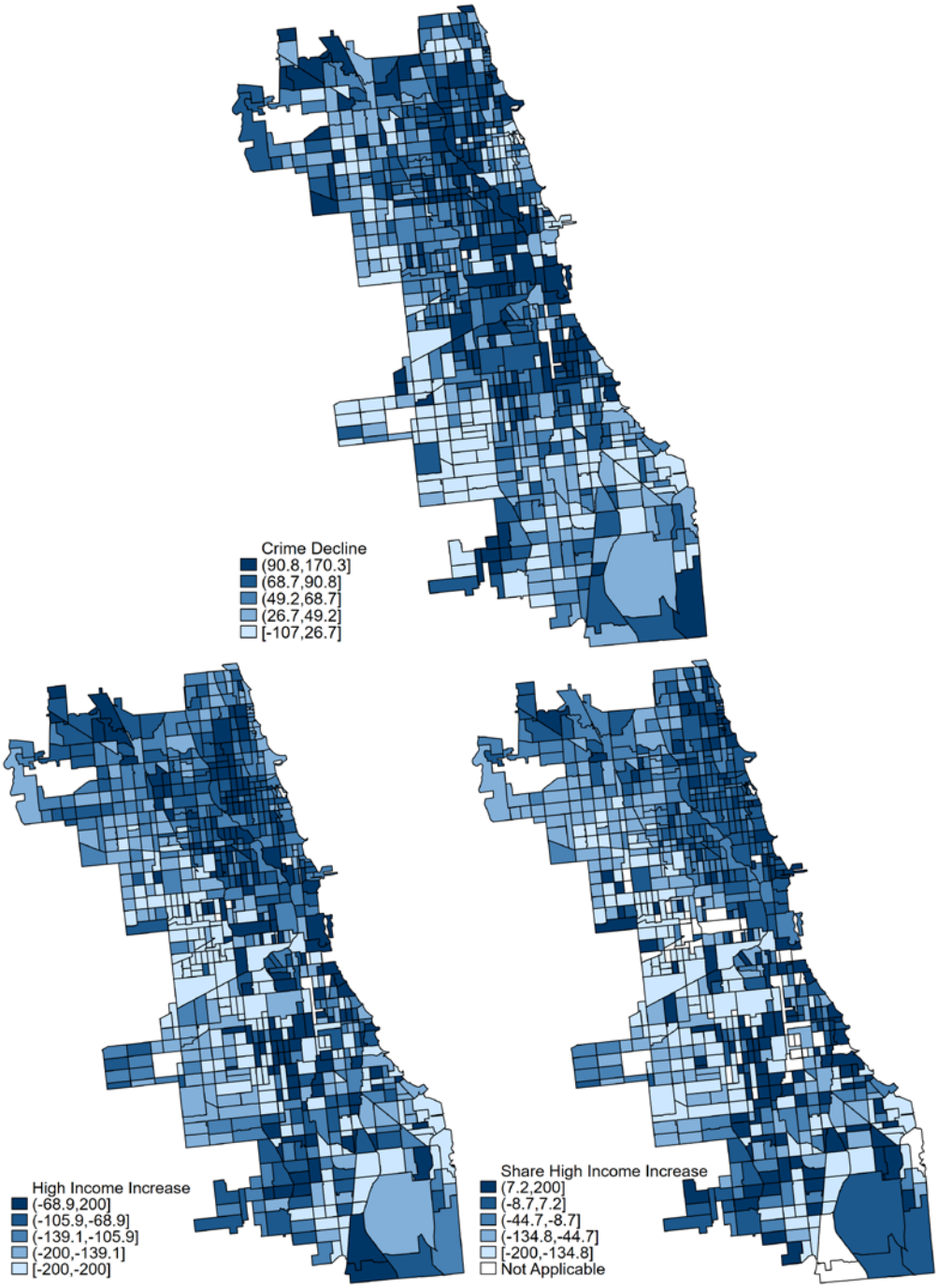
Su, Yichen (2018). The Rising Value of Time and the Origin of Urban Gentrification. Working Paper.

Figure 1: Variation in Changes in Neighborhood-Level Violent Crime Per Capita, 1999-2000 to 2009-2010



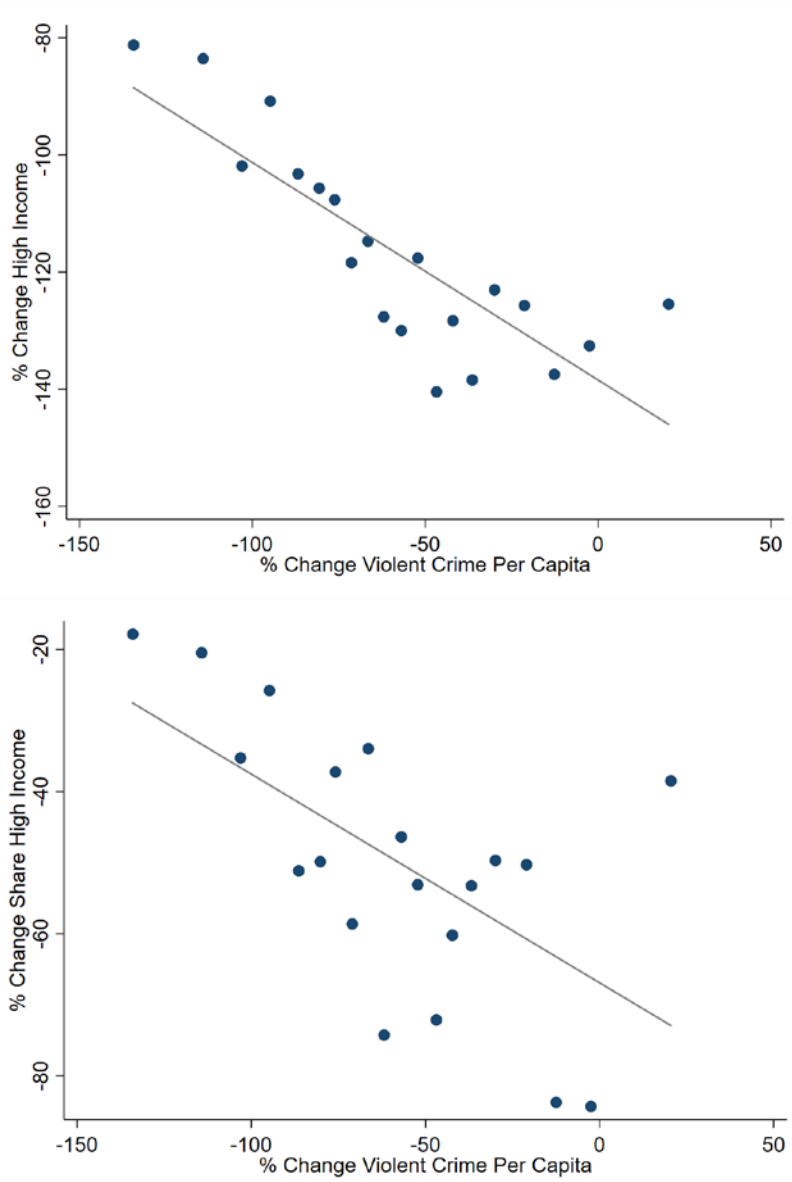
Note: Neighborhood level violent crime per capita is measured as the average of 1999-2000 tract level violent crime per capita and 2009-2010 tract level violent crime per capita. The percent change in violent crime per capita from 2000 to 2010 is calculated using these two measures and the midpoint method so that tracts with zero violent crime per capita in either period are not excluded from the sample. 1 indicates a 100 percent increase in crime and -1 a 100 percent decrease in crime.

Figure 2: Quintiles of Neighborhood Crime Declines and Homebuyer Percent Changes in Chicago, 2000 to 2010



Note: Crime decline measured as in Figure 1: percent change in violent crime per capita from 2000 (1999-2000 average) to 2010 (2009-2010 average). High-income increase is the percent change in the number of high-income buyers from 2001 to 2011. Share High-Income Increase is the percent change in the share of all buyers who are high-income, from 2001 to 2011. All changes are measured using the midpoint method and then scaled by 100, so that the possible range is from -200 to 200. Categories are quintiles of the given variable.

Figure 3: Correlations Between Neighborhood Crime Changes and Homebuyer Changes in Chicago, 2000 to 2010



Note: Binned scatterplots of the relationship between changes in crime and changes in the number and share of high-income home buyers. Data are identical to those used in Figure 2. Crime decline is the percent change in violent crime per capita from 2000 (1999-2000 average) to 2010 (2009-2010 average). High-income increase is the percent change in the number of high-income buyers from 2001 to 2011. Share High-Income Increase is the percent change in the share of all buyers who are high-income, from 2001 to 2011. All changes are measured using the midpoint method and then scaled by 100, so that the possible range is from -200 to 200. Bin scatters group the X variable into 20 equally sized bins, then plot the mean of the X variable and the mean of the Y variable in each bin. Stata code created by Michael Stepner: https://michaelstepner.com/binscatter/.

Table 1: Changes in Crime Levels for Sample of CBSAs

Year	**1996-1998 avg.**	**2006-2008 avg.**
Central City Crime: Violent crime per 100,000 population	888.0	782.7
Central City Crime: Homicides per 100,000 population	10.1	9.3
Suburban Crime: Violent crime per 100,000 population	354.0	303.2
Suburban Crime: Homicides per 100,000 population	4.2	3.7
Observations	227	227

Note: Mean across all central cities in sample, weighted by 2010 central city population.

Table 2: Distribution of Crime Changes for Sample of CBSAs

	Change in Log Violent Crime, Central City, 1996-1998 to 2006-2008	Change in Log Violent Crime, Suburbs 1996-1998 to 2006-2008	Change in Log of City/Suburb Ratio in Violent Crime 1996-1998 to 2006-2008
10%	-72%	-43%	-43%
25%	-56%	-41%	-28%
50%	-21%	-22%	-1%
75%	-3%	-9%	11%
90%	20%	13%	33%
Mean	-26%	-21%	-5%
Observations	227	227	227

Note: Distributions of central city and suburban crime changes across our sample of 227 CBSAs. Column 3, "Central City minus Suburbs," is calculated as the change over time in the log of the central city / suburban violent crime ratio: ln(central city violent crime_2010 / suburban violent crime_2010) - ln(central city violent crime_2000 / suburban violent crime_2000). It captures how central city relative to suburban violent crime is changing over time, and the log ratio is the crime variable used in our city-level models.

Table 3: Percent of Households Moving Into Different Neighborhoods, CBSA Sample

	2000	**2010**
All Households: Central city low-income	23.5	25.2
All Households: Central city high-income	9.5	10.9
All Households: Suburban	67.0	63.9
High Income Households: Central city low-income	13.8	15.7
High Income Households: Central city high-income	12.9	15.7
High Income Households: Suburban	73.3	68.6
College-Educated Households: Central city low-income	18.2	21.4
College-Educated Households: Central city high-income	15.2	17.0
College-Educated Households: Suburban	66.6	61.6
White Households: Central city low-income	16.2	18.8
White Households: Central city high-income	10.5	12.2
White Households: Suburban	73.3	69.0

Note: Characteristics of analytical sample, which includes individuals moving in 2000 or 2010 in sample of 227 CBSAs.

Table 4: Household Characteristics, CBSA Sample

	All households
College education or more	30%
High-income	39%
White, non-Hispanic	65%
Married	38%
Male headed	5%
Female headed	15%
Presence of children under 18	40%
Linguistically isolated	7%
Foreign born	17%
Employed	74%
Age less than 35	49%
Age 35 to 65	44%
Age over 65	7%
Observations	2,390,000
CBSAs	227

Note: Characteristics of CBSA-level analytical sample, which includes individuals moving in 2000 or 2010 in sample of 227 CBSAs

Table 5: Probability of Moving to Central City vs. Suburbs As a Function of Central City Minus Suburban Characteristics, 2000 to 2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Violent Crime	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Violent Crime * High-Income	-0.0280**	-0.0144**	-0.0148**						
	(0.01)	(0.01)	(0.01)						
Violent Crime * College-Educated				-0.0350***	-0.0172**	-0.0354***			
				(0.01)	(0.01)	(0.01)			
Violent Crime * White							-0.01	-0.01	-0.0249***
							(0.01)	(0.01)	(0.01)
Household controls	X	X	X	X	X	X	X	X	X
Current controls		X			X			X	
Lagged controls			X			X			X
Observations									2,391,000

Notes: Violent crime is specified as the difference between log central city and log suburban crime per capita, with violent crime measured as the average of 1996-1998 violent crime and 2006-2009 violent crime respectively. Household level controls include family type (married, single mother, single father, and other), presence of children under 18, household income, householder race/ethnicity, householder foreign born status and linguistic isolation, employment status, age and householder education level. City vs. suburban current controls include controls from the same census year as the residential moves. We include a set of city vs. suburban characteristics that are less likely to be a direct measure of our key dependent variable, specifically median gross rent, the median value of owner occupied housing, share of households who are foreign born, share of housing units built before 1940, share of housing units built in the past 10 years and share of CBSA employment that is in the central city. City vs. suburban lagged controls are drawn from the previous decade, and include the full set of metropolitan controls in our analysis. They include median gross rent; the median value of owner occupied housing; median household income; share of households in poverty; share of households who are non-white; share of households who are foreign born; share of housing units built before 1940; share of housing units built in the past 10 years; and share of CBSA employment that is in the central city.
Standard errors clustered at the CBSA level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 6A: Moves into Low Income Central City vs. High Income Central City vs. Suburban Tracts As a Function of Central City Minus Suburban Characteristics, 2000 to 2010, **Panel A: High-Income Household Interactions**

	Move to low-income CC	Move to high-income CC	Move to suburbs (reference)	Move to low-income CC	Move to high-income CC	Move to suburbs (reference)	Move to low-income CC	Move to high-income CC	Move to suburbs (reference)
	(1)			(2)			(3)		
Violent Crime	0.00	-0.04		0.00	0.05		0.00	0.02	
	(0.03)	(0.05)		(0.03)	(0.06)		(0.03)	(0.05)	
Violent Crime * High-Income	-0.200***	-0.08		-0.132***	0.01		-0.123***	-0.03	
	(0.03)	(0.06)		(0.05)	(0.04)		(0.04)	(0.04)	
Household controls	X	X	X	X	X	X	X	X	X
Current controls				X	X	X			
Lagged controls							X	X	X
Observations									2,391,000

Table 6B: Moves into Low Income Central City vs. High Income Central City vs. Suburban Tracts As a Function of Central City Minus Suburban Characteristics, 2000 to 2010, **Panel B: College-Educated Household Interactions**

	Move to low-income CC	Move to high-income CC	Move to suburbs (reference)	Move to low-income CC	Move to high-income CC	Move to suburbs (reference)	Move to low-income CC	Move to high-income CC	Move to suburbs (reference)
	(4)			(5)			(6)		
Violent Crime	0.00	-0.01		0.00	0.06		0.01	0.04	
	(0.04)	(0.05)		(0.03)	(0.05)		(0.03)	(0.05)	
Violent Crime * College-Educated	-0.225***	-0.12		-0.140***	0.01		-0.221***	-0.120*	
	(0.07)	(0.10)		(0.05)	(0.07)		(0.05)	(0.07)	
Household controls	X	X	X	X	X	X	X	X	X
Current controls				X	X	X			
Lagged controls							X	X	X
Observations									2,391,000

Table 6C: Moves into Low Income Central City vs. High Income Central City vs. Suburban Tracts As a Function of Central City Minus Suburban Characteristics, 2000 to 2010, **Panel C: White Household Interactions**

	Move to low-income CC	Move to high-income CC	Move to suburbs (reference)	Move to low-income CC	Move to high-income CC	Move to suburbs (reference)	Move to low-income CC	Move to high-income CC	Move to suburbs (reference)
	(7)			(8)			(9)		
Violent Crime	-0.02	-0.11		-0.02	-0.01		0.04	0.02	
	(0.06)	(0.08)		(0.06)	(0.08)		(0.05)	(0.07)	
Violent Crime	-0.104*	0.04		-0.05	0.08		-0.140***	-0.01	
* White	(0.06)	(0.07)		(0.06)	(0.08)		(0.05)	(0.07)	
Household controls	X	X	X	X	X	X	X	X	X
Current controls				X	X	X			
Lagged controls							X	X	X
Observations									2,391,000

Notes: Violent crime is specified as the difference between log central city and log suburban crime per capita, with violent crime measured as the average of 1996-1998 violent crime and 2006-2009 violent crime respectively. Household level controls include family type (married, single mother, single father, and other), presence of children under 18, household income, householder race/ethnicity, householder foreign born status and linguistic isolation, employment status, age and householder education level. City vs. suburban current controls include controls from the same census year as the residential moves. We include a set of city vs. suburban characteristics that are less likely to be a direct measure of our key dependent variable, specifically median gross rent, the median value of owner occupied housing, share of households who are foreign born, share of housing units built before 1940, share of housing units built in the past 10 years and share of CBSA employment that is in the central city. City vs. suburban lagged controls are drawn from the previous decade, and include the full set of metropolitan controls in our analysis. They include median gross rent; the median value of owner occupied housing; median household income; share of households in poverty; share of households who are non-white; share of households who are foreign born; share of housing units built before 1940; share of housing units built in the past 10 years; and share of CBSA employment that is in the central city.
Standard errors clustered at the CBSA level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 7A: Change in Homebuyers As a Function of Changing Neighborhood Violent Crime, 2000 to 2010, ***All Neighborhoods***

	% Change Number High Income Buyers (1)	% Change Number High Income Buyers (2)	% Change Number Low Income Buyers (3)	% Change Number Low Income Buyers (4)	% Change Share High Income Buyers (5)	% Change Share High Income Buyers (6)
Percent change violent crime	-0.300***	-0.167***	-0.124***	-0.0546	-0.239***	-0.160***
	(0.0452)	(0.0454)	(0.0441)	(0.0443)	(0.0469)	(0.0480)
Neighborhood controls, 2000		X		X		X
City FE	X	X	X	X	X	X
R-squared	0.192	0.262	0.028			
Observations	1,613	1,613	1,613	1,613	1,554	1,554

Table 7B: Change in Homebuyers As a Function of Changing Neighborhood Violent Crime, 2000 to 2010, ***Initially Low-Income Neighborhoods***

	% Change Number High Income Buyers (1)	% Change Number High Income Buyers (2)	% Change Number Low Income Buyers (3)	% Change Number Low Income Buyers (4)	% Change Share High Income Buyers (5)	% Change Share High Income Buyers (6)
Percent change violent crime	-0.448***	-0.254***	-0.251***	-0.168***	-0.336***	-0.219***
	(0.0592)	(0.0609)	(0.0539)	(0.0549)	(0.0631)	(0.0665)
Neighborhood controls, 2000		X		X		X
City FE	X	X	X	X	X	X
R-squared	0.215	0.278	0.054			
Observations	1,307	1,307	1,307	1,307	1,248	1,248

Note: Home purchases measured in 2001 and 2011. Crime per capita measured as the average of 1999 and 2000 violent crime and 2009 and 2010 violent crime. Neighborhood controls are drawn from 2000 Decennial Census and measured as levels. These controls include share minority, share college educated, poverty rate, median household income, share of units built before 1940, share of units built in the past decade, median housing value, an indicator for whether a tract is low income, the distance of the tract to the nearest high income tract, the distance of the tract to the central business district, the distance of the tract to the shore (if applicable), the density of each census tract, the average age of the housing stock in a tract. Percent change calculated using the midpoint method, so that values range from -2 (if the outcome is non-zero in 2000 and zero in 2010) to 2 (if the reverse is true). Last two columns have a smaller sample size because some tracts have an undefined outcome variable due to having zero total movers in either 2000 or 2010.
Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1