Banks Against Crime: The Impact of Home Mortgages on Neighborhood Crime*

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Abstract

Home mortgages are thought to enhance social capital among neighbors and encourage neighborhood revitalization. Research suggests that residential lending is associated with less crime, but most studies overlook the impact on acquisitive crime and heterogeneous effects across communities while facing the challenge of endogeneity biases. This study uses a shift-share instrumental variables approach by leveraging the differential exposure to banks' local market share and common national mortgage shocks across 27 US cities. This research finds that when banks make more home loans, communities experience a significant decrease in burglaries, thefts, aggravated assaults, and low-level offenses and an increase in motor vehicle thefts. The effects are larger in Black, Hispanic, and poor neighborhoods and seem driven by a decrease in vacant homes without signs of gentrification. The evidence suggests that home loans contribute to neighborhood revitalization and reducing prevalent crimes.

Keywords: home loans, neighborhood crime, community investments, shift-share instrument variables

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1 Introduction

Community investments have been proposed as a strategy to reduce neighborhood crime (Krivo, 2014; Sharkey, 2018; Vélez and Lyons, 2014). Public and non-profit neighborhood programs have shown promising results in decreasing criminal activity (Branas et al., 2018; Chalfin et al., 2022; Heller, 2014; Sharkey et al., 2017). The role of private investments in influencing public safety is less clear. The misalignment between private and social benefits can lead to the underprovision of local investments. In addition, liquidity constraints can make several investments unfeasible without external support. Banks can bridge this gap as they are a source of credit for myriad activities (Allen et al., 2008). They can influence crime by lending external resources to the neighborhood (Velez et al., 2012).

The impact of credit access on the local economy is substantial. The closure or merger of banks worsens local labor markets and economies, decreasing the opportunity costs of youth crime (Garmaise and Moskowitz, 2006; Ghosh and Contreras, 2022). While important, these events focus on high-impact, infrequent changes relative to a more common and localized banking activity: providing mortgages. Home loans may influence neighborhoods. Actions that increase the value of the neighborhood benefit the household, so residents have strong incentives to influence the local space (Molotch, 1976). Shared values and mutual trust encourage the neighbors' willingness to intervene for the common good (Sampson et al., 1997). Homeowners are more likely to invest in social capital and local networks than renters (DiPasquale and Glaeser, 1999). Moreover, the lack of access to home credit can become a source of racial and wealth inequalities and neighborhood decay (Krivo and Kaufman, 2004).

Previous research finds that home mortgages reduce violent (Kirk, 2020; Saporu et al., 2011; Shrider and Ramey, 2018; Vélez and Richardson, 2012) and major crimes (Bunting, 2020). Except for homicides, there is limited evidence on the effects on crime subcategories, which is critical to assess which property, violent, and low-level crimes are most affected. Acquisitive and non-acquisitive offenses respond differently to incentives. There is also a lack of research on the heterogeneous effects of mortgages on racial and ethnic communities. This research aims to fill this knowledge gap by advancing the scholarship on the differential effects of neighborhood investments on historically marginalized groups and understanding which places benefit the most. Furthermore, this study relies on data from 27 US cities. A larger sample size increases the statistical power to detect impacts across communities and focuses on detailed crime subcategories while reducing concerns about external validity. This situation is relevant as most previous research uses a single city case study.

Given the many factors that contribute to neighborhood crime, this research uses a shift-share instrumental variable approach to isolate the effects of mortgages on crime. It relies on crimes reported to law enforcement and residential lending data at the census tract level from 27 US cities. It leverages the time and spatial variation caused by banks' mortgage shocks with distinct market shares across neighborhoods. It assesses neighborhood crime changes due to differential exposure to lending. To understand the instrumental variable, let's use two banks as examples: PNC and Citibank. Both are large commercial banks. They likely have similar knowledge of their local market, but one had a nationwide yearly decrease in home loans, while the other experienced a large increase, probably due to conditions unrelated to local crime. The identification strategy compares similar census tracts where these banks operate but are exposed to different yearly changes in the banks' nationwide lending outside the city of study. These different nationwide shocks are a key source of exogenous variation in local lending, allowing for the estimation of its causal effect on neighborhood crime. Instead of using only two banks, this research uses 1,118 banks to leverage variation across space and time.

The evidence suggests that mortgages reduce crime, specifically theft, burglary, aggravated assaults, and non-major crimes, although they lead to more motor vehicle thefts. Overall, property crimes decrease when banks lend mortgages to individuals. The impacts are larger in Black, Hispanic, and poor communities, suggesting that historically marginalized neighborhoods benefit more from an increase in mortgage lending. A decrease in vacant homes partially explains the effects, and no discernible gentrification impacts are detected, measured through sociodemographic changes. The results suggest that private investments act as crime prevention strategies without affecting current residents. Home loans contribute to neighborhood revitalization and prevent acquisitive crimes. Still, they are insufficient to decrease serious violent offenses. Other alternatives are needed to deter such criminal events.

The remaining article is organized as follows. Section 2 reviews the literature on mortgages and crime. Sections 3 and 4 explain the data and empirical strategy. Section 5 presents the results, and Section 6 concludes.

2 Background

Banks do not randomly lend money across communities; they respond to the institutional, local, and individual context. Addressing the endogeneity biases from common causes, reverse causality, and omitted variables has been a common challenge in the literature. For example, mortgages influence crime, and crime also affects lending. Specifically, criminal activity impacts property prices negatively (Dealy et al., 2017; Gibbons, 2004; Lens and Meltzer, 2016). Properties with diminishing prices will find it more difficult to obtain a mortgage. Banks are less willing to lend money for properties that, in case of default, would be challenging to resell.

Confounders that affect crime and mortgages simultaneously are another concern. Higher unemployment rates relate to more crime (Aaltonen et al., 2013; Raphael and Winter-Ebmer, 2001), and steady income and employment records are common factors to provide lending. More broadly, access to credit is a potential mechanism that could contribute to neighborhood revitalization. Withholding loans to creditworthy, minority ethnic groups (e.g., redlining) has been shown to lead to disinvestment and a myriad of social problems, including more crime (Aaronson et al., 2021; Faber, 2020; Lyons et al., 2023; Mitre-Becerril, 2024).

Collective efficacy could also affect the role of mortgages on public safety. Residential stability creates a stronger attachment to the neighborhood (Morenoff et al., 2001; Sampson et al., 1997). Local friendship networks may strengthen social controls and mutual trust and facilitate well-organized communities (Sampson and Groves, 1989). Homeowners are less likely to migrate to other areas (Modestino and Dennett, 2013), and have been found to invest in social ties and do civic duties (DiPasquale and Glaeser, 1999). If home loans encourage resident stability, it would facilitate establishing formal and informal norms that prevent crime. Likewise, crime could also decrease via changes in the housing tenure (Disney et al., 2023).

The role of the built environment and situational opportunities could also explain the relationship between mortgages and crime. Home loans are also provided to renovate properties. Physical investments in the property may shape offenders' perceptions of guardianship, making it more risky to commit crimes (Taylor and Gottfredson, 1986). Moreover, if homeowners occupy vacant or foreclosed properties rather than replacing existing tenants, the number of blighted and vacant properties would decrease, along with crime (Branas et al., 2018; Hohl et al., 2019; Kondo et al., 2015).

While mortgages could make neighborhoods safer, not everyone may benefit. An abrupt increase in housing demand (hence, more mortgages) may lead to higher property prices and, hence, taxes too. Renters may also find it expensive to pay higher prices. Long-term, low-income, minority-prevalent residents could be displaced, leading to new tenants with a higher socioeconomic background. Gentrification-induced displacement is a concern in assessing neighborhood changes (Zuk et al., 2018). Studies point toward a negative relationship between crime and gentrification (MacDonald and Stokes, 2020; Papachristos et al., 2011). Accordingly, identifying compositional changes due to the mortgage increase in the community is a relevant research and policy question when assessing localized housing developments.

Residential loans can also encourage opportunities for crime. Property improvements may signal the availability of high-value goods, attracting potential offenders and increasing crime. Evidence suggests that offenders respond to higher valued goods (Draca et al., 2019). People can also refinance an original loan with longer terms or lower interest rates, freeing resources for other activities. This situation could increase crime opportunities, as homeowners may become potential targets as they change their spending patterns.

Mortgages may lead to neighborhood revitalization, though they may not mechanically translate to fewer crimes across the board. Auto theft is pro-cyclical to the economy, meaning that it increases as the economic activity improves (Bushway et al., 2012; Cook and Zarkin, 1985). Finally, mortgage indebtedness could bring psychological distress, driven by fears of being unable to keep up the monthly payments or cash constraints, particularly during difficult economic periods (Cairney and Boyle, 2004). This additional psychological burden could lead to more antisocial and criminal behaviors due to the negative stimuli and a mismatch between available means and aspirational goals (Agnew, 1992; Merton, 1938).

Previous literature includes persuasive descriptive studies finding a negative association between residential lending and violent crime.[1] Saporu et al. (2011) pools three years of data into a single average period and accounts for the dependence of observations in nested units (e.g., tracts embedded within cities) and multiple neighborhood and city-level characteristics, finding decreases in violent and property crimes, with larger changes in Black and Latino communities. Vélez and Richardson (2012) also uses a three-year average sample and controls for spatial lag autocorrelation (e.g., the mean value of adjacent areas), finding a decrease in homicides. Kirk (2020) uses a similar method, controlling for collective efficacy, showing that mortgage denials lead to more violent offenses. Shrider and Ramey (2018) uses a random-effects model, finding a decrease in violent crime in areas providing more mortgages.

Instrumental variable studies have also found negative impacts on crime. Veléz (2009) uses the age of the housing stock in the broad community as an instrument, finding a negative effect of mortgages on homicides. Velez et al. (2012) find a negative impact on violent crime, using first-differences and lagged variables as an instrument to address confounding relationships. Bunting (2020) uses a shift-share instrument variable, similar to this research, finding that mortgages reduce major crimes.

Most previous studies have focused on a single city (e.g., Seattle, Chicago, or Boston) or a county (e.g., Los Angeles). They have examined only homicides or an aggregated measure of violent or major crimes. We lack evidence on the impacts of the different crime subcategories that may respond differently to neighborhood dynamics. A large oversight has been non-major offenses and financially motivated crimes, which may also be sensitive to local changes, particularly localized urban development. Similarly, we have

[1] There is a related literature on the impact of foreclosures on crime (Ellen et al., 2013; Lacoe and Ellen, 2015). However, foreclosures measure what happens when people lose their property, so they may be measuring home abandonment. The mortgage studies focus on what happens when people own and occupy a house and have an incentive to protect their investment.

limited evidence on the heterogeneous impacts across communities. A large sample size study would be more likely to detect such impacts. This research aims to fill this knowledge gap.

3 Data

3.1 Data sources

There is no national repository of crime incidents at the census tract level. The common data source is the Federal Bureau of Investigation's Uniform Crime Reporting (UCR), replaced in 2021 with the National Incident-Based Reporting System. Their smallest geographical breakdown is the agency level, which usually matches a city, town, or county. This dataset is not appropriate for studying sub-city level changes. To overcome this data limitation, this research hand-collected time-stamped crime incident information from 27 of the most populated US cities, representing 33.3 million people or about 10 percent of the US population. These cities were chosen based on having available crime data from the last decade.[2]

Some cities only publish the address of the incident, so three geocoders (US Census, ArcGIS, and OpenStreetMap) sequentially attempted to obtain the latitude-longitude data. The geocoding hit rate was above the minimum acceptable hit rate (Ratcliffe, 2004). To ensure accuracy in the geocoding and data aggregation processes, the crime incidents were compared to the UCR dataset. The crimes matched well in levels and trends. The incidents were categorized as major and nonmajor crimes. Major crimes include murder, robbery, and aggravated assault, comprising violent crimes and burglary, theft, and motor vehicle theft, forming property crimes. Non-major crimes are all other offenses reported to the police.

The residential loans come from the Home Mortgage Disclosure Act (HMDA) data collected by the Consumer Financial Protection Bureau. It requires financial institutions to report and disclose de-identified mortgage-level data. In October 2015, there was a change in the legislation, increasing the data fields reported in the HMDA data and changing the financial institution identifier for all data collected in 2018 and onward. This study uses data up to 2017 to avoid introducing measurement errors in the analysis.[3] The mortgages consider the originated loans (e.g., excludes loans purchased by the financial institution in

[2] Some cities release data from the mid-2000s, but 2011 is the first year when most cities have complete information, so this year was chosen as the beginning of the study period. **Appendix Figure A.1** shows the geographical distribution of the cities included in this study: Atlanta, GA; Aurora, CO; Austin, TX; Buffalo, NY; Chicago, IL; Cincinnati, OH; Columbus, OH; Houston, TX; Indianapolis, IN; Kansas City, MO; Los Angeles, CA; Louisville, KY; Memphis, TN; Mesa, AZ; Milwaukee, WI; Minneapolis, MN; New Orleans, LA; New York, NY; Orlando, FL; Philadelphia, PA; Pittsburgh, PA; Raleigh, NC; San Francisco, CA; Seattle, WA; St. Louis, MO; Tucson, AZ; and Washington, DC.

[3] The 2015 Home Mortgage Disclosure Regulation C amendment explains their data collection changes, See `https://www.federalregister.gov/documents/2015/10/28/2015-26607/home-mortgage-disclosure-regulation-c`. Pre-2018 data is stored at `https://www.consumerfinance.gov/data-research/hmda/`, while post-2018 data is available at `https://ffiec.cfpb.gov/data-publication/`. Merging pre and post-2018 data would cause mismatches (e.g., typos in identifiers).

the secondary market) for single-family properties (e.g., excludes manufactured housing and multifamily loans). The mortgage's purpose can be home purchase, improvement, or refinancing. The first two loan types focus on new investments in the community (acquiring or renovating a property). Refinancing could lead to lower monthly mortgage payments, increasing the households' cash liquidity.

The analysis includes socioeconomic and demographic variables collected from the American Community Survey (ACS). It considers the five-year census tract-level estimates on the percentage of Black, White, and Hispanic population, age groups (below 14, 15-24, 25-39, 40-54, and over 55 years old), schooling attainment (less than high school, high school, some college, and college education), the unemployment and poverty rates, and the number of vacant and occupied properties.

The HMDA and ACS data come at the census tract level. In 2012, the Census Bureau updated its geographical boundaries, as it does every decade. This process usually means partitioning high-populated tracts. The pre-2012 data was apportioned to the new boundaries using the relationship files published by the Census Bureau.[4]

3.2 Analytical database

Table 1 presents the descriptive statistics in selected years (2011, 2014, and 2017) for the 7,810 census tracts included in the study.[5] The average census tract experienced a decrease of 13 percent in non-major crimes between 2011 and 2017. The reduction in major crimes was about 7 percent, as aggravated assaults and thefts showed no decrease during these years. Property crimes are almost five times more common than violent ones. Theft is the most recurrent crime reported to the police, followed by burglary, motor vehicle theft, and aggravated assault. The mean census tract experienced around one murder every two years, but the large standard deviation suggests that homicides have a skewed distribution (e.g., most areas experience no such crime). Overall, the crime distribution is consistent with national crime data.

The average census tract had an increase in mortgages, moving from 44 to 60 per census tract per year. Their value went from 12.1 to 19.7 million dollars in the average neighborhood. Consequently, the loan amount per mortgage increased from 277 to 328 thousand dollars between 2011 and 2017. These numbers mean a yearly growth rate of 4.6, 7.2, and 2.4 percent for the number of approved mortgages, monetary value, and amount per loan. These annual growth rates relate to a stronger mortgage and housing market after the Great Recession.

The average census tract sociodemographics remained relatively stable over these seven years. Census

[4] See https://www.census.gov/geographies/reference-files/2010/geo/relationship-files.html.

[5] Seattle, WA and San Francisco, CA do not report georeferenced murders. Similarly, Atlanta, GA, Houston, TX, Indianapolis, IN, Mesa, AZ, Minneapolis, MI, and Washington DC do not report non-major crimes.

tracts have nearly four thousand residents. Most of them identify as White (51%) and to a less extent as Black (27%) or Hispanic (24%). These characteristics are consistent with cities being more racially and ethnically diverse than the rest of the country. Individuals in their prime age (25 to 54 years old) represent nearly 45 percent of the population, while teenagers and young adults (15 to 24 years old) account for 15 percent of the tracts' residents. Almost 40 percent have a college degree or higher, while fewer than 20 percent have less than a high school diploma. The characteristics resemble the country's sociodemographics.

The unemployment rate ranged between 10.9 and 8.5 during these seven years. In 2011, it was similar to the national average but higher in 2014 and 2017. The poverty rate was consistently above that of these 27 cities by about six percentage points compared to the rest of the US (17 vs 11 percent). Finally, the mean census tract experienced a marginal rise in occupied housing units of 4.7 percent between 2011 and 2017 (a half-percent yearly change) and a decrease of about 8 percent (1.1 yearly percent growth) in vacant properties. These numbers show that the average census tract had a reduction in crime and an increase in mortgages. The main objective of this research is to assess whether this relationship holds once potential confounders are taken into account.

4 Empirical strategy

4.1 Econometric model

Estimating the causal effect of mortgages on crime is challenging due to unobserved confounders creating an endogeneity bias. Cross-sectional design is unlikely to provide causal estimates. One plausible approach for estimating the relationship between mortgages and crime is a fixed-effects model, like Equation (1), regressing crime, y_{it}, on home loans, L_{it}, in tract i and year t, controlling for a vector, X_{it}, of time-variant, observed sociodemographic variables. To account for time-invariant, tract-specific unobserved variables (e.g., stable neighborhood preferences about housing and crime) and time-varying, tract-invariant confounders (e.g., national yearly economic shocks), the model also includes census tract, γ_i, and year, μ_t, fixed effects.

$$y_{it} = \gamma_i + \mu_t + \beta L_{it} + X_{it}\alpha_X + e_{it} \tag{1}$$

Another strategy could be a random effects model, which accounts for the hierarchical structure of the observations. Despite adding controls, the fixed and random effects model may not provide causal estimates because time-varying, unobserved factors may influence crimes and loans simultaneously, leading to bias.

Other models are needed to overcome the concern of endogeneity.[6] An instrumental variable approach is a prime candidate to eliminate the bias by only using the variability in mortgages that is uncorrelated with the omitted variable (Angrist and Krueger, 2001). A Bartik or shift-share instrument is appropriate given the institutional context. This method leverages the presence of multiple banks in a census tract and the banks' lending patterns outside the city of study, which are likely uncorrelated in time and place with local crime changes once accounting for fixed effects and observed controls.

The shift-share instrument has two components. The shift, g_{ikt}, is the nationwide growth in mortgage loan amount by bank k between year t and $t-1$, excluding loans in city j where tract i is located. The empirical design assesses whether differential exposure to external shocks relates to differential changes, so a growth rate rather than levels is preferred (Goldsmith-Pinkham et al., 2020). As it is customary in the shift-share literature, this research uses a symmetric growth rate calculated as $(L_{it} - L_{it-1})/(0.5 * L_{it} + 0.5 * L_{it-1})$, so the values range between -2 and 2. This formula has the advantage of being symmetric, additive, bounded, and handles changes increasing from a zero baseline (Törnqvist et al., 1985).

The share, s_{ikt_0}, is the proportion of the mortgage loan amount of bank k in tract i and year t_0, so it ranges from zero to one. Fixing the shares to a specific time, usually a pre-study period, is common in this research design. For this study, it was defined $t_0 = 2007$, which is one year before the Great Recession. By fixing the shares to one period, the method relates to a difference-in-differences with a single cross-sectional variation difference used in the research design (Goldsmith-Pinkham et al., 2020). The shift-share instrument, Z_{it}, is the inner product of the nationwide bank component of the mortgage growth rate and the bank-tract shares. Formally, it is defined as Equation (2):

$$Z_{it} = \sum_{k=1}^{K} s_{ikt_0} g_{ikt} \tag{2}$$

Once the instrument is built, the model uses the standard two-stage least squares regression method. The first stage follows Equation (3):

$$L_{it} = \gamma_i + \mu_t + \beta_1 Z_{it} + X_{it} \alpha_X + e_{it} \tag{3}$$

where L_{it} is the logarithm of the mortgages loan amount in tract i and year t, and X_{it}, γ_i, and μ_t are

[6]Research studying whether banks increase lending in census tracts facing a closer inspection from regulatory agencies than in comparable areas has used a regression discontinuity design leveraging the discontinuous threshold of the Community Reinvestment Act eligibility status (Avery and Brevoort, 2015; Bhutta, 2011; Bostic and Lee, 2017; Ding and Hwang, 2020). A preliminary examination of this model in these 27 cities suggested a significant change in mortgages but failed basic robustness checks (e.g., alternative thresholds). Consequently, this design is not warranted for this sample.

sociodemographic controls and fixed effects. The reduced-form specification follows Equation (4):

$$y_{it} = \gamma_i + \mu_t + \beta_2 Z_{it} + X_{it}\alpha_X + e_{it} \tag{4}$$

where y_{it} is the logarithm of crimes in tract i and year t. Finally, the second stage or instrumental variable specification follows Equation (5):

$$y_{it} = \gamma_i + \mu_t + \beta_3 \hat{L}_{it} + X_{it}\alpha_X + e_{it} \tag{5}$$

where $\hat{L}_{it}$ is the predicted growth rate of the mortgage loan amount in tract i and year t based on the first stage in Equation (3). The standard errors are clustered at the census tract level. Some outcomes, particularly homicides, have zero incidents in any given year tract. The inverse hyperbolic sine function was used, which approximates to $\log(2y)$, and it can be interpreted in the same way as a standard logarithmic dependent variable (Burbidge et al., 1988). The robustness checks use alternative functional forms.

The shift-share instrument model became common in urban, regional, and international trade economics since Bartik (1991) examined the impacts of state and local policies on job growth.[7] Instrumental variables based on bank lending data have been used previously to assess the effect of credit market shocks in the real economy (Abras and de Paula Rocha, 2020; Greenstone et al., 2020). In the crime literature, the shift-share instrument method has been used to examine the public safety effects of mortgages (Bunting, 2020), migration waves (Dehos, 2021), labor market shocks (Dell et al., 2019; Ghosh, 2018; Gould et al., 2002), gun ownership (Billings, 2020), and stop, question, and frisk strategies (Weisburd et al., 2016).

The shift-share instrument has features similar to the instrumental variable methods used in the crime literature. For instance, the shifts are built using the national lending made by a bank, excluding the loans in the city of interest, which is similar to the leave-one-out average sentence approach used in the judge instrumental variable studies aiming to assess the impact of incarceration on recidivism (Aizer and Doyle Jr, 2015; Loeffler and Nagin, 2022). Likewise, historical population shares have been used as instrumental variables to predict future population concentrations, but theoretically independent from current crime rates, to examine the impact of immigration on neighborhood crime (MacDonald et al., 2013).

[7] Bartik (1991) was not the first one using this approach. Still, the author popularized this method and explained its logic, carrying the author's name (Broxterman and Larson, 2020; Goldsmith-Pinkham et al., 2020). A Google Scholar search of the terms *Bartik instrument* or *shift-share instrument* returns more than 1,800 results. While not all hits probably use this instrument, it signals the widespread use of the method in the literature.

4.2 Building the instrumental variable

Previous research has relied on the same shift-share instrumental variable using mortgage data to study the effects of residential lending on crime (Bunting, 2020). This research builds upon this idea, but instead of using a single county as the area of study, it examines 27 cities. This large sample size adds more exogenous variation to the research design. It also increases the statistical power to measure impacts on crime subcategories and heterogeneous effects across communities, which is the main contribution of this paper.

This research identifies 1,118 banks offering mortgages in the 27 cities included in the study between 2007 and 2017. These banks are used to build the Bartik instrument. **Appendix Figure A.2** shows that these banks jointly cover practically all US counties. The mean (median) county has 81 (96) out of the 1,118 banks. These financial institutions have widespread coverage across the US. This section examines the instrumental variable.

The shift-share instruments have two sources of variation: the shifts and the shares. The shifts need to be uncorrelated with the error term to satisfy the exogenous condition (Borusyak et al., 2025). For this research, it means that the loans given outside the city where the census tract is located (the shifts) are not systematically different in banks concentrating in neighborhoods (shares) with high versus low lending patterns (error term). It also requires a large number of shifts. The shifts, which are the nationwide growth rate, come from the loans occurring outside the cities of interest for this research. The shifts are likely exogenous to the crime incidents in the census tracts included in the analysis. The exclusion restriction would be violated if the crime incidents in the 27 cities affect lending in the rest of the country. It is unlikely that this situation is the case. Bank lending depends on the local market and is geographically close to the lender (Nguyen, 2019). Lending is also contingent on the decisions set by the central banking system (e.g., the Federal Reserve System for the US). A tight monetary policy translates into higher lending costs for banks, and they transfer such costs to consumers by setting higher interest rates on loans, decreasing their demand (Chopra, 2022).[8]

While banks face similar macroeconomic conditions, their lending has a distinctive component that depends on their unique strategies and management decisions (e.g., CEO's leadership, advertising strategies, client management). These characteristics influence the banks' revenue and cost strategy and how much resources they will lend to consumers and expect to recover successfully. **Figure 1**, Panel A, shows

[8] **Appendix Figure A.3** shows a negative correlation between the national mortgage loan amount and the US Treasury market yield. It also shows that the change in mortgages in the 27 cities and the rest of the country has followed the same trend during the last decade.

the mean national mortgage growth (excluding the 27 cities) of the 1,118 banks between 2011 and 2017.[9] The average bank increased its mortgage lending amount by 4.2 percent annually. Still, there is considerable variation between banks. Many financial institutions experienced yearly contractions, while others experienced expansion periods. Moreover, Panel B visualizes substantial variation within banks across time. Practically, all banks experienced positive and negative yearly changes over the seven years of study (2011-2017). This temporal exogenous variation across banks forms the shifts of the instrumental variables.

The second component of the instrumental variables is the shares. If the shifts are exogenous, the estimator is consistent even if the shares are not exogenous (Goldsmith-Pinkham et al., 2020). Nevertheless, the distribution of shares across time and space contributes to the variation used to compare areas with different levels of exposure to lending. **Figure 2** shows the distribution of the 1,118 banks' mortgage share per census tract in 2007, the base period (s_{ikt_0}). It presents the experience of a typical bank in a census tract. The average (median) bank has 6.1 (2.5) percent of the proportion of the census tract mortgage loan market. Nearly 90 percent of the banks are below 15 percent of the local share. In contrast, 1.2 percent of the banks have more than 51 percent of the neighborhood market. To understand the situation of a typical census tract, **Appendix Figure A.5** aggregates the 2007 banks' share at the census tract, $s_{it_0} = f_k(s_{ikt_0})$, to estimate the mean, median, and maximum bank share per census tract. Panel A shows that banks have 13 percent of the neighborhood market share in the average census tract. This pattern is confirmed in Panel B, showing that in the median census tract, banks have a 9 percent of the local market share. The differences between the mean and median typical census tract suggest a slightly skewed distribution. Panel C confirms this situation by plotting the distribution of the maximum market share of a bank per census tract. The leading bank has one-third of the local market share in the typical census tract.

While one bank usually has one-third of the local mortgage market, the remaining share is scattered across other financial institutions. Specifically, the mean (median) census tract has 14 (16.5) banks offering mortgages. In most census tracts, people can choose from many financial institutions to obtain a home loan. This result should not be surprising, as people look for mortgages online or visit several banks scattered around the city; they are not limited to the banks in their neighborhood. Said differently, banks are unlikely to have strong market power at such a small geographical level. The large number of shares across tracts is the other source of variation that the shift-share instrumental variables approach leverages (cross-sectional variation).[10]

[9] **Appendix Figure A.4** shows that the yearly mortgage growth rates. The yearly macroeconomic conditions seem to influence most banks to increase or decrease their lending. Still, there is a large variation within any given year.

[10] **Appendix Figure A.6** shows there is a positive correlation of the banks' tract shares across time: having larger shares in 2007 relates to higher shares in 2010, although there is a considerable unexplained variation.

5 Results

5.1 Main results

To assess the impact of mortgage lending on crime, this section first presents the specifications used in previous studies: random effects, fixed effects, and first differences using the lag of the independent variable as an instrument. **Table 2** Panel A shows that the random effects model suggests increases in property crimes, finding significant reductions in murders and aggravated assaults. Panel B shows the fixed effects model, showing a positive relationship between mortgages and property crimes. Murders and aggravated assaults have a negative, non-significant correlation with residential lending, while a rise in robberies drives the increase in violent crime. Finally, the first difference with the lag of the independent variable as an instrument, Panel C, shows significant decreases in property and violent crimes. A reduction in robberies explains the decrease in violent crimes. None of the three models shows significant effects on non-major crimes. These models have different results, as it is unlikely they remove the endogeneity biases of reverse causality and omitted time-variant confounders.

Table 3 shows that the instrumental variable –meaning the inner product of the banks' tract share and the banks' national growth rate outside of the city where the tract is located– strongly predicts the census tract mortgages. This model includes tract and year fixed effects. Adding covariates to the model does not change the result. The coefficients imply that a ten percent growth in the mortgage outside of the 27 cities relates to a 2.3 percent increase in the census tract mortgages ($(e^{\beta_1} - 1)/10$ percent). The estimate is similar to Bunting (2020), suggesting that the relationship holds in other jurisdictions. The F-statistic is well above the common threshold level (Stock et al., 2002). These results suggest that the instrumental variables model is strongly associated with local mortgage changes; hence, the relevance condition holds.

Table 4 presents the reduced form and the second-stage least squares (or instrumental variable) estimates. They differ in magnitude as the instrumental variable estimate equals the reduced form coefficient divided by the first stage (the scaled version of the reduced form). The second stage least squares results suggest that a 10 percent increase in the mortgage loan amount relates to a 1.1 percent reduction in major crimes, driven mainly by a 3.0 and 1.7 percent decrease in theft and burglary. Motor vehicle thefts experience a 5.1 percent increase when there is a 10 percent change in neighborhood mortgages, probably related to more crime opportunities and population movement. This result is consistent with their pro-cyclical relationship with the economy (Cook and Zarkin, 1985; Bushway et al., 2012). Violent crime shows a negative, non-statistically significant decrease. Aggravated assault shows a significant 2.4 percent decrease for every 10 percent increase in lending. Murders and robberies have no statistically significant changes, which is a different finding relative to previous studies. Finally, there was also a significant decrease in non-serious crimes, 1.7 percent, which suggests that low-level offenses are also affected by having more mortgages in the neighborhood.

5.2 Robustness

This section assesses the robustness of the results to different analytical decisions taken in the research process. **Figure 3** presents the second-stage least-squares estimates and confidence intervals for alternative specifications. **Appendix Figure A.7** shows the robustness checks for the reduced form estimates. The first concern is that the inverse hyperbolic sine transformation of the data drives the results. The models are also estimated using the $\log(y+1)$ as an alternative functional form. This function also avoids excluding outcomes with zero crimes, likely in small populated areas or for rare outcomes (e.g., murder). The decision to add one is arbitrary, though common in the literature. The results hold for this alternative functional form.

The main specification estimates the crime outcomes using counts rather than rates. Counts and rates may not reflect the same victimization risk, particularly when residents are used to computing the rates (Massenkoff and Chalfin, 2022). This situation is a concern in areas with many transient visitors and pedestrians (e.g., tourist places or commercial areas) but few residents. Given the intra-city movement of people, counts are preferred to rates at small geographical levels, such as neighborhoods. Still, using crime rates rather than counts leads to the same results.

A third concern is whether the results change by giving more importance to densely populated areas. Two models were estimated to test this concern. One model weights the observations by the number of housing units in the census tract. It gives more importance to areas with a larger potential for receiving mortgages, as they have more residential properties. A second model weights the observations by the population living in the census tract, giving more importance to places with more potential victims. Both alternatives provide the same conclusions.

Next, one could be concerned that jurisdictions could have specific regulations affecting the local economy. This is particularly relevant as banks are also regulated by state governments. Two models were estimated: one adding city-time-trends and another with state-time trends to control for different trajectories regarding how they implement regulations over time. Adding time trends makes robbery statistically significant. However, only two of the ten alternative specifications for this offense are significant. The significant results could be due to a false discovery rate.

A fifth concern is that some census tracts have banks with a large mortgage market share, so their presence may be correlated with local public safety trends that could influence the results. An alternative instrumental variable was built, excluding banks with more than two-thirds of the local market share, so the inner product of the shifts and shares only considers banks without a dominant market concentration. Burglary is now imprecisely estimated, but everything else has practically the same magnitude and statistical significance.

A final robustness check assesses whether the results are sensitive to excluding banks regardless of their market share. **Appendix Figure A.8** provides a leave-one-out estimator. It builds the instrumental variable, excluding twenty banks at a time, and estimates the regression model, repeating the process 50 times. Some banks affect the precision of the estimates. Nevertheless, the sign and magnitude of the coefficients are similar between the specifications and the main results.

5.3 Heterogeneity

The main results show that increasing mortgages reduces crime, particularly theft, burglary, aggravated assaults, and low-level offenses. There are reasons to expect differential effects by racial, ethnic, and concentrated disadvantage levels. For example, racial and ethnic minorities, due to redlining, have faced more challenges getting credit, affecting long-term neighborhood and individuals' life outcomes (Aaronson et al., 2021; Faber, 2020; Lyons et al., 2023; Mitre-Becerril, 2024). Residing in disadvantaged neighborhoods affects whether individuals experience discrimination in market transactions (Besbris et al., 2019). Even if there is no discrimination, to the extent that minority-prevalent neighborhoods have lower baseline mortgage levels, a marginal increase could have a larger impact relative to places with widespread credit availability due to decreasing marginal returns.

To contextualize these results, **Appendix Figure A.9** shows the distribution of the Black, Hispanic, and poor population in census tracts between 2011 and 2017. All distributions are skewed to the right, which means that most neighborhoods have little Black and Hispanic population, though a sizable number of tracts are mostly composed of these groups. A descriptive comparison finds that tracts with over 50 percent of Black (Hispanic) residents receive 17.7 (15.6) million dollars per year, or about 126 (53) thousand dollars per loan, less than their non-Black (non-Hispanic) areas.

To test for heterogeneous effects, the specification interacts the loan amount with a relevant dimension variable: the proportion of the Black, Hispanic, and poor population. Then, it instruments the endogenous variable with the shift-share instrument and its interaction term.[11] The interaction term assesses whether

[11] The same arguments that support the use of a shift-share instrument (Z_{it}) for mortgages (L_{it}) holds for using $D_{it}Z_{it}$ for $D_{it}L_{it}$, where D_{it} is the relevant heterogeneity dimension variable.

prevalent minority neighborhoods have larger crime changes due to increased mortgages.

Table 5 shows the heterogeneous treatment effects. Panel A suggests that Black neighborhoods benefit more from receiving mortgages than census tracts without this racial group. The effects are significant for non-major, property –caused by theft reductions– and violent crimes –caused by aggravated assaults decreases. The results imply that a 10 percent increase in the mortgages in tracts with a 25 percent prevalence of Black residents experience an additional 0.45 percent reduction in property crime than tracts with no members of this race group, which experience only a 0.25 percent reduction (computed as $(e^{\beta_1 * 0.5} - 1)/10$ percent). For context, the average neighborhood has 27 percent Black residents. Panel B shows that more mortgages also benefit Hispanic communities. They experience a larger decrease in property –driven by thefts and burglary– and non-major crimes. The increase in motor vehicle thefts is almost twice in Hispanic areas.

There is a high correlation between minority communities and poverty.[12] Race can intensify inner-city unemployment, poverty, and inequality rates due to historical and current structural disadvantages. Consequently, assessing differential changes due to poverty prevalence in the community is also relevant. Panel C points toward larger impacts of home loans on crime in poor places relative to affluent places. An increase of 10 percent in mortgages results in an additional decrease of 1.4 percent in property crimes in census tracts with a 25 percentage point difference in poverty rates (the average neighborhood has a 17 percent poverty level). The interaction terms of poverty are larger than the differential estimates of the Black and Hispanic populations, suggesting that concentrated disadvantage is more relevant than the ethno-racial neighborhood composition to explain the differential effects of mortgages on crime. This result is consistent with evidence highlighting that economic disadvantage can be more important than race in determining social outcomes (Sampson et al., 2018; Wilson, 2003). There are no heterogeneous effects on homicides and robberies.

The marginal effect of increasing mortgages in places with widespread lending services could differ from those with limited credit access. To assess such heterogeneous effects, the specification interacts the mortgage amount with an indicator variable of being on the first, second, or third tercile of the mean local mortgage amount during the study period. **Appendix Table A.1** shows the instrumental variable estimates. The effects are larger in the bottom tercile than in the middle and top distribution groups. There are statistically significant differences across tercile groups for property crimes, theft, motor vehicle thefts, aggravated assaults, and non-major crimes. For major crimes, the differences are imprecisely measured (p-

[12] Black (Hispanic) prevalence and the percent of poverty in a census tract have a significant correlation of 0.42 (0.29) in the sample used for this study.

value < 0.12), and burglary shows limited evidence of differential impacts among tercile groups. Murder and robberies do not show any statistically significant impacts in any of the three tercile groups. The evidence suggests that the impact of mortgages on crime is larger in areas where lending is scarce.

5.4 Potential causal mechanisms

This study shows that mortgages reduce crime, particularly property criminal incidents. This section assesses changes in the neighborhood dynamics to examine plausible explanations for the main estimates. Individuals can buy an occupied home, replacing a renter or a previous homeowner. Alternatively, people could buy a vacant home, meaning a property where no one was living there because it was just built by a construction company, it is a secondary home (e.g., neither for permanent residency nor for rent), or it was foreclosed by a bank, among other reasons. The consequence of occupying and remediating a vacant property is likely a crime decrease as evidence suggests (Hohl et al., 2019; Kondo et al., 2015), which could be related to having *more eyes upon the street* (Jacobs, 1961).

Table 6 examines this potential mechanism by measuring the effect of mortgages on occupied and vacant units. There are negligible impacts on the occupied or vacant housing stock when using any mortgage type (home purchase, improvement, or refinancing) for building the instrumental variable. However, subsetting the instrument to only mortgages meant for home purchase, the coefficient suggests that a 10 percent increase in mortgages increases (decreases) the occupied (vacant) units by 0.2 percent.[13] The treatment effects are small. However, let's remember that the occupied and vacant units outcomes come from the American Community Survey five-year estimates. The US Census combines data from five consecutive years of the survey to provide more accurate and reliable estimates for smaller areas. While it is common to use this data source when assessing impacts on census tracts in the literature, more attention should be paid to the sign rather than the magnitude of the estimate. The significant relationship suggests that having more natural surveillance due to fewer vacant units is one of the driving mechanisms causing crime changes.

One concern in expanding mortgage services for residential housing is gentrification. More lending could replace current residents, particularly those from minority and disadvantaged communities, with more affluent individuals. The physical place may be better off at the expense of displaced individuals. **Table 7** assesses this concern by examining whether the sociodemographic composition of the neighborhoods has changed. This situation does not seem to be the case. The proportion of White, Black, and educated individuals, common metrics for measuring gentrification, did not change. It could be possible that some

[13] The first stage of this alternative mortgage instrumental variable is significant. Results are available upon request.

areas may have experienced compositional changes, but the average neighborhood did not experience them. Accordingly, most residents seem to benefit from a safer community.

6 Discussion and conclusions

Home loans are a quintessential private investment that ties landowners' well-being to the property and neighborhood prospects. They have strong incentives to protect their investment. At the same time, localized investments may bring more opportunities for crime. What is the net effect of residential lending on the different types of criminal offenses? Do the effects vary by neighborhood composition? This research contributes to the literature by answering these questions. It relies on a shift-share instrumental variable and crime incident data collected from 27 major US cities. The evidence suggests that increasing mortgages decreases property crime -driven by thefts and burglary reductions– and aggravated assaults. There is an increase in motor vehicle thefts, probably caused by a larger supply of potential opportunities and targets and their pro-cyclical relationship with the local economic activity. Alternative model specifications and robustness checks confirm these findings.

The crime changes are considerably larger in Black and Hispanic neighborhoods and concentrated disadvantaged areas, implying that minority prevalent and poor communities benefit more from an increase in residential lending. These heterogeneous impacts likely result from decreasing marginal returns as minority-prevalent neighborhoods (usually low-income areas) have considerably lower lending than their White counterparts. These findings are consistent with significantly larger impacts in communities where lending is scarce than in areas with widespread availability of mortgage access. One potential mechanism of the effect of home mortgages seems to be fewer vacant houses and an increase in occupied units without experiencing discernible gentrification changes, measured through sociodemographic changes.

This study finds limited reductions in serious violent offenses from having more mortgages in the neighborhood. The decline, driven by aggravated assaults, is suggestive as it is not consistently significant in all specifications. Why do mortgages reduce property and non-major crimes but not more serious violent felonies? Reducing acquisitive and other violent offenses may mechanically prevent murders and robberies, but this study may not have distinguished the noise from the signal. This explanation cannot be unequivocally rejected, but given the large sample size, it is unlikely to be the main reason behind the null impacts on murder and robbery. A second explanation could be that context matters. Violent offenses are more likely to happen due to anger outbursts, disputes going badly, retaliation, and interpersonal conflicts. It may be that private investments are affecting only the opportunities for acquisitive crime, but not the conditions for offenses happening in the heat of the moment. Future studies should also focus on people's perceptions and behavioral habits, which could explain the differential impacts between property and violent offenses. A third plausible explanation could be the research design. Cross-sectional designs and random effects models may have overestimated the impacts relative to an instrumental variables approach.

This study is not without limitations. First, it uses data from 27 major US cities. Many of them face high living costs and unaffordable housing, so the effect of lending may be different in rural areas or cities with large housing inventories. Future research should explore the impact at the national level. Likewise, researchers should continue assessing the impact of property and violent offenses on other samples. Finally, the study period (2011-2017) was marked by a post-financial crisis era, with relatively low mortgage interest rates and a consistent increase in home prices. The interest rates have changed drastically, particularly since the COVID-19 pandemic. Future studies should examine the effects of lending in other market conditions.

Finally, this research contributes to the promising literature finding that localized investments can promote safer neighborhoods. While traditionally, these investments have come from public and non-profit sources, this research highlights that private investments can also deter crime. Financial institutions, maybe inadvertently, are contributing to reducing crime by providing credit to acquire a property or improve a current home. The effects of lending are larger in minority-prevalent and lower-income neighborhoods. This research highlights that home loan credits may be creating positive externalities in the community. Periods of low interest rates encourage credit and, with it, safer neighborhoods. However, it is possible that a tight, unaffordable housing industry, like the one the US is facing right now, could exacerbate neighborhood crime by constraining credit. Given the wide geographical presence and large financial asset size of banks, using lending to promote neighborhood revitalization is a key and promising area of research.

References

Aaltonen, M., Macdonald, J. M., Martikainen, P., and Kivivuori, J. (2013). Examining the generality of the unemployment–crime association. *Criminology*, 51(3):561–594.

Aaronson, D., Faber, J., Hartley, D., Mazumder, B., and Sharkey, P. (2021). The long-run effects of the 1930s holc "redlining" maps on place-based measures of economic opportunity and socioeconomic success. *Regional Science and Urban Economics*, 86:103622.

Abras, A. and de Paula Rocha, B. (2020). Bank credit shocks and employment growth: An empirical framework for the case of brazil. *The Journal of Developing Areas*, 54(1).

Agnew, R. (1992). Foundation for a general strain theory of crime and delinquency. *Criminology*, 30(1):47–88.

Aizer, A. and Doyle Jr, J. J. (2015). Juvenile incarceration, human capital, and future crime: Evidence from randomly assigned judges. *The Quarterly Journal of Economics*, 130(2):759–803.

Allen, F., Carletti, E., and Gu, X. (2008). The roles of banks in financial systems. *Oxford handbook of banking*, pages 32–57.

Angrist, J. D. and Krueger, A. B. (2001). Instrumental variables and the search for identification: From supply and demand to natural experiments. *Journal of Economic perspectives*, 15(4):69–85.

Avery, R. B. and Brevoort, K. P. (2015). The subprime crisis: Is government housing policy to blame? *Review of Economics and Statistics*, 97(2):352–363.

Bartik, T. J. (1991). Who benefits from state and local economic development policies?

Besbris, M., Faber, J. W., and Sharkey, P. (2019). Disentangling the effects of race and place in economic transactions: Findings from an online field experiment. *City & Community*, 18(2):529–555.

Bhutta, N. (2011). The community reinvestment act and mortgage lending to lower income borrowers and neighborhoods. *The Journal of Law and Economics*, 54(4):953–983.

Billings, S. B. (2020). Smoking gun? linking gun ownership to neighborhood crime. *Linking Gun Ownership to Neighborhood Crime (April 29, 2020)*.

Borusyak, K., Hull, P., and Jaravel, X. (2025). A practical guide to shift-share instruments. *Journal of Economic Perspectives*, 39(1):181–204.

Bostic, R. W. and Lee, H. (2017). Small business lending under the community reinvestment act. *Cityscape*, 19(2):63–84.

Branas, C. C., South, E., Kondo, M. C., Hohl, B. C., Bourgois, P., Wiebe, D. J., and MacDonald, J. M. (2018). Citywide cluster randomized trial to restore blighted vacant land and its effects on violence, crime, and fear. *Proceedings of the National Academy of Sciences*, 115(12):2946–2951.

Broxterman, D. A. and Larson, W. D. (2020). An empirical examination of shift-share instruments. *Journal of Regional Science*, 60(4):677–711.

Bunting, W. (2020). Does increased access to home mortgage money reduce local crime rates? evidence from san diego county. *Regional Science and Urban Economics*, 84:103570.

Burbidge, J. B., Magee, L., and Robb, A. L. (1988). Alternative transformations to handle extreme values of the dependent variable. *Journal of the American Statistical Association*, 83(401):123–127.

Bushway, S., Phillips, M., and Cook, P. J. (2012). The overall effect of the business cycle on crime. *German Economic Review*, 13(4):436–446.

Cairney, J. and Boyle, M. H. (2004). Home ownership, mortgages and psychological distress. *Housing studies*, 19(2):161–174.

Chalfin, A., Hansen, B., Lerner, J., and Parker, L. (2022). Reducing crime through environmental design: Evidence from a randomized experiment of street lighting in new york city. *Journal of Quantitative Criminology*, 38(1):127–157.

Chopra, R. (2022). The fed is raising interest rates. what does that mean for borrowers and savers? Technical report, Consumer Financial Protection Bureau.

Cook, P. J. and Zarkin, G. A. (1985). Crime and the business cycle. *The Journal of Legal Studies*, 14(1):115–128.

Dealy, B. C., Horn, B. P., and Berrens, R. P. (2017). The impact of clandestine methamphetamine labs on property values: Discovery, decontamination and stigma. *Journal of Urban Economics*, 99:161–172.

Dehos, F. T. (2021). The refugee wave to germany and its impact on crime. *Regional Science and Urban Economics*, 88:103640.

Dell, M., Feigenberg, B., and Teshima, K. (2019). The violent consequences of trade-induced worker displacement in mexico. *American Economic Review: Insights*, 1(1):43–58.

Ding, L. and Hwang, J. (2020). Effects of gentrification on homeowners: Evidence from a natural experiment. *Regional Science and Urban Economics*, 83:103536.

DiPasquale, D. and Glaeser, E. L. (1999). Incentives and social capital: Are homeowners better citizens? *Journal of urban Economics*, 45(2):354–384.

Disney, R., Gathergood, J., Machin, S., and Sandi, M. (2023). Does homeownership reduce crime? a radical housing reform from the uk. *The Economic Journal*, 133(655):2640–2675.

Draca, M., Koutmeridis, T., and Machin, S. (2019). The changing returns to crime: do criminals respond to prices? *The Review of Economic Studies*, 86(3):1228–1257.

Ellen, I. G., Lacoe, J., and Sharygin, C. A. (2013). Do foreclosures cause crime? *Journal of Urban Economics*, 74:59–70.

Faber, J. W. (2020). We built this: consequences of new deal era intervention in america's racial geography. *American Sociological Review*, 85(5):739–775.

Garmaise, M. J. and Moskowitz, T. J. (2006). Bank mergers and crime: The real and social effects of credit market competition. *the Journal of Finance*, 61(2):495–538.

Ghosh, A. and Contreras, S. (2022). Local banking market frictions and youth crime: Evidence from bank failures. *Journal of Financial Services Research*, pages 1–33.

Ghosh, P. K. (2018). The short-run effects of the great recession on crime. *Journal of Economics, Race, and Policy*, 1(2):92–111.

Gibbons, S. (2004). The costs of urban property crime. *The Economic Journal*, 114(499):F441–F463.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624.

Gould, E. D., Weinberg, B. A., and Mustard, D. B. (2002). Crime rates and local labor market opportunities in the united states: 1979–1997. *Review of Economics and statistics*, 84(1):45–61.

Greenstone, M., Mas, A., and Nguyen, H.-L. (2020). Do credit market shocks affect the real economy? quasi-experimental evidence from the great recession and" normal" economic times. *American Economic Journal: Economic Policy*, 12(1):200–225.

Heller, S. B. (2014). Summer jobs reduce violence among disadvantaged youth. *Science*, 346(6214):1219–1223.

Hohl, B. C., Kondo, M. C., Kajeepeta, S., MacDonald, J. M., Theall, K. P., Zimmerman, M. A., and Branas, C. C. (2019). Creating safe and healthy neighborhoods with place-based violence interventions. *Health Affairs*, 38(10):1687–1694.

Jacobs, J. (1961). The death and life of great american cities.

Kirk, E. M. (2020). Obstructing the american dream: Homeownership denied and neighborhood crime. *Housing Policy Debate*, pages 1–21.

Kondo, M. C., Keene, D., Hohl, B. C., MacDonald, J. M., and Branas, C. C. (2015). A difference-in-differences study of the effects of a new abandoned building remediation strategy on safety. *PloS one*, 10(7):e0129582.

Krivo, L. J. (2014). Reducing crime through community investment: Can we make it work. *Criminology & Pub. Pol'y*, 13:189.

Krivo, L. J. and Kaufman, R. L. (2004). Housing and wealth inequality: Racial-ethnic differences in home equity in the united states. *Demography*, 41(3):585–605.

Lacoe, J. and Ellen, I. G. (2015). Mortgage foreclosures and the changing mix of crime in micro-neighborhoods. *Journal of Research in Crime and Delinquency*, 52(5):717–746.

Lens, M. C. and Meltzer, R. (2016). Is crime bad for business? crime and commercial property values in new york city. *Journal of Regional Science*, 56(3):442–470.

Loeffler, C. E. and Nagin, D. S. (2022). The impact of incarceration on recidivism. *Annual Review of Criminology*, 5:133–152.

Lyons, C. J., Vélez, M. B., and Chen, X. (2023). Inheriting the grade: Holc "redlining" maps and contemporary neighborhood crime. *Socius*, 9:23780231231197030.

MacDonald, J. M., Hipp, J. R., and Gill, C. (2013). The effects of immigrant concentration on changes in neighborhood crime rates. *Journal of Quantitative Criminology*, 29(2):191–215.

MacDonald, J. M. and Stokes, R. J. (2020). Gentrification, land use, and crime. *Annual Review of Criminology*, 3:121–138.

Massenkoff, M. and Chalfin, A. (2022). Activity-adjusted crime rates show that public safety worsened in 2020. *Proceedings of the National Academy of Sciences*, 119(46):e2208598119.

Merton, R. K. (1938). Anomie and social structure. *American sociological review*, 3(5):672–682.

Mitre-Becerril, D. (2024). The long-term effects of structural discrimination on public safety: The 1930s redlining maps. Technical report.

Modestino, A. S. and Dennett, J. (2013). Are american homeowners locked into their houses? the impact of housing market conditions on state-to-state migration. *Regional Science and Urban Economics*, 43(2):322–337.

Molotch, H. (1976). The city as a growth machine: Toward a political economy of place. *American journal of sociology*, 82(2):309–332.

Morenoff, J. D., Sampson, R. J., and Raudenbush, S. W. (2001). Neighborhood inequality, collective efficacy, and the spatial dynamics of urban violence. *Criminology*, 39(3):517–558.

Nguyen, H.-L. Q. (2019). Are credit markets still local? evidence from bank branch closings. *American Economic Journal: Applied Economics*, 11(1):1–32.

Papachristos, A. V., Smith, C. M., Scherer, M. L., and Fugiero, M. A. (2011). More coffee, less crime? the relationship between gentrification and neighborhood crime rates in chicago, 1991 to 2005. *City & Community*, 10(3):215–240.

Raphael, S. and Winter-Ebmer, R. (2001). Identifying the effect of unemployment on crime. *The journal of law and economics*, 44(1):259–283.

Ratcliffe, J. H. (2004). Geocoding crime and a first estimate of a minimum acceptable hit rate. *International Journal of Geographical Information Science*, 18(1):61–72.

Sampson, R. J. and Groves, W. B. (1989). Community structure and crime: Testing social-disorganization theory. *American journal of sociology*, 94(4):774–802.

Sampson, R. J., Raudenbush, S. W., and Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *science*, 277(5328):918–924.

Sampson, R. J., Wilson, W. J., and Katz, H. (2018). Reassessing "toward a theory of race, crime, and urban inequality": Enduring and new challenges in 21st century america. *Du Bois Review: Social Science Research on Race*, 15(1):13–34.

Saporu, D. F., Patton III, C. L., Krivo, L. J., and Peterson, R. D. (2011). Differential benefits? crime and community investments in racially distinct neighborhoods. *Race and Justice*, 1(1):79–102.

Sharkey, P. (2018). Op-ed: Community investment, not punishment, is key to reducing violence. Technical report, Los Angeles Times.

Sharkey, P., Torrats-Espinosa, G., and Takyar, D. (2017). Community and the crime decline: The causal effect of local nonprofits on violent crime. *American Sociological Review*, 82(6):1214–1240.

Shrider, E. A. and Ramey, D. M. (2018). Priming the pump: public investment, private mortgage investment, and violent crime. *City & Community*, 17(4):996–1014.

Stock, J. H., Wright, J. H., and Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics*, 20(4):518–529.

Taylor, R. B. and Gottfredson, S. (1986). Environmental design, crime, and prevention: An examination of community dynamics. *Crime and justice*, 8:387–416.

Törnqvist, L., Vartia, P., and Vartia, Y. O. (1985). How should relative changes be measured? *The American Statistician*, 39(1):43–46.

Veléz, M. B. (2009). Banks and the racial patterning of homicide: A study of chicago neighborhoods. *International Journal of Conflict and Violence (IJCV)*, 3(2):154–171.

Vélez, M. B. and Lyons, C. J. (2014). Making or breaking neighborhoods: Public social control and the political economy of urban crime. *Criminology & Pub. Pol'y*, 13:225.

Velez, M. B., Lyons, C. J., and Boursaw, B. (2012). Neighborhood housing investments and violent crime in seattle, 1981–2007. *Criminology*, 50(4):1025–1056.

Vélez, M. B. and Richardson, K. (2012). The political economy of neighbourhood homicide in chicago: The role of bank investment. *The British Journal of Criminology*, 52(3):490–513.

Weisburd, D., Wooditch, A., Weisburd, S., and Yang, S.-M. (2016). Do stop, question, and frisk practices deter crime? evidence at microunits of space and time. *Criminology & public policy*, 15(1):31–56.

Wilson, W. J. (2003). Race, class and urban poverty: A rejoinder. *Ethnic & Racial Studies*, 26(6):1096–1114.

Zuk, M., Bierbaum, A. H., Chapple, K., Gorska, K., and Loukaitou-Sideris, A. (2018). Gentrification, displacement, and the role of public investment. *Journal of Planning Literature*, 33(1):31–44.

Table 1: Descriptive statistics by selected years, census tract year data

	Mean (std. dev)		
	2011	2014	2017
Non-Major crimes	215.0 (290.7)	191.7 (235.6)	186.4 (226.0)
Major crimes	141.0 (151.4)	132.7 (157.4)	131.5 (161.8)
Violent	25.5 (28.3)	24.2 (28.2)	26.3 (31.1)
Murder	0.4 (0.8)	0.3 (0.8)	0.4 (1.0)
Robbery	11.9 (14.0)	10.6 (13.1)	10.3 (13.0)
Aggravated assault	13.3 (16.4)	13.4 (17.1)	15.6 (20.6)
Property	115.5 (132.7)	108.5 (139.9)	105.1 (142.6)
Burglary	28.9 (31.5)	22.8 (24.5)	18.7 (20.4)
Theft	72.2 (104.8)	72.6 (116.7)	73.0 (121.1)
Motor vehicle theft	14.4 (15.6)	13.0 (15.9)	13.4 (16.0)
Number of loans	43.8 (66.5)	51.5 (65.2)	60.0 (72.4)
Loan amount (million dollars)	12.1 (26.3)	15.0 (24.7)	19.7 (30.7)
Population (thousands)	3.8 (2.0)	3.9 (2.1)	4.0 (2.2)
White (%)	51.1 (30.3)	51.3 (30.1)	51.0 (29.4)
Black (%)	27.7 (32.4)	27.3 (31.8)	26.9 (31.2)
Hispanic (%)	23.3 (25.4)	23.9 (25.4)	24.2 (25.2)
Age 0-14 (%)	18.5 (7.6)	18.2 (7.2)	17.9 (7.1)
Age 15-24 (%)	15.1 (8.7)	14.5 (8.8)	13.6 (8.8)
Age 25-39 (%)	24.3 (9.0)	24.6 (9.1)	25.3 (9.4)
Age 40-54 (%)	20.3 (5.6)	19.8 (5.3)	19.1 (4.8)
Age 55+ (%)	21.7 (9.3)	22.8 (9.4)	24.1 (9.4)
Less than high school (%)	19.7 (14.7)	18.6 (14.2)	17.1 (13.2)
High school (%)	25.1 (11.3)	24.4 (11.1)	24.0 (11.3)
Some college (%)	18.3 (7.2)	18.5 (7.1)	18.1 (7.1)
College+ (%)	37.0 (22.1)	38.5 (22.4)	40.8 (22.6)
Unemployment rate (%)	10.8 (7.3)	11.7 (7.7)	8.5 (6.2)
Family income (thousands)	63.6 (38.2)	65.1 (39.7)	72.0 (43.1)
Poverty rate (%)	16.8 (14.3)	18.1 (14.8)	16.4 (13.7)
Occupied housing units	1,472.5 (795.3)	1,498.9 (829.6)	1,542.3 (875.0)
Vacant housing units	192.3 (176.2)	185.1 (172.2)	177.0 (168.2)

Notes: Census tract level mean (standard deviation) in selected years from the 27 US cities included in the study, representing 7,810 tracts. Major crimes include murder, robbery, aggravated assault, burglary, theft, and motor vehicle theft. Non-major crimes refer to all the other crimes reported to the police departments.

Table 2: Models used in previous studies on the effect of mortgages on crime

	Major crime	Property	Theft	Burglary	Motor vehicle theft	Violent	Murder	Robbery	Assault	Nonmajor crime
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Random effects										
Loan amount	0.006**	0.008***	0.007***	0.008**	0.021***	−0.004	−0.007***	−0.0003	−0.015***	0.002
	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)	(0.004)	(0.002)	(0.004)	(0.004)	(0.002)
Observations	54,174	54,174	54,174	54,174	54,174	54,174	51,934	54,174	53,876	44,161
B. Fixed effects										
Loan amount	0.006**	0.006**	0.004	0.005	0.012**	0.008**	−0.001	0.012**	−0.001	0.003
	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.005)	(0.005)	(0.002)
Observations	54,174	54,174	54,174	54,174	54,174	54,174	51,934	54,174	53,876	44,161
C. First differences using the lagged value as IV										
Loan amount	−0.071	−0.054	−0.006	−0.057***	0.001	−0.015	−0.001	−0.019***	0.007	0.097
	(0.050)	(0.049)	(0.042)	(0.015)	(0.017)	(0.010)	(0.001)	(0.007)	(0.007)	(0.139)
Observations	38,679	38,679	38,679	38,679	38,679	38,679	37,079	38,679	38,232	31,528

Notes: Panels A and B show the random effects and fixed effects models, using the inverse hyperbolic sine transformation in the dependent and independent variables. The estimates are interpreted as elasticities (e.g., a 10 percent change in the mortgages loan amount, relate to a $\beta_1/10$ percent change in crime incidents). Panel C shows the first differences model instrumenting the loan amount with its lagged value. The estimates are interpreted as level changes (e.g., a one million change in the mortgages loan amount relates to a β_1 change in crime incidents). All models include sociodemographic controls. Major crimes include the part I Uniform Crime Reporting categories of murder, robbery, aggravated assault, burglary, theft, and motor vehicle theft. Non-major crimes refer to all the other crimes reported to the police departments. Robust standard errors clustered at the census tract level are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 3: First stage estimates on census tract mortgages

	Loan amount	
	(1)	(2)
Nation loan growth	0.218***	0.215***
	(0.025)	(0.025)
Mean dep. var.	19.86	20.01
Observations	54,628	54,174
F-statistic	78.0	74.6
Year FE	X	X
Tract FE	X	X
Covariates	-	X

Notes: First stage estimates using ordinary least squares regression of the shift-share instrumental variable. The instrument is the inner product of the nation wide bank loan growth rates outside of the 27 cities and the bank-tract share on mortages. Regression follows equation (3). The independent variable uses the symmetric growth rate. The dependent variable uses the inverse hyperbolic sine transformation. The results are expressed as an increase of 10 percent in the nation loan growth, implies a $(e^{\beta_1} - 1)/10$ percent change in the census tract residential lending. The bottom row shows the mean dependent variable, expressed as the total mortgage loan in the average census tract (in millions of dollars). Robust standard errors clustered at the census tract level in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 4: Main estimates: Reduced form and 2SLS estimates of mortgages on crime

	Major crime	Property	Theft	Burglary	Motor vehicle theft	Violent	Murder	Robbery	Assault	Nonmajor crime
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Reduced form										
Instrument	-0.024^{**}	-0.034^{***}	-0.078^{***}	-0.040^{**}	0.089^{***}	-0.023	0.013	-0.004	-0.059^{***}	-0.033^{***}
	(0.010)	(0.011)	(0.013)	(0.019)	(0.023)	(0.016)	(0.017)	(0.019)	(0.019)	(0.008)
B. Second-stage least squares										
Loan amount	-0.111^{**}	-0.157^{***}	-0.361^{***}	-0.184^{**}	0.415^{***}	-0.107	0.057	-0.018	-0.276^{***}	-0.188^{***}
	(0.048)	(0.055)	(0.076)	(0.094)	(0.115)	(0.075)	(0.078)	(0.090)	(0.097)	(0.055)
Mean crime	138.06	112.33	74.92	23.85	13.55	25.73	0.39	11.18	14.25	198.69
Observations	54,174	54,174	54,174	54,174	54,174	54,174	51,934	54,174	53,876	44,161
2SLS change	-1.1%	-1.5%	-3.0%	-1.7%	5.1%	-1.0%	0.6%	-0.2%	-2.4%	-1.7%

Notes: Panel A shows the reduced form estimates following equation (4). Panel B presents the second stage least squares (instrumental variable) estimates following equation (5). Outcomes use the inverse hyperbolic sine transformation. The results are expressed as percent changes ($e^{\beta_1} - 1$). Major crimes include the part I Uniform Crime Reporting categories of murder, robbery, aggravated assault, burglary, theft, and motor vehicle theft. Non-major crimes refer to all the other crimes reported to the police departments. The bottom row shows the mean dependent variable, expressed as the average number of yearly crimes in a census tract. It is followed by the implied percent change of the second stage least squares estimates caused by a 10 percent increase in the local mortgages. Robust standard errors clustered at the census tract level are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 5: Heterogeneity: 2SLS estimates of mortgages on crime interacted by sociodemographic dimension

	Major crime	Property	Theft	Burglary	Motor vehicle theft	Violent	Murder	Robbery	Assault	Nonmajor crime
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Black population = D										
Loan amount	−0.071**	−0.104***	−0.204***	−0.138**	0.243***	−0.016	−0.068	0.054	−0.145**	−0.065**
	(0.029)	(0.033)	(0.043)	(0.058)	(0.069)	(0.048)	(0.048)	(0.058)	(0.063)	(0.031)
Loan amount*D	−0.130	−0.177*	−0.524***	−0.161	0.572***	−0.294**	0.393**	−0.235	−0.426***	−0.443***
	(0.085)	(0.098)	(0.141)	(0.169)	(0.215)	(0.130)	(0.192)	(0.171)	(0.165)	(0.117)
Mean crime	138.06	112.33	74.92	23.85	13.55	25.73	0.39	11.18	14.25	198.69
Observations	54,174	54,174	54,174	54,174	54,174	54,174	51,934	54,174	53,876	44,161
B. Hispanic population = D										
Loan amount	−0.096**	−0.138***	−0.325***	−0.144	0.353***	−0.094	0.061	−0.028	−0.251***	−0.162***
	(0.046)	(0.052)	(0.073)	(0.089)	(0.109)	(0.072)	(0.074)	(0.085)	(0.093)	(0.056)
Loan amount*D	−0.117*	−0.154*	−0.272**	−0.318**	0.475***	−0.112	−0.025	0.068	−0.196	−0.184***
	(0.069)	(0.085)	(0.114)	(0.152)	(0.180)	(0.114)	(0.156)	(0.150)	(0.149)	(0.065)
Mean crime	138.06	112.33	74.92	23.85	13.55	25.73	0.39	11.18	14.25	198.69
Observations	54,174	54,174	54,174	54,174	54,174	54,174	51,934	54,174	53,876	44,161
C. Poverty level = D										
Loan amount	−0.055**	−0.070***	−0.144***	−0.027	0.142**	0.005	−0.017	0.065	−0.123**	−0.013
	(0.022)	(0.026)	(0.038)	(0.047)	(0.057)	(0.040)	(0.042)	(0.046)	(0.051)	(0.029)
Loan amount*D	−0.419	−0.672*	−1.751***	−1.272**	2.282**	−0.949*	0.572	−0.684	−1.294**	−1.301**
	(0.303)	(0.375)	(0.653)	(0.644)	(0.916)	(0.491)	(0.632)	(0.567)	(0.638)	(0.553)
Mean crime	138.18	112.42	74.97	23.88	13.57	25.76	0.39	11.19	14.27	198.79
Observations	54,080	54,080	54,080	54,080	54,080	54,080	51,840	54,080	53,782	44,078

Notes: Second stage least squares (instrumental variable) estimates interacting the loan amount with the relevant heterogeneity dimension. Specifically, it follows $y_{it} = \gamma_i + \mu_t + \beta_2 \hat{L}_{it} + \beta_3 \hat{L}_{it} D_{it} + X_{it}\alpha_X + e_{it}$, where D_{it} is the relevant heterogeneity dimension, which also is included in the control variables. All other parameters are as explained in the main text. Crimes and loan amount outcomes use the inverse hyperbolic sine transformation. The heterogeneity variable is the census tract proportion of the relevant group (variable goes from zero to one). Hence, the results are expressed as a ten percent increase in the mortgages loan amount in tracts with a 50 percent prevalence of the group relates to a $(e^{\beta_1 * 0.5} - 1)/10$ percent change relative to not having any members of that group. Major crimes include the part I Uniform Crime Reporting categories of murder, robbery, aggravated assault, burglary, theft, and motor vehicle theft. Non-major crimes refer to all the other crimes reported to the police departments. The bottom row shows the mean dependent variable, expressed as the average number of yearly crimes in a census tract. Robust standard errors clustered at the census tract level are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 6: Potential mechanisms: 2SLS estimates of mortgages on housing units

	Occupied units	Vacant units
	(1)	(2)
A. All mortgages		
Loan amount	0.005	−0.005
	(0.008)	(0.009)
Mean dep. var.	1.52	0.19
Observations	54,137	54,137
B. Home purchase mortgages		
Loan amount	0.018*	−0.024*
	(0.010)	(0.013)
Mean dep. var.	1.52	0.19
Observations	51,057	51,057

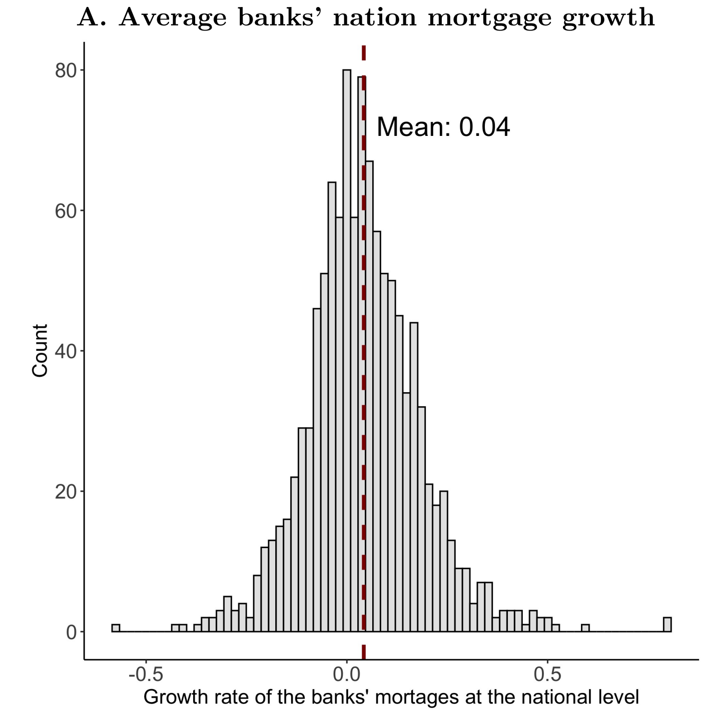
Notes: Second stage least squares (instrumental variable) estimates of mortgages on the number of housing units in the census tract. Panel A uses all mortgages for the instrument and the endogeneous variable, which is the same approach as the main estimates. Panel B uses only mortgages with the purpose of buying a home for the instrument and the endogenous variable (it excludes mortgages for home improvement and refinancing). All outcomes use the inverse hyperbolic sine transformation. The results are expressed as percent changes ($e^{\beta_1} - 1$). The bottom row shows the mean dependent variable, expressed as the average number of yearly property units in a census tract (in thousands). Robust standard errors clustered at the census tract level in parentheses. *p<0.1; **p<0.05; ***p<0.01.

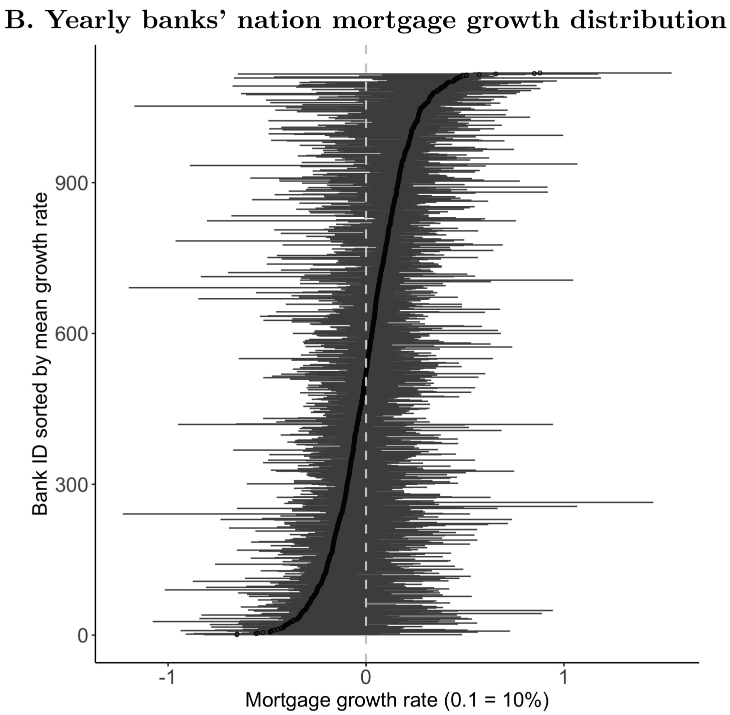
Table 7: Potential mechanisms: 2SLS estimates of mortgages on sociodemographics

	White (1)	Black (2)	Some college (3)	College+ (4)
Loan amount	0.008	−0.005	−0.004	−0.001
	(0.010)	(0.008)	(0.006)	(0.007)
Mean dep. var.	0.48	0.26	0.18	0.38
Observations	54,177	54,177	54,174	54,174

Notes: Second stage least squares (instrumental variable) estimates of mortgages on census tract sociodemographics. It shows the reduced form estimates following equation (4). Outcomes use the inverse hyperbolic sine transformation, so the results are expressed as percent changes ($e^{\beta_1} - 1$). The bottom row shows the mean dependent variable, expressed as the average proportion of the relevant sociodemographic dimension in census tract. Robust standard errors clustered at the census tract level in parentheses. *p<0.1; **p<0.05; ***p<0.01.

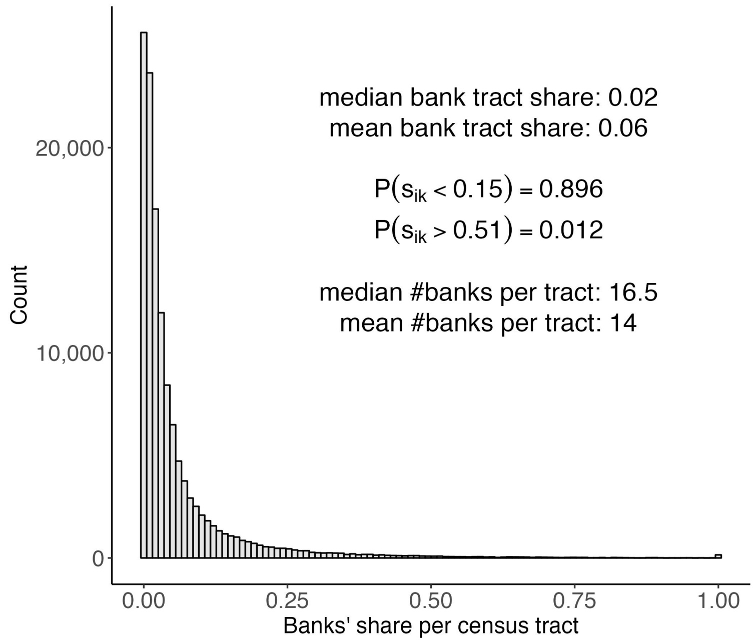
Figure 1: Banks' nation mortgage growth, 2011-2017





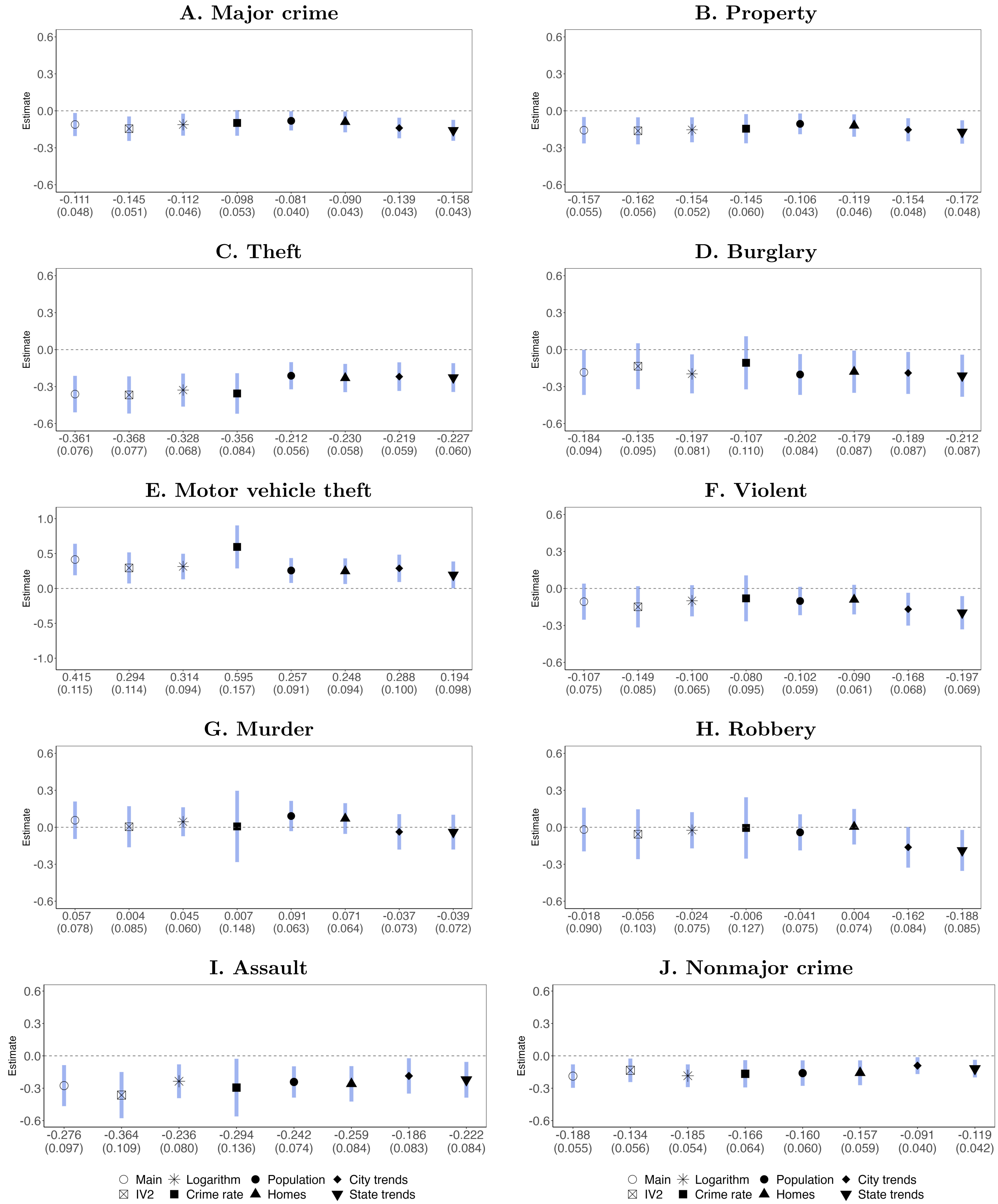
Notes: The symmetric growth measure is calculated as $(L_{it} - L_{it-1})/(0.5 * L_{it} + 0.5 * L_{it-1})$, so the values range between -2 and 2. Panel A shows the mean yearly growth rate in the nation's mortgages (excluding the 27 US cities included in this research) for each of the 1,118 banks used to build the Bartik instrument between 2011 and 2017. The vertical dashed line represents the mean bank's growth. Panel B shows the first, second (median), and third quartile of the yearly national mortgage growth (excluding the 27 cities) between 2011 and 2017 for each of the 1,118 banks. The vertical dashed line marks the zero growth rate.

Figure 2: Histogram of banks' mortgage share, 2007



Notes: The figure shows the 2007 banks' share of the mortgage loan amount per census tract. It is the *share* (s_{ikt_0}) component from the instrumental variable presented in Equation 1. There are 7,804 census tracts and 1,118 banks. The figure only includes banks with a positive presence in the census tract ($s_{ikt_0} > 0$); many banks only operate in some states. The results suggest that the typical bank has little local market concentration in the sample.

Figure 3: Alternative specifications: Second stage least squares estimates of mortgages on crime



Notes. Main: preferred estimates. IV2: IV uses only banks with less than 66% of the tract market share. Logarithm: dependent variable uses log(x+1). Population: weighted by the census tract population. Homes: weighted by the census tract residential units. Crime rate: dependent variable is crimes per 10,000 people. City trends: adds city time trends. State-trends: adds state-time trends. Outcomes use the inverse hyperbolic sine transformation, except as noted. Robust standard errors clustered at the census tract level are in parentheses. Motor vehicle theft, panel E, is the only outcome using a larger vertical scale to facilitate presenting the results.

ONLINE APPENDIX

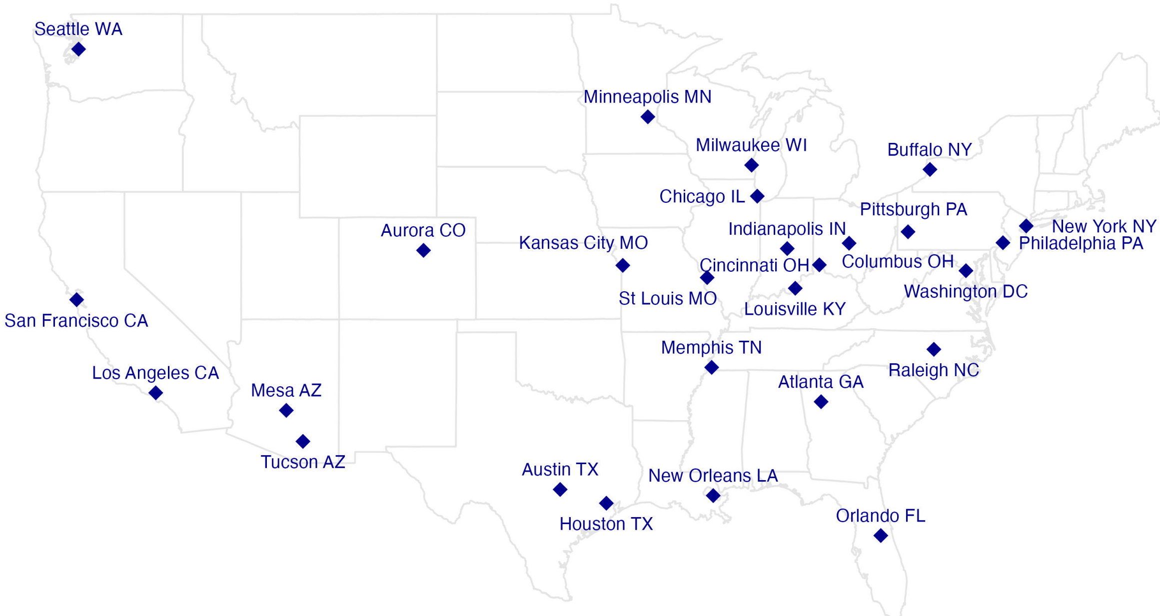
A Appendix: Tables and Figures

Table A.1: Heterogeneity: 2SLS estimates of mortgages on crime by mortgage growth tercile groups

	Major crime	Property	Theft	Burglary	Motor vehicle theft	Violent	Murder	Robbery	Assault	Nonmajor crime
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mortgage*1st tercile	-0.434^{*}	-0.625^{**}	-1.552^{***}	-0.691	1.753^{***}	-0.603^{*}	0.363	-0.339	-0.969^{**}	-0.835^{**}
	(0.237)	(0.289)	(0.545)	(0.441)	(0.662)	(0.362)	(0.353)	(0.405)	(0.470)	(0.353)
Mortgage*2nd tercile	-0.127^{**}	-0.184^{**}	-0.429^{***}	-0.203^{*}	0.463^{***}	-0.110	0.040	0.0002	-0.326^{**}	-0.199^{**}
	(0.062)	(0.074)	(0.121)	(0.116)	(0.153)	(0.096)	(0.078)	(0.110)	(0.128)	(0.082)
Mortgage*3rd tercile	-0.070^{**}	-0.097^{**}	-0.208^{***}	-0.122^{*}	0.249^{***}	-0.049	0.012	0.014	-0.183^{**}	-0.086^{*}
	(0.034)	(0.040)	(0.070)	(0.063)	(0.088)	(0.054)	(0.044)	(0.061)	(0.072)	(0.046)
$\beta_{tercile1} = \beta_{tercile2}$	0.10	0.06	0.01	0.16	0.02	0.09	0.29	0.29	0.08	0.03
$\beta_{tercile2} = \beta_{tercile3}$	0.12	0.04	0.00	0.24	0.01	0.31	0.57	0.84	0.06	0.01
$\beta_{tercile1} = \beta_{tercile3}$	0.08	0.04	0.01	0.14	0.01	0.08	0.28	0.32	0.06	0.02
Mean crime	138.06	112.33	74.92	23.85	13.55	25.73	0.39	11.18	14.25	198.69
Observations	54,174	54,174	54,174	54,174	54,174	54,174	51,934	54,174	53,876	44,161

Notes: Second stage least squares (instrumental variable) estimates interacting the loan amount with the tercile group of the average mortgage growth between 2011 and 2017. Specifically, it follows $y_{it} = \gamma_i + \mu_t + \sum_{j=1}^{3} \beta_j \hat{L}_{it} D_i^j + X_{it}\alpha_X + e_{it}$, where D_i^j is an indicator variable of the tercile group of the mortgage growth. All other parameters are as explained in the main text. Crimes and loan amount outcomes use the inverse hyperbolic sine transformation. The results are expressed as percent changes ($e^{\beta_j} - 1$). Major crimes include the part I Uniform Crime Reporting categories of murder, robbery, aggravated assault, burglary, theft, and motor vehicle theft. Non-major crimes refer to all the other crimes reported to the police departments. The bottom rows show the pvalue of the hypothesis testing whether the coefficients across tercile groups are equal, followed by the mean dependent variable, expressed as the average number of yearly crimes in a census tract. Robust standard errors clustered at the census tract level are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

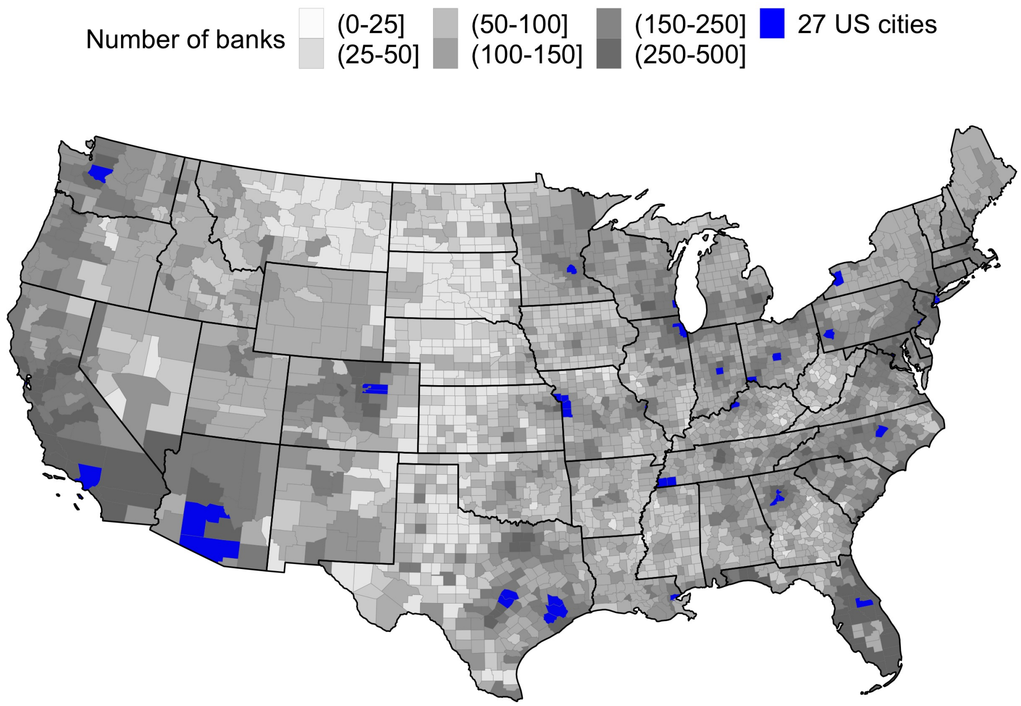
Figure A.1: Cities included in the analysis



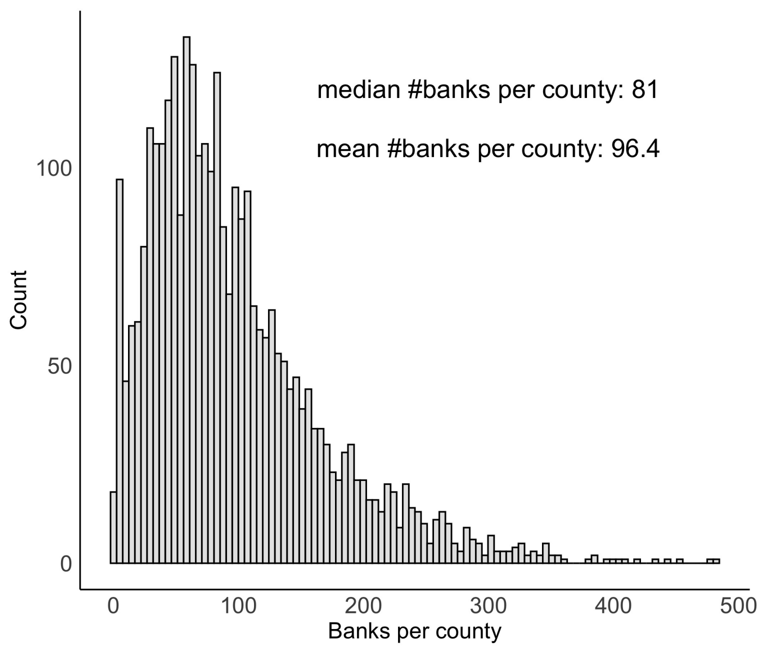
Notes: The map shows the location of the 27 US major cities included in this research. These cities had public crime data that could be aggregated to the census tract-year level.

Figure A.2: Banks' coverage across counties

A. Geographical distribution of banks' across counties



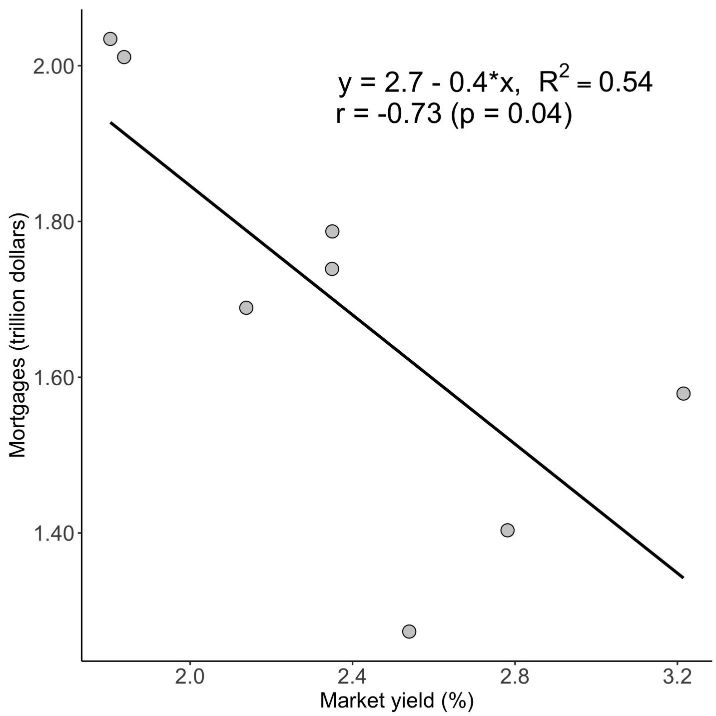
B. Distribution of banks' across counties



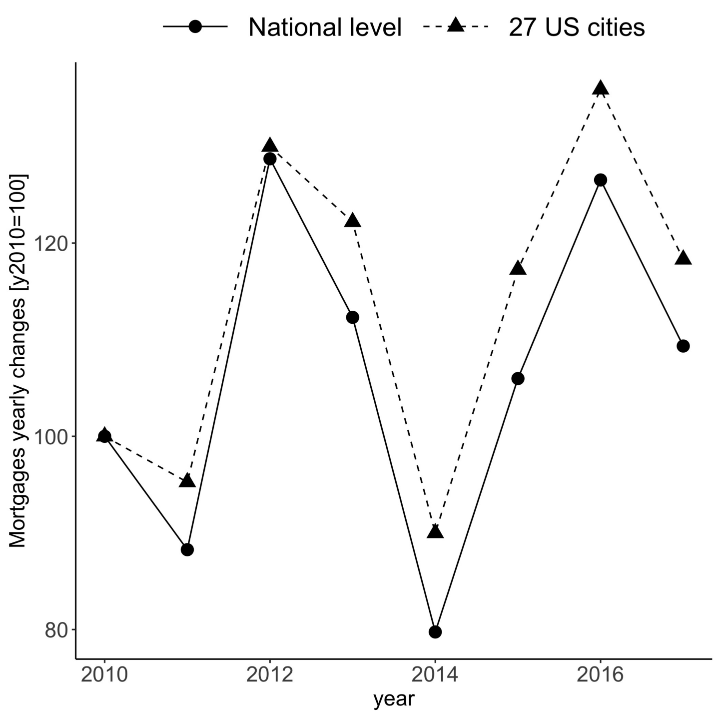
Notes: Panel A shows the number of banks per US county. It only includes the 1,118 financial institutions used in the instrumental variable. The blue-colored counties are the ones where the 27 cities included in the analysis are located. While each of the 1,118 banks do not cover all the lower 48 states, they operate jointly across the country. Panel B presents the histogram of the banks' presence by county, showing that the mean (median) county has 96 (81) banks.

Figure A.3: Mortgages trend across time and correlation with Treasury market yield

A. Correlation of US mortgages and Treasury market yield, 2010-2017

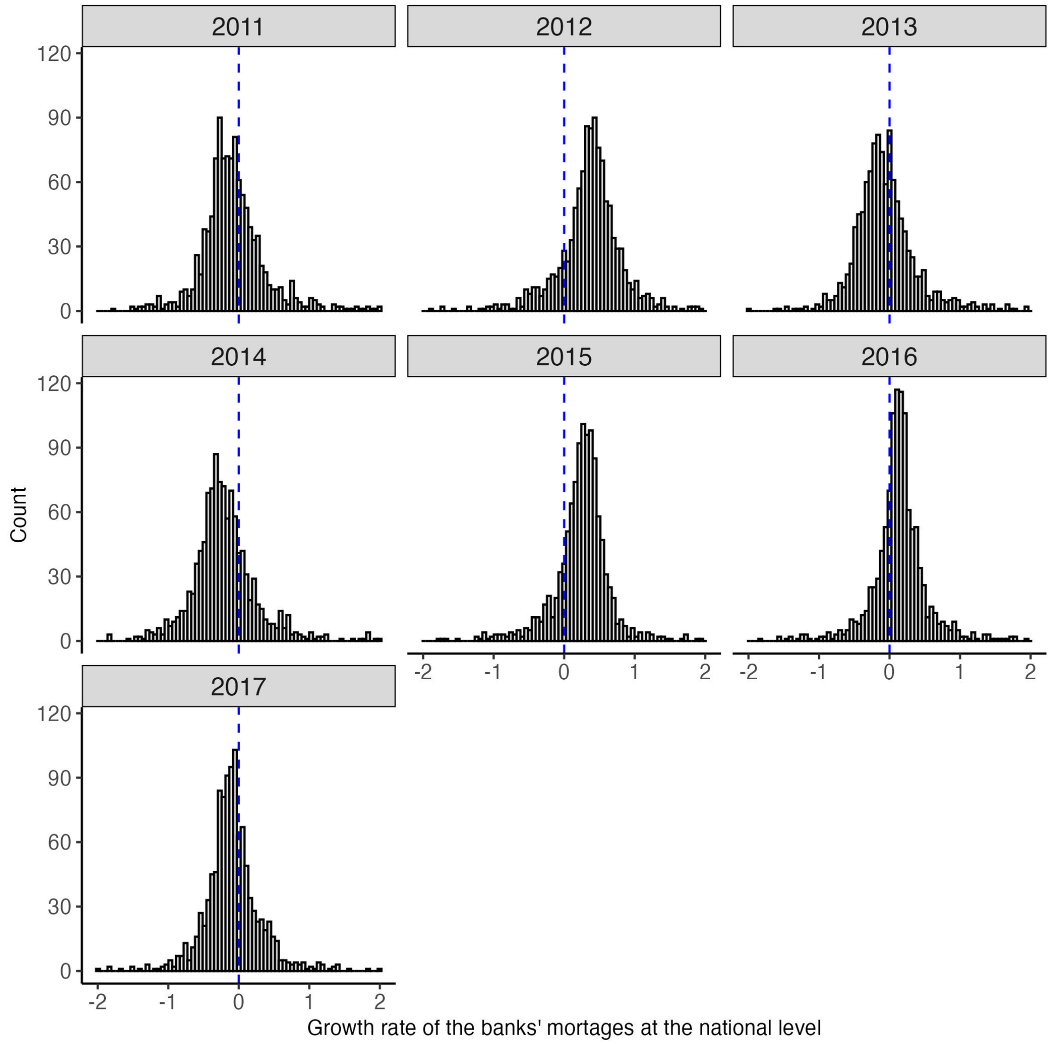


B. Mortgages changes by sample group



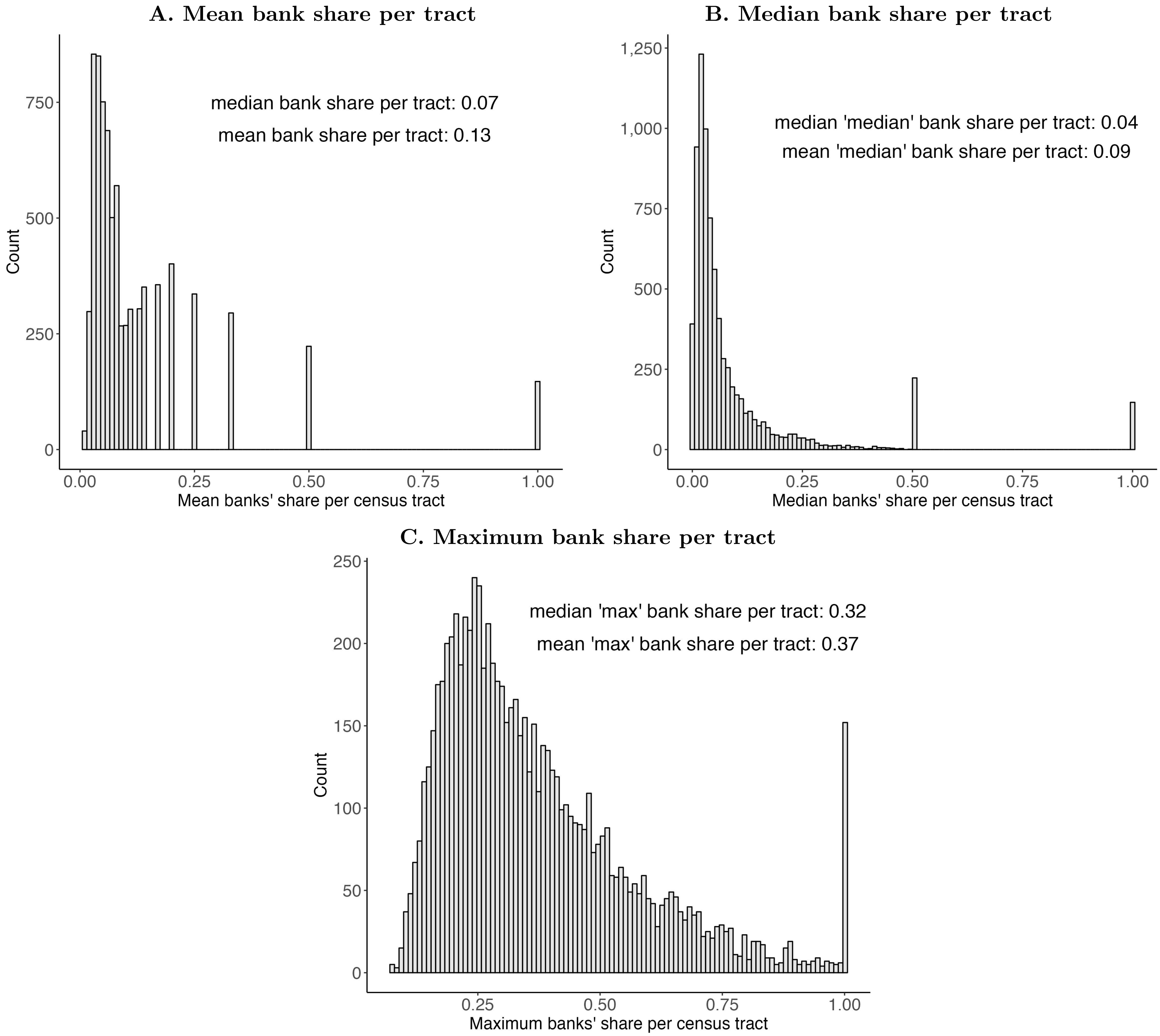
Notes: Panel A shows in the horizontal axis the mean Market Yield on US Treasury Securities at 10-Year Constant Maturity, which is the interest rate that the government pays to borrow money and influences other interest rates and lending patterns. The vertical axis shows the value of the national mortgages. The correlation also holds for each of the 27 cities used in the sample, ranging their coefficient from -0.40 to -0.92. Panel B shows the relative changes in the nation's (excluding the 27 US cities) and the 27 US cities' mortgage debt. Both follow the same pattern.

Figure A.4: Correlation of banks' tract shares across time, 2007 vs 2010



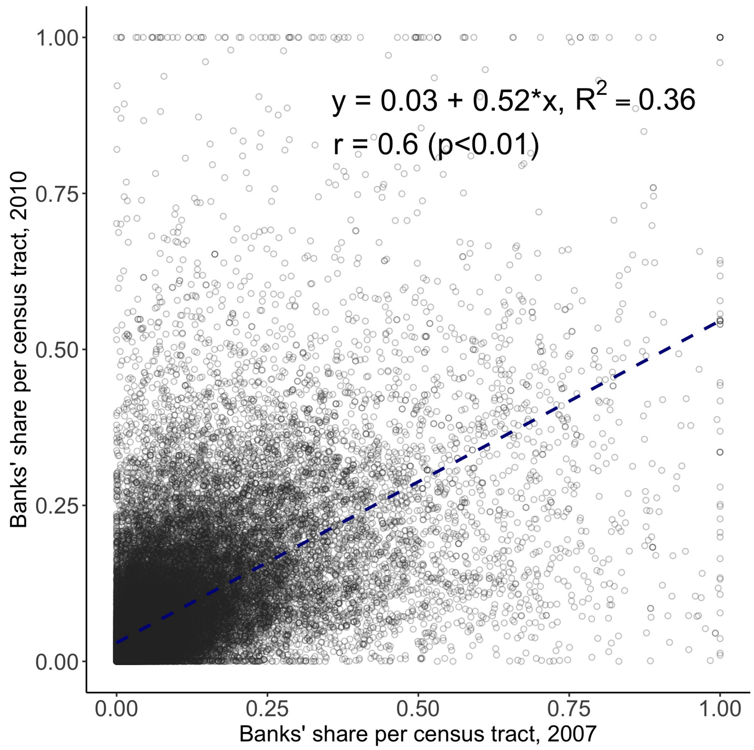
Notes: The symmetric growth measure is calculated as $L_{it} - L_{it-1})/(0.5 * L_{it} + 0.5 * L_{it-1})$, so the values range between -2 and 2. The figure shows the yearly growth rate in the nation's mortgages (excluding the 27 US cities included in this research) for each of the 1,118 banks used to build the Bartik instrument by year.

Figure A.5: Banks' shares per census tract, 2007



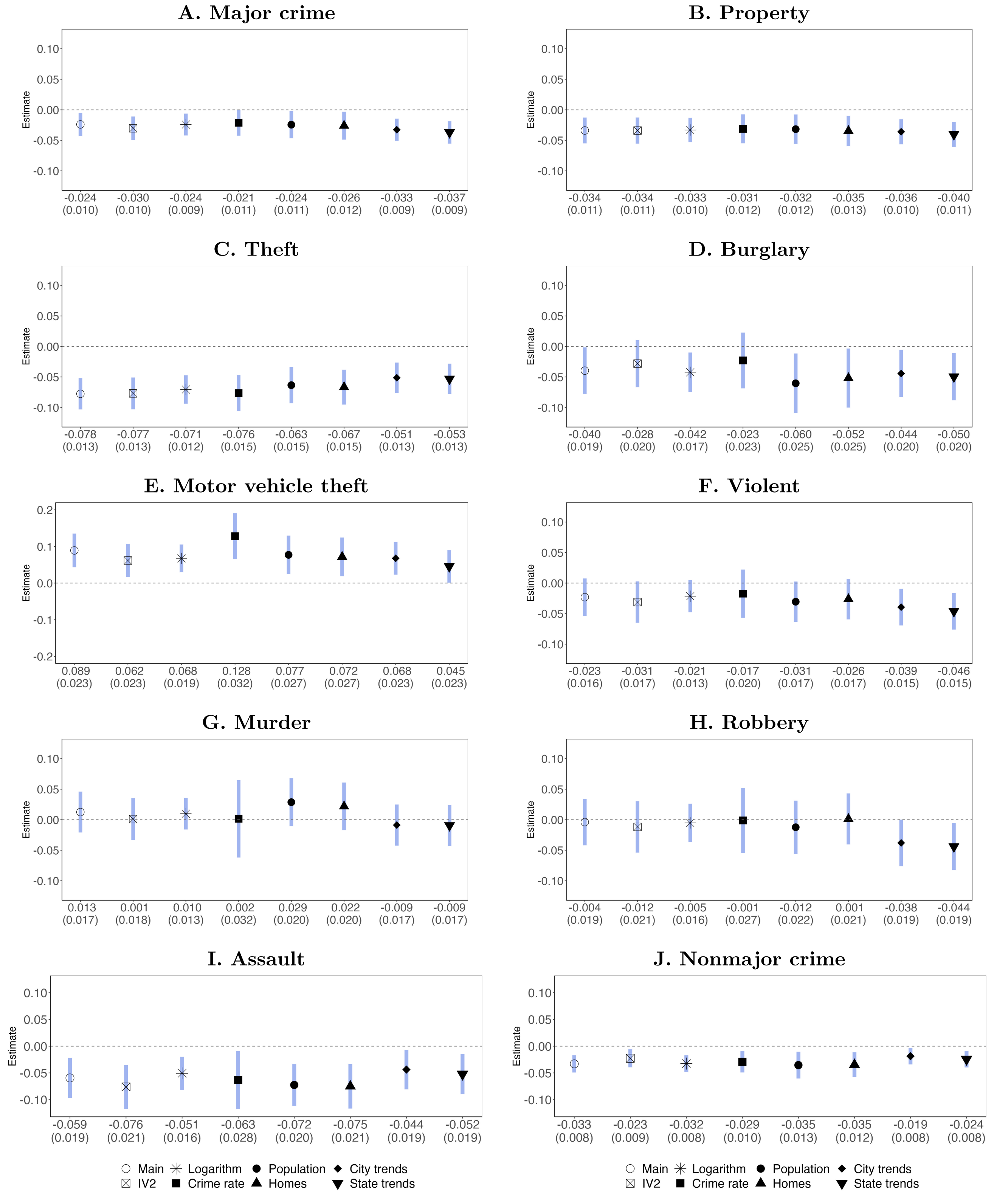
Notes: Each panel shows the mean (Panel A), median (Panel B), and maximum (Panel C) bank share per census tract. It only includes the banks used to build the instrumental variable. Each panel presents the median and mean of its distribution. Overall, the three census tract statistics and distributions suggest that while one bank usually has one-third of the local mortgage market, the remaining share is scattered across a considerable number of banks.

Figure A.6: Correlation of banks' tract shares across time, 2007 vs 2010



Notes: The figure shows the census tract banks' share of the mortgage loan amount four (2007) and one year (2007) before the study period. While having a large share in 2007 correlates with a high share in 2010, there is considerable unexplained variation in the sample. A best-fit dashed line is drawn through the data. The figure also shows its regression equation, R^2, correlation coefficient (r), and the pvalue (p) of the correlation.

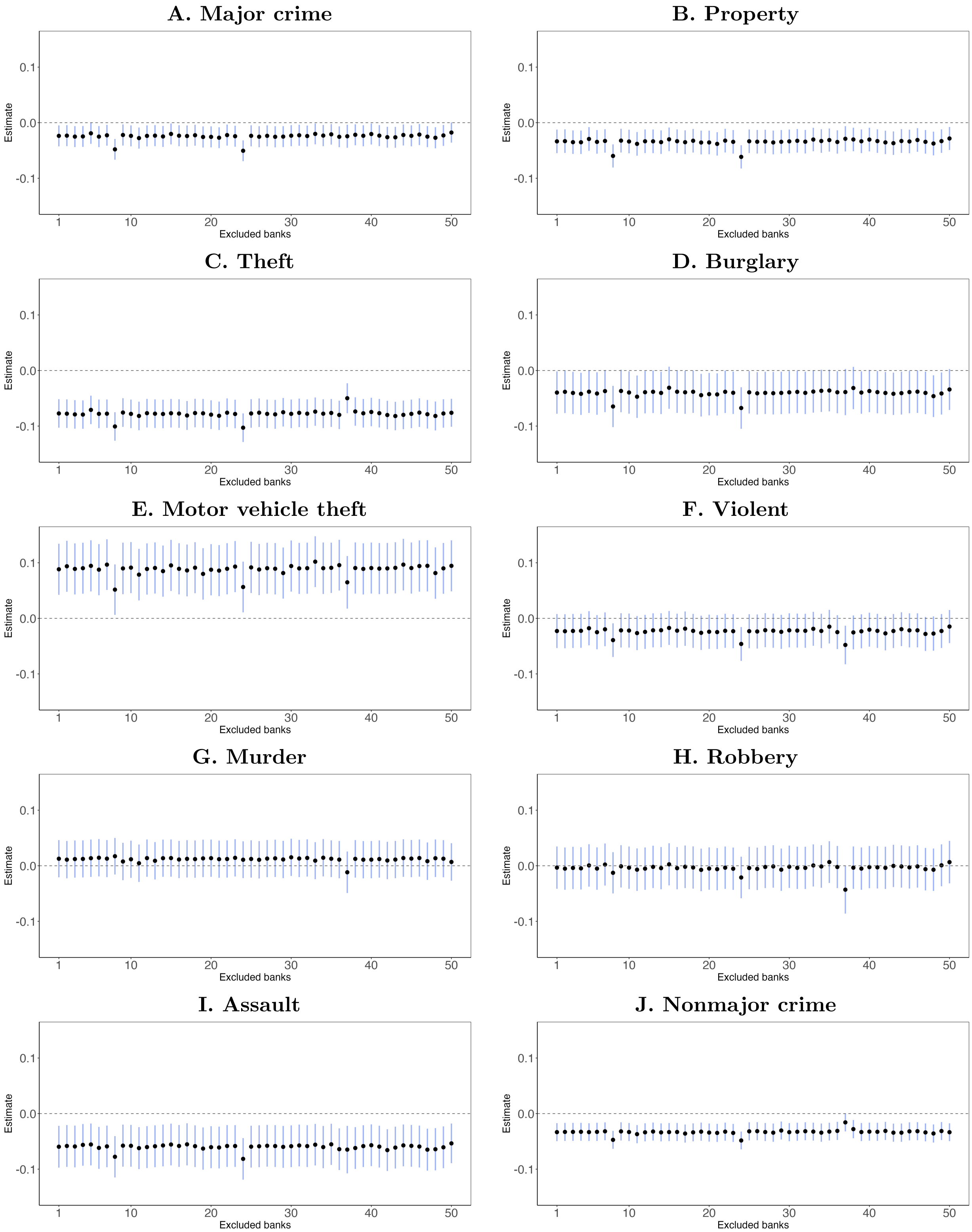
Figure A.7: Alternative specifications: Reduced form estimates of mortgages on crime



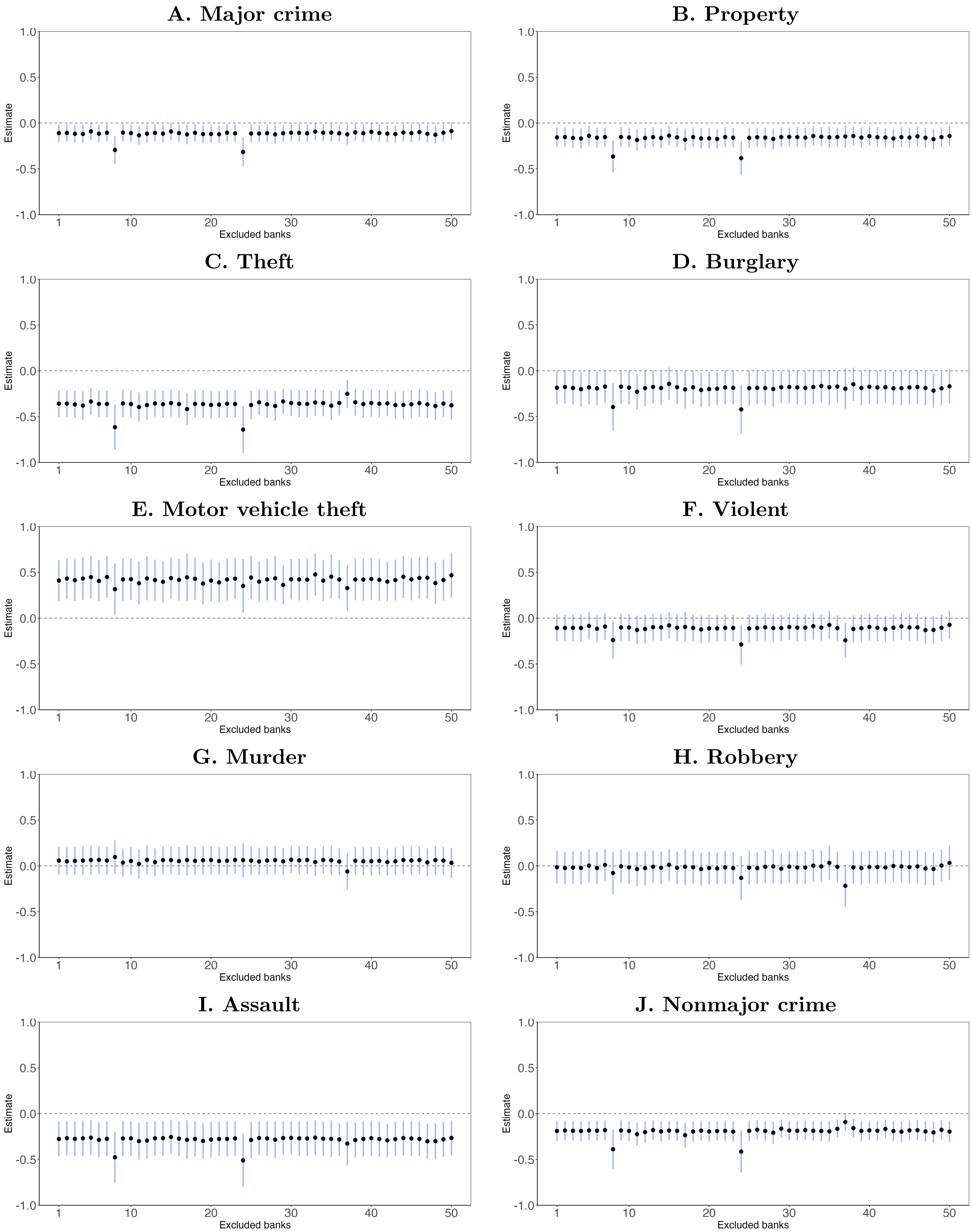
Notes. Main: preferred estimates. IV2: IV uses only banks with less than 66% of the tract market share. Logarithm: dependent variable uses log(x+1). Population: weighted by the census tract population. Homes: weighted by the census tract residential units. Crime rate: dependent variable is the crimes per 10,000 people. City trends: adds city-time trends. State-trends: adds state-time trends. Outcomes use the inverse hyperbolic sine transformation, except as noted. Robust standard errors clustered at the census tract level are in parentheses.

Figure A.8: Leave-one-out-estimator: Estimates of mortgages on crime

I. Reduced form estimates

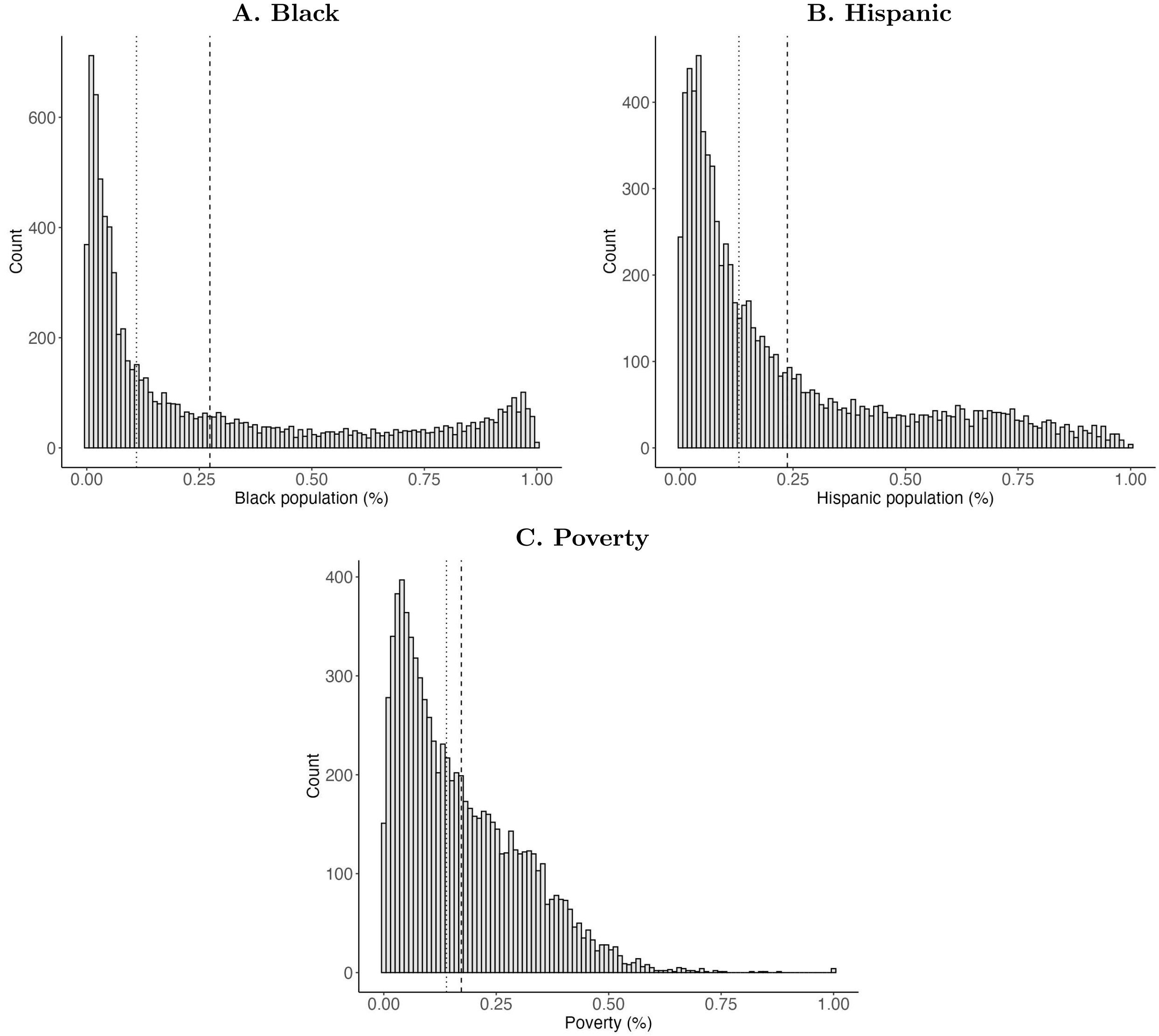


II. Second stage least squares



Notes. Figures show the second-stage least squares (instrumental variable) estimates of mortgages on crime. It builds the instrumental variable, excluding twenty banks at a time, and estimates the regression model, repeating the process 50 times. Outcomes use the inverse hyperbolic sine transformation, so the results are expressed as percent changes ($e^{\beta_1} - 1$). Robust standard errors clustered at the census tract level are in parentheses.

Figure A.9: Census tracts sociodemographics, 2011-2017



Notes: The figure shows the distribution of the average sociodemographics of census tracts between 2011 and 2017. The vertical dotted (dashed) line marks the median (mean).