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 suffer from endogeneity biases through common causes and omitted variables. This study helps to overcome the endogeneity bias in the mortgage and crime link by leveraging 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 paper 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 are a driving factor in 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 rather than punishment have been proposed as an essential strategy to reduce neighborhood crime (Krivo, 2014; Sharkey, 2018; Vélez and Lyons, 2014). While public and non-profit programs targeting high-risk individuals and areas with a clear nexus to crime-reducing components have shown promising results (Blattman et al., 2017; Branas et al., 2018; Chalfin et al., 2022; Heller, 2014; Sharkey et al., 2017), whether private investments reduce crime is unclear. The incentives of private actors are usually misaligned with social welfare maximizing strategies due to externalities causing an under-provision of private investments. Still, banks can play a role against crime by bringing external resources to revitalize neighborhoods (Vélez and Richardson, 2012; Velez et al., 2012), and given their widespread geographical presence and large financial asset size, their potential for change is substantial.

Banks influence the real economy (employment, businesses, production, and investments) as they act as safe deposit institutions and a source of credit for myriad activities (Allen et al., 2008; Berger et al., 2020). One such activity is providing home mortgages. Home acquisition is a cornerstone component of households' wealth accumulation because it is usually the largest household asset, it is inheritable, and, to the extent that house prices increase, the wealth rises over time (Turner and Luea, 2009). Homeownership also influences neighborhood dynamics. Landowners' well-being and wealth are linked to the prospects of the property. Actions that increase the value of the neighborhood benefit the household, so individuals have strong incentives to form coalitions to influence local regulations (Molotch, 1976). Despite the reduction in geographical mobility, homeownership relates to increases in housing tenure, local networks, and social capital investments (DiPasquale and Glaeser, 1999). Furthermore, as neighbors become aware of their common values and there is mutual trust, solidarity, and willingness to intervene for the common good, informal social control mechanisms can regulate the community's behavior, leading to crime decreases (Sampson et al., 1997; Sampson and Raudenbush, 1999).

The lack of access to credit to acquire property or improve the existing one can become a source of racial disparities, wealth inequality, and neighborhood decay (Krivo and Kaufman, 2004). Nevertheless, aggressive, high-risk lending practices are not an optimal solution either.[1] While in the short-term, these loans can improve property values (Pavlov and Wachter, 2011), they can have deleterious effects on communities once homeowners cannot make their regular payments and foreclosures and vacant properties rise, leading to more crime (Cui and Walsh, 2015; Stucky et al., 2012). Risky lending practices can destabilize local and global economic markets.[2]

[1] A related literature examines the adverse crime impacts of payday lenders in distressed communities (Kubrin et al., 2011).

[2] For a broader explanation on global effects of widespread risky lending patterns, see the *Final Report of the National*

Previous research argues that home mortgages reduce violent crime with an emphasis on homicides. The literature includes persuasive descriptive studies, but they are mostly correlational (Kirk, 2020; Saporu et al., 2011; Shrider and Ramey, 2018; Vélez and Richardson, 2012) or have not used strong identification strategies to remove the endogeneity bias (Veléz, 2009; Velez et al., 2012). These studies do not address the concern that areas receiving home mortgages differ in observable and unobservable characteristics from neighborhoods receiving fewer loans; hence, the crime differences could be caused by other factors besides lending. Bunting (2020) uses the only credible instrumental variables research, but the author does not analyze the effects on the different crime categories, which is critical to assess whether loans influence property, violent, and low-level crimes, nor provide evidence of heterogeneous effects on racial or ethnic communities. Moreover, the study only focuses on Los Angeles County, California, during the Great Recession, limiting the external validity of the results.

Accordingly, this research makes five contributions. First, using a shift-share instrumental variables approach reduces the concerns of not isolating the effects of mortgages on crime and provides a stronger identification strategy than previous criminological studies. Second, this research offers insights into which crimes are the most sensitive to residential lending by examining the results on property, violent, and low-level criminal offenses. Third, it investigates whether there are differential impacts in historically marginalized communities, a relevant margin that most studies have overlooked,[3] and it is essential to understand which communities benefit most from community investments. Next, as there is no public national repository of sub-city crime incidents, this research overcomes this data limitation by collecting and geo-referencing crime incident level information at the census tract from 27 US cities, representing around 10 percent of the US population. The large sample size provides the statistical power to detect small changes, and it reduces concerns of external validity, which are common in single-city case studies. Finally, analyzing data from the last decade covers the post-Great Recession period marked by stringent financial regulations on the mortgage housing market.

By relying on crimes reported to the police departments and residential lending data, as well as using a shift-share instrumental variables approach that leverages the time and spatial variation caused by banks' idiosyncratic mortgage shocks with different market shares across communities, this research assesses whether such differential exposure leads to different changes in crime incidents. The evidence suggests that mortgages reduce crime, specifically theft, burglary, aggravated assaults, and non-major crimes, although

Commission on the Causes of the Financial and Economic Crisis in the United States.

[3]Only one study has examined the impacts of residential lending on property crimes and its differential impacts based on race and ethnicity (Saporu et al., 2011), but given its cross-sectional design, the findings have to be taken cautiously as it cannot assign a causal order in the mortgage-crime relationship.

they lead to motor vehicle theft. Still, overall property and major crime decreases when banks lend to individuals acquiring properties. The impacts are larger in Black, Hispanic, and poor communities, suggesting that historically marginalized neighborhoods benefit more from an increase in mortgage lending. The effects appear to be driven by a decrease in vacant homes, and there are no discernible gentrification changes measured through sociodemographic changes. However, in contrast to previous studies, there is no impact on murders, and the evidence of violent crime decreases is weak. Accordingly, the results suggest that residential loans drive neighborhood revitalization and prevent acquisitive crimes. Still, extra-local investments via home mortgages are not enough to prevent murders, one of the most egregious violent felonies affecting society. Other alternatives are needed to prevent such crimes.

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

2 Background

2.1 Mortgage market in the US

Banks contribute to solving asymmetric information problems and sharing risks between lenders and borrowers by acting as intertemporal smoothing institutions (Allen et al., 2008). Put simply, some people deposit money, while others acquire debt. The economic relevance of these activities is clear: banks' deposit money assets represent 62 percent of the US GPD, and consumer loans and mortgages 82 percent.[4]

Some features of the US market stand out from other jurisdictions. First, the US has a strong presence of government-sponsored agencies in the mortgage market. These institutions have a substantial influence on the secondary mortgage market, where lenders and investors sell and buy loans.[5] The public aid in the secondary mortgage funding allows banks to benefit by selling loans to these public institutions –that have a lower capital-to-assets ratio than banks–, making lending less expensive than their European counterparts (Coles and Hardt, 2000). Second, mortgage lending involves design, selling, marketing, packaging, managing, and funding the loan, as well as risk and delinquency management. The US mortgage lending process is spread across several institutions, offering a competitive advantage that translates into a larger lending

[4]See https://fred.stlouisfed.org/series/DDDI02USA156NWDB and https://fred.stlouisfed.org/series/HDTGPDUSQ163N

[5]For example, the Government National Mortgage Association (Ginnie Mae), created in 1968, guarantees pools of loans from mortgage banks and is backed by the US government. The Federal National Mortgage Association (Fannie Mae), created in 1968, and the Federal Home Loan Mortgage Corporation (Freddie Mac), created in 1970, securitize (e.g., sell a pool of loans) mortgages to provide liquidity and stability to the housing market.

market (Coles and Hardt, 2000). Third, most loans have a fixed rate and no-fee prepayment options. This feature runs the risk of shortening the mortgage duration, avoiding paying interest on the principal, and increasing the uncertainty in the market. US banks hedge against this volatility by selling the loans in secondary markets and sharing the risks with other investors. The increased demand for these financial instruments provides liquidity and lowers the funding costs, even during financial distress periods (Green and Wachter, 2005).

In short, the US mortgage market characteristics contribute to increasing its size, liquidity, and widespread use nationwide. While these differences would not affect the underlying driving mechanisms of the impact of lending on neighborhood dynamics, they most likely influence its magnitude.

2.2 Prior literature

Acquiring or renovating a property requires large upfront investments that are out of reach to most individuals unless credit is available. Banks are key institutions influencing neighborhood dynamics by facilitating these investments. However, banks do not randomly provide lending across communities; they respond to incentives and the institutional context. Banks can react positively to national laws, such as the Community Reinvestment Act, aiming to encourage lending in low-income communities without increasing the delinquency rates (Avery and Brevoort, 2015; Bhutta, 2011; Ding et al., 2020).[6] Banks can also influence the political economy as community outcomes can be contingent on how extra-local forces and institutions view and treat the neighborhood (Vélez and Richardson, 2012; Carr, 2003; Ramey and Shrider, 2014). There is evidence of banks withholding loans to credit-worthy individuals in minority prevalent areas. For example, the practice known as redlining, explicitly prohibited in the 1968 Fair Housing Act, has caused long-run negative impacts on neighborhood disinvestment and community and individuals' life outcomes, including criminal behaviors (Aaronson et al., 2021a,b; Anders, 2023; Appel and Nickerson, 2016; Faber, 2020; Jacoby et al., 2018; Mitre-Becerril, 2024). Likewise, banks' corporate decisions to merge financial institutions can lead to the closing of local branches, reducing small business lending and employment growth (Nguyen, 2019), and decrease local credit competition, affecting the local economic activity and increasing property crimes (Garmaise and Moskowitz, 2006).

Intra-neighborhood dynamics, such as social disorganization and collective efficacy, are another approach to understanding the role of mortgages on public safety. Local friendship networks may decrease social disorganization and crime by strengthening social controls and mutual trust and facilitating well-

[6] Other studies argue that the Community Reinvestment Act does not affect banks' behavior (Bostic and Lee, 2017; Dahl et al., 2002).

organized communities (Sampson and Groves, 1989). Residential stability creates a stronger attachment to the neighborhood (Morenoff et al., 2001; Sampson et al., 1997). Home loans can provide such stability by limiting migration to other areas. Homeowners face more constraints in their geographic mobility than renters (DiPasquale and Glaeser, 1999), particularly during economic downturns causing reductions in property equity, making it more challenging to relocate, even if it is for job purposes (Modestino and Dennett, 2013).

As one primary objective of mortgages is property acquisition (the other is home improvement), crime can decrease via changes in the housing tenure. Policies encouraging homeownership can reduce crime, particularly burglaries and robberies, by motivating behavioral changes rather than altering the sociodemographic composition of the community (Disney et al., 2023). Homeownership can also influence the subjective measures of crime and risk. Homeownership is associated with a decrease in fear of crime and perceptions of disorder, but longer periods of residence in the community may relate to a higher fear of crime (Lee et al., 2022; Lindblad et al., 2013). Moreover, to the extent that homeowners occupy vacant or foreclosed properties rather than replacing existing tenants and decrease the prevalence of blighted properties in the community, crime should decrease (Branas et al., 2018; Hohl et al., 2019; Kondo et al., 2015).

While mortgages could make neighborhoods safer, it does not necessarily imply that all residents will benefit from such improvements due to gentrification. An increase in mortgages related to a housing boom could cause property price and rent increases and displace long-term, low-income, minority-prevalent residents, leading to new tenants with a higher socioeconomic background. Homeowners facing liquidity constraints could face problems paying a higher property tax, forcing them to liquidate their housing wealth and move to a different place. Renters may find it too expensive to pay higher prices, forcing them to also move out. Although homeowners' out-migration may not happen when accompanied by targeted tax relief programs (Ding et al., 2020) and there is disagreement on whether gentrification induces displacement, it is still a concern in assessing neighborhood changes (Zuk et al., 2018). From a criminological perspective, studies point toward a negative relationship between crime and gentrification (MacDonald and Stokes, 2020; Papachristos et al., 2011). Accordingly, identifying who benefits from an increase in mortgages and neighborhood revitalization is still an open research question.

The previous mechanisms relating mortgages to crime imply improvements in public safety. However, the opposite effect may happen to the extent that loans encourage opportunities for crime. Mortgages can be used for property improvements, and while some renovations are unlikely to be visible to outsiders, other changes signaling the availability of high-value goods could attract potential offenders and cause crime increases. This situation is plausible as evidence suggests that criminals respond to higher prices on goods (Draca et al., 2019). Furthermore, people can also apply for mortgages to refinance an original loan with new conditions, such as longer time terms or lower interest rates, translating into smaller monthly payments, freeing money to be spent on other activities. This cash liquidity increase would imply fewer incentives to commit crimes, particularly for those living paycheck to paycheck (Foley, 2011). However, it could increase crime opportunities to the extent that homeowners become a potential target as they increase their spending patterns.

Neighborhood revitalization may not mechanically translate to fewer crimes across the board. Some crimes, like auto theft, are pro-cyclical so that they increase as the local economic activity improves (Bushway et al., 2012; Cook and Zarkin, 1985). Finally, mortgage indebtedness could also bring psychological distress –driven by fears of being unable to keep up the mortgage payments or cash constraints– relative to owning a home without a mortgage, 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).

2.3 Do previous studies identify a causal relationship?

Previous studies find a negative association between residential lending and violent crime, specifically murders. Kirk (2020) pools three-year data into a single period and controls for collective efficacy, spatial autocorrelation (e.g., mean value of adjacent areas), and standard sociodemographics, finding that mortgage denials increase violent crime. Vélez and Richardson (2012) use a similar method finding a decrease in homicides. Saporu et al. (2011) also pools three years of data and accounts for the dependence of observations in nested units (e.g., tracts nested in cities), and extends the analysis to multiple crime outcomes, finding decreases in violent and property crimes, with larger benefits in Black and Latino communities in comparison to White areas. Shrider and Ramey (2018) use longitudinal data and a random-effects model finding a significant decrease in violent crime in areas providing more mortgages.

These studies provide relevant descriptive patterns between residential lending and violent crime. Nevertheless, they control only for observable characteristics confounding the mortgage-crime relationship. They are limited by not addressing the endogeneity biases arising from common causes and omitted variables. Reverse causality is a serious concern where mortgages influence crime, but crime also affects lending. Causal evidence suggests that crime impacts property prices negatively (Dealy et al., 2017; Gibbons, 2004; Lens and Meltzer, 2016), which is one of the reasons real estate agencies use crime information to guide customers on their decision to buy a property.[7] Banks are unwilling to lend money for properties that, in case of default, would have a challenging time reselling. Another concern is not accounting for unobserved variables affecting simultaneously crime and mortgages (e.g., omitted variable bias). The issue usually arises from time-variant unobserved characteristics. For example, collective efficacy seems to be a malleable, dynamic process subject to yearly changes (Hipp, 2016), so crime differences could be due to collective efficacy and not home loans. Similar arguments can be made with an extensive list of unobserved variables (e.g., social networks, individual preferences, risk attitudes, social capital). These unobserved variables mean self-selection into the intervention.

Previous research does not address these endogeneity biases, so they cannot assure that confounding variables drive the effect between mortgages and crime. Cross-sectional studies have no temporal or spatial exogenous variation (Kirk, 2020; Saporu et al., 2011; Vélez and Richardson, 2012), and they unlike can establish a causal relationship. Research using random-effects models does not solve this problem either (Shrider and Ramey, 2018) because it assumes that the unobserved heterogeneity and the primary variable of interest are uncorrelated, which is a likely unrealistic assumption. The violation of this assumption is the reason for using quasi-experimental design models to obtain a causal relationship.

Instrumental variable studies are a more appropriate method to overcome the endogeneity biases. Veléz (2009) and Velez et al. (2012) find a negative effect of mortgages on violent crime, particularly homicides, using an instrumental variables approach. Bunting (2020) also uses an instrumental variables model, finding that mortgages reduce major crimes but do not distinguish between property and violent crime and its subcategories. However, some of these instruments are likely correlated with the omitted variable or error term, which could lead to a greater bias than an ordinary least squares estimation (Angrist and Krueger, 2001). Specifically, Veléz (2009) use the age of the housing stock in a census tract as an instrument, but this variable relates to mortgages and crime through other channels. Older properties could result from residents organizing against new developments either via a *not in my backyard* movement, homeowners associations, or pushing for a historic designation, among others, to impose residential limitations and add a property price premium. Likely, these areas also attract additional private and public investments in law enforcement, affecting crime through other mechanisms beyond mortgages. Finally, older properties could mean an area is socially disadvantaged, which could affect crime through mechanisms besides mortgages (e.g., under-policing).

Velez et al. (2012) apply a first-differences transformation (e.g., $\Delta x_{it} = x_{it} - x_{it-1}$) and instruments

[7] In 2021, several real estate listing websites stopped providing crime data due to concerns that this practice perpetuates racial inequality. See https://magazine.realtor/daily-news/2021/12/16/realtorcom-redfin-remove-crime-data-on-listings

the endogenous variable with its past levels (e.g., Δx_{it-2} as instrument for Δx_{it-1}). This approach became common in the literature some time ago. Still, it is problematic because it assumes that the lagged values of the independent variable are uncorrelated with the differenced error term (Angrist and Krueger, 2001). This assumption is unlikely to hold if the error terms are serially correlated, a common issue in panel data, violating the assumption that the instrument is uncorrelated with the omitted variable.[8]

The only well-identified instrumental variable uses a shift-share instrument (Bunting, 2020). While the study provides credible evidence that mortgages reduce major crimes, it does not distinguish between property and violent crime and its subcategories, making it difficult to compare the results to previous studies. Furthermore, it does not examine any heterogeneous impacts in minority prevalent areas, which is a relevant margin to analyze, nor provides evidence on the potential causal mechanisms driving the impacts. This manuscript addresses those concerns.

3 Data

3.1 Data sources

There is no national repository of crime incidents at the census tract level. The common crime 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 data source is not appropriate for understanding the crime effects at the sub-city level. 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.[9] Some cities only publish the address of the incident rounding the locations to the nearest hundred block or blurring the address' last two digits; such cases were replaced with a five-zero number (e.g., 12XX Street Name became 1250 Street Name) and three geocoders (US Census geocoder, ArcGIS Online Geocoding Service, and the Nominatim OpenStreetMap search engine)

[8] See Reed (2015) for a detailed explanation of the problems of using lagged variables as instruments. Importantly, testing a non-significance relationship of the residuals with the problematic variable is not enough to show that the exclusion restriction holds. The residual is not the same as the error term. The residual is the difference between the observed and model's predicted values ($\hat{u}_{it} = \hat{y}_{it} - y_{it}$), while the error term is unobservable and it is part of the population model (e.g., $u_{it} = y_{it} - \beta x_{it}$). The exclusion restriction is a non-testable assumption guided by theory.

[9] 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.

sequentially attempted to geocode the address. The geocoding hit rate was above the minimum acceptable hit rate suggested by 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 the property crimes. Non-major crimes are all other offenses reported to the police.

The home loans come from the Home Mortgage Disclosure Act (HMDA) data collected by the Consumer Financial Protection Bureau, which 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 a change in 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.[10] The mortgages consider the originated loans (e.g., excludes loans purchased by the financial institution in 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.[11]

[10] The 2015 Home Mortgage Disclosure Regulation C amendment explains such changes, available at 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).

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

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.[12] The average census tract experienced a decrease of 13 percent in non-major crimes between 2011 and 2017. The reduction in major crimes was more muted (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, and, in third place, aggravated assault and motor vehicle thefts are equally likely. The mean census tract experienced less than one murder per year, 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. The number of approved loans moved from 43 to 60 per census tract year, while the total neighborhood amount went from 12.1 to 19.7 million dollars. Consequently, the loan amount per mortgage increased, moving from around 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, total census tract amount, and amount per loan. These yearly growth rates relate to a stronger mortgage and housing market that took some time to recover after the Great Recession.

The census tract sociodemographics remained stable across these seven years, suggesting no overall census tract compositional changes. Census tracts have nearly four thousand residents. Most of them identify as White (51%) and around a quarter of them as Black (27%) or Hispanic (24%). While these characteristics differ from the US estimates, they 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. Nearly 40 percent have a college degree or higher, while fewer than 20 percent have less than a high school diploma. These characteristics resemble the country's sociodemographics.

The unemployment rate ranged between 10.9 and 8.5 between these seven years. While the rate was similar to the 2011 US estimates, it was higher in 2014 and 2017 than in the rest of the country (the national unemployment rate was 7.2 and 5.7 in 2014 and 2017). The poverty rate was also consistently higher in these 27 cities than in the rest of the US by about six percentage points (17 vs 11 percent).

[12] 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. Consequently, the sample size decreases for these outcomes relative to the other crimes.

Finally, the mean census tract experienced a marginal raise in the number of occupied housing units of about 4.7 percent between 2011 and 2017 (about a negative half percent yearly change) and a decrease of about 8 percent (1.1 yearly percent growth) in vacant properties. These numbers show that the mean census tract had a crime reduction and an increase in mortgages. Assessing whether this relationship is causal is the main objective of this research.

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. Pooled or random effects models do not 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. Despite adding controls and fixed effects, this model is unlikely to provide causal estimates because there are time-varying, unobserved factors, such as collective efficacy, not accounted for in the model that influence crimes and loans simultaneously.

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

Other causal inference models are available to overcome the concern of endogeneity.[13] An instrumental variable approach is a prime candidate to eliminate the endogeneity bias by only using the variability in mortgages that is uncorrelated with the omitted variable bias (Angrist and Krueger, 2001). A Bartik or shift-share instrument is appropriate given the institutional context. This method exploits the presence of multiple banks in a census tract and the banks' idiosyncratic lending patterns following corporate decision-makers and national trends likely uncorrelated in time and place with local crime changes.

The shift-share instrument has two components. The shift, g_{ikt}, is the nationwide growth in mortgage

[13] 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 exploiting the discontinuous threshold of the Community Reinvestment Act eligibility status (Avery and Brevoort, 2015; Bhutta, 2011; Bostic and Lee, 2017; Ding et al., 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 analysis.

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 common shocks relates to differential changes, so a growth rate rather than levels is needed (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 mortgage loan amount of bank k in tract i and year t_0, so it ranges from zero to one. It is customary in the literature to fix the shares to a specific time, usually a pre-study period. For this research, it was defined $t_0 = 2007$, which is one year before the Great Recession, when major institutional and regulatory changes happened in the banking industry. 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:

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

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 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 is:

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

where γ_i, μ_t, and X_{it} are defined as previously, and $\hat{L}_{it}$ is the predicted growth rate of the mortgage loan amount in tract i and year t based on the first stage (equation (3)). In all models, the standard errors are clustered at the census tract level. As some outcomes, particularly violent crimes, have zero incidents in any given year-tract, the inverse hyperbolic sine function was used instead of the logarithm function for all outcomes. This transformation 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 an alternative functional form: $\log(y+1)$.

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.[14] Instrument 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 specific case of crime literature, the shift-share instrument method has been used to examine the public safety effects of mortgages (Bunting, 2020), migrations 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).

More broadly, 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).

4.2 Building the instrumental variable

To understand the motivation for using the shift-share design, this section examines the shift and share components of the instrumental variable. First, to construct the shares, this research identifies 1,118 banks offering mortgages in any of the 27 cities included in the study between 2007 and 2017. **Figure 1** shows the distribution of each bank's mortgage share per census tract (s_{ikt_0}) in 2007, the base period. The mean (median) bank's tract share of the mortgage loan amount is 6.1 (2.5) percent. Nearly 90 percent of the banks' tract shares are below 15 percent. In contrast, fewer than 0.6 percent of the banks' tract shares are higher than 66 percent. Furthermore, **Appendix Figure A.2** aggregate the banks' share at the census tract ($s_{it_0} = f_k(s_{ikt_0})$) to estimate the mean, median, and maximum bank's share per census

[14] Bartik (1991) was not the first one using this approach, but the author popularized this method and explained its logic, so it carries 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.

tract, suggesting that while one bank usually has one-third of the local mortgage market, the remaining share is scattered across a considerable number of banks. Specifically, the mean (median) census tract has 13 (9) 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. Banks are unlikely to have strong market power at such a small geographical level. The large number of shares across tracts is one of the sources of variation that the shift-share instrumental variables approach leverages (cross-sectional variation).[15]

Banks rarely operate nationwide; only one bank (JPMorgan Chase) has branches in the lower 48 states. Still, **Appendix Figure A.4** shows that jointly, these banks are practically scattered across all counties in the US as the mean (median) county has 81 (96) out of the 1,118 banks used to build the instrumental variable. Do the crime incidents in the 27 cities affect lending behavior in the rest of the country? It is extremely 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).[16]

Another factor influencing lending is banks' idiosyncratic strategies and management decisions (e.g., CEO's leadership, advertising strategies, human resources management, assessing clients, etc.). These characteristics influence the banks' revenue and cost strategy and, hence, how much resources they can lend to consumers and successfully recover. **Figure 2** shows the mean nation mortgage growth (excluding the 27 cities) of the 1,118 banks between 2011 and 2017. The mean bank had a yearly increase in the mortgage loan amount of 4.2 percent, but there is a large dispersion across banks. While some financial institutions experienced yearly decreases, others had equally large increases. Practically, all banks experienced positive and negative changes over these seven years, consistent with the national trend in mortgages associated with changes in interest rates. This temporal variation across different banks forms the shifts of the instrumental variables, g_{ikt}.

[15] **Appendix Figure A.3** 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.

[16] **Appendix Figure A.5** 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.

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 to address the selection bias: random effects, fixed effects, and first differences using the lagged of the independent variable as an instrument. **Table 2** Panel A shows that the random effects model suggests increases in property crimes, and similar to previous correlational studies, it also finds significant reductions in murders and aggravated assaults, and non-significant violent crime reductions. Panel B shows the fixed effects model, finding a positive relationship between mortgages and property crimes. Murders and aggravated assault have a negative non-significant correlation with residential lending, while the increase in violent crime is driven by a rise in robberies. Finally, using the first differences with the lagged of the independent variable as an instrument, Panel C shows significant decreases in property and violent crimes. The decrease in violent crimes is driven by a reduction in robberies, still, murder has a negative coefficient too. None of the three models show significant effects on non-major crimes. These models show different results, as it is unlikely they address the endogeneity biases of reverse causality and omitted time-variant confounders.

A more appropriate model to identify the causal effect is using a shift-share instrumental variables approach. **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. Reassuringly, this result does not change when covariates are included in the model. The coefficients imply that a ten percent growth in the mortgage outside of the 27 cities relates to a 2.3 percent change increase in the census tract mortgages ($(e^{\beta_1}-1)/10$ percent). The estimate has a similar magnitude as Bunting (2020), suggesting that the relationship holds in other jurisdictions. The F-statistic is well above the common threshold level (Stock et al., 2002). Accordingly, 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 their magnitude as the instrumental variable estimate is equal to the reduced form coefficient divided by the first stage (it is 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 3.1 and 1.6 percent decrease in theft and burglary (changes estimated as $(e^{\beta_1}-1)/10$ percent). 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, and consistent with being procyclical with the economy (Cook and Zarkin, 1985; Bushway et al., 2012). Violent crime shows a negative but statistically insignificant decrease. Aggravated assault shows only a significant 2.4 percent decrease for every 10 percent increase in lending. Murders and robberies have no significant changes, and their point estimates are close to zero, which is a finding different from previous studies that argue that mortgages reduce homicides. Finally, there is also a significant decrease in non-serious crimes of 1.6 percent due to a 10 percent in mortgages.

5.2 Robustness

This section assesses the robustness of the results to alternative specifications and their sensitivity to different analytical decisions taken in the research process. One 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. **Appendix Table A.1** estimate the reduced form and second stage least squares estimates with an alternative instrument. This new instrument excludes banks with more than 66 percent of the local market, so the inner product of the shifts and shares only considers banks without local market concentration. The results hold to this alternative specification. I highlight two findings. First, the burglary estimate is no longer significant at the conventional levels (p-value equals 0.17). This result is unsurprising as this crime category is the only significant crime at a p-value of 0.10 in the main estimates. Second, violent crime shows a statistically significant change driven by a decrease in aggravated assault. Once again, this result is unsurprising; in the main estimates, violent crime was significant at a p-value of 0.11, and now it has crossed the 0.10 threshold. Hence, the results are practically the same.

A second concern is the chosen functional form of using an inverse hyperbolic sine transformation of the data. While this choice was chosen for practical purposes as it can be interpreted as a standard logarithm dependent variable (Burbidge et al., 1988), one can be concerned that this transformation is driving significant changes. **Appendix Table A.2** shows that this situation is not the case. Using the $\log(y + 1)$ as an alternative functional form leads to the same conclusions. This function also avoids excluding outcomes with zero crimes, which are more likely to happen in small populated areas or for rare crimes (e.g., murder and robbery). One can argue that no place is without crime, particularly during one year, so adding a positive value is warranted to ensure that every outcome is positive. Nevertheless, there is no strong underlying reason for adding one, two, or twenty to the outcome. Despite these limitations, the results hold to these alternative functional forms.

A third concern is that the crime outcomes were estimated using incidents rather than rates. Incidents are preferred to rates at small geographical levels where residents may not reflect the victimization risk in the area (Massenkoff and Chalfin, 2022). For instance, some areas have many transient visitors and pedestrians (e.g., touristic places or commercial areas) but few residents. Still, **Appendix Table A.3** use the inverse hyperbolic sine transformation of crime rates rather than incidents. The results show the same pattern: significant reductions in property crime –excepting motor vehicle theft– aggravated assaults and non-major crimes, but no significant changes in homicides and robberies.

Another way to assess the sensitivity of the results to the more densely populated areas driving the results is by weighting the observations with the number of housing units in the census tract. The underlying idea of this robustness check is placing more weight on areas with a larger potential for receiving mortgages as they have more residential properties. **Appendix Table A.4** shows that the results hold to using a weighted regression. Weighting by the population in the census tract also leads to the same conclusions (**Appendix Table A.5**). If anything, this specification suggests a significant increase in homicides, but it is likely a false discovery rate.

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, credit-worthy racial minorities, due to redlining, have been denied loans affecting long-term neighborhood and individuals' life outcomes (Aaronson et al., 2021a,b; Anders, 2023; Appel and Nickerson, 2016; Faber, 2020; Jacoby et al., 2018; 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 in such neighborhoods than in those with widespread credit availability due to non-linear effects.[17]

Table 5 tests for heterogeneous effects by interacting the loan amount with a relevant dimension variable –the proportion of the Black or Hispanic population or poverty level in the census tract–, and then instrumenting these endogenous variables with the shift-share instrument and its interaction with the race-ethnic dimension.[18] The interaction term assesses whether prevalent minority neighborhoods

[17] A raw comparison finds that tracts with over 50 percent of Black (Hispanic) residents receive 17.7 (15.6) fewer million dollars per year or about 126 (53) fewer thousand dollars per loan than their non-Black (non-Hispanic) areas.

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

have larger changes in crime due to an increase in mortgages. Panel A suggests that Black neighborhoods benefit more from receiving mortgages than census tracts with no Black residents. The effects are significant for non-major, property –driven by theft reductions– and violent crimes –caused by aggravated assaults decreases. To understand the magnitude of the change, a 10 percent increase in the mortgages in tracts with a 50 percent prevalence of Black residents experience an additional 0.9 percent reduction in property crime than tracts with no members of this race group, which experience only a 0.5 percent reduction. Murders have a significant positive change, suggesting that, if anything, Black communities may benefit less from more mortgages to reduce murders, but as the main estimate is not significant, this result should be taken cautiously. Panel B shows that more mortgages in a census tract also benefit Hispanic communities by causing 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. The coefficient on aggravated assaults is negative, but it is imprecisely measured (pvalue of 0.150), and so is the violent crime category. Murders and robberies show no differential effects on Hispanic communities.

There is a high correlation between minority communities and poverty.[19] 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 presents the second stage least squares estimates, adding the interaction for the proportion of families under the poverty level. The results point toward larger marginal impacts of home loans on crime in poor places relative to affluent places. For instance, an increase of 10 percent in mortgages results in an additional property crime decrease of 2.8 percent in census tracts with a 50 percentage point difference in poverty rates. Overall, property –theft, burglary, and motor vehicle theft–, violent –aggravated assaults–, and low-level offenses experience differential changes in criminal incidents due to more mortgages. 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 availability of lending services could be different in areas experiencing limited credit access. To assess such heterogeneous effects, **Appendix Table A.6** shows the instrumental variable estimates interacting the mortgage amount with an

[19] 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.

indicator variable of being on the first, second, or third tercile of the mean local mortgage amount during the study period. The estimates are larger in the bottom tercile than the middle and top distribution groups. Particularly, 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-value < 0.10), and burglary shows limited evidence of differential impacts among tercile groups. The evidence supports that the impact of mortgages on crime is larger in areas where lending is scarce. Murder and robberies do not show any statistically significant impacts in any of the three tercile groups, suggesting that even in places where lending is scant, murders and robberies have little relationship with mortgages. Preventing serious violent crimes requires other strategies.

5.4 Potential causal mechanisms

This study shows that mortgages reduce crime, particularly financially motivated 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. Using the same instrument and endogenous variable as the main estimates, meaning mortgages for a

There are negligible impacts on the occupied or vacant housing stock when using any mortgage type (home purchase, improvement, or refinancing). However, subsetting the instrument to only mortgages meant for home purchase, the point estimates suggest that a 10 percent increase in mortgages increases (decreases) the occupied (vacant) units by 0.2 percent.[20] The estimates are small, but considering that the housing stock comes from the American Community Survey and not from administrative records, 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

[20]The first stage of this alternative mortgage instrumental variable is significant and strong.

more affluent individuals. The physical place may be better off at the expense of some 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, which are common metrics to measure gentrification, did not change. It could be possible that some areas may have experienced compositional changes, but the average neighborhood did not experience them. Accordingly, the original residents seem to benefit from a safer community.

6 Discussion and conclusions

Public and non-profit community investments focusing on high-risk individuals and areas with a clear nexus with crime-reducing factors have shown promising results (Blattman et al., 2017; Branas et al., 2018; Chalfin et al., 2022; Heller, 2014). Private investments can also encourage public safety improvements. Does residential lending reduce serious criminal offenses? This research relies on a shift-share (or Bartik) instrumental variables approach to overcome the endogeneity bias confounding the mortgage-crime relationship. The instrument leverages the differential exposure to banks' local market presence (*shares*) and common national mortgage shocks (*shifts*) to assess differential changes in neighborhood crime. The instrument is the inner product of the banks' market shares at the census tract level and the banks' nation residential lending happening outside of the 27 cities included in the study. Once controlling for tract and year fixed effects, along with sociodemographics, the mortgage growth outside of these cities is unlikely correlated with factors explaining crime in the neighborhood level in time and place beyond its effect through residential lending. This instrument is a prime candidate to approximate the effect of mortgages on crime.

By analyzing crime incident microdata 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 (Bushway et al., 2012; Cook and Zarkin, 1985). Alternative model specifications and robustness checks confirm these findings. Furthermore, 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 impact of home mortgages seems to be fewer vacant houses and an increase in occupied units without experiencing discernible gentrification changes, measured through sociodemographic changes.

In contrast to previous research, this study finds no reductions in murders and robberies; at best, the decline in violent crime, driven by aggravated assaults, is suggestive (e.g., not consistently significant in all specifications). Why do mortgages reduce property and non-major crimes but not more serious felonies, as previous correlational evidence has suggested? One possible explanation is that the mortgage increase has to be substantial. Despite the large sample size, this study may not have precisely measured it. Each offender-victim interaction has an underlying probability of ending in the murder of the victim. For example, aggravated assaults have a risk of death of about 33 in 10,000 incidents or a 0.33 mortality probability, while theft and burglary have substantially lower probabilities of about 0.001 and 0.0058 percent (Cohen, 1988). This research finds that increasing mortgages by 10 percent relates to a 2.4, 3.1, and 1.6 percent decrease in aggravated assaults, theft, and burglary. Accordingly, some murders may be mechanically prevented by reducing other crime incidents, but as the risk of death from these crimes is small, their compounded effect is not large enough to distinguish the noise from the signal. This explanation cannot be unequivocally rejected, but it is unlikely the main reason behind the null impacts on murder and robberies. The heterogeneity analysis based on poverty and minority prevalence, as well as scarcity of lending, still suggests that mortgages do not affect violent crimes.

A second explanation for the null effects on homicides is that context matters. Homicides measure the willful or nonnegligent killing of a person by another person,[21] but variations in their motive, victims' and offenders' characteristics, and place and circumstances of commission, make them responsive to alternative factors. The motive for a considerable share of homicides is anger outbursts, robberies going badly, retaliation, and interpersonal conflicts. The presence of substances, guns, and offenses committed by people the victims knew are common characteristics of homicides. Some structural characteristics –like concentrated disadvantage–, seem to affect most murders, but others –like residential mobility and population structure– affect only some of them (Kubrin, 2003; McCall et al., 2010). These associations have more nuances once homicides are disaggregated by race due to rooted, systemic factors affecting violence (Kubrin and Wadsworth, 2003). Accordingly, finding no significant effects between mortgages and all homicides does not unambiguously imply that some specific types of homicides may have an association. However, limited by data availability, this research cannot examine such a detailed relationship.

[21] See the FBI's UCR crime definitions https://ucr.fbi.gov/additional-ucr-publications/ucr_handbook.pdf.

A third and more plausible explanation is that the previous studies did not address the endogeneity bias confounding the lending and crime relationship. The bias was not addressed by using cross-sectional, random effects, or weak instruments, leading to overestimating the effects. Weak instruments can lead to greater bias than ordinary least squares (Angrist and Krueger, 2001). This research shows that the relationship between lending and crime mostly applies to property and low-level offenses but not to violent felonies.

Framing the results more broadly into community investments and crime scholarship facilitates understanding their relevance. There is a growing, rigorous literature evaluating non-policing neighborhood interventions finding crime decreases, but whether they reduce serious violent felonies, like homicides, which are infrequent but costly, is still an open research question. Most studies do not analyze the murder crime category separately. For example, providing strategic street lighting reduces serious crime, including robberies and aggravated assaults (Chalfin et al., 2022), restoring blighted vacant lots decreases burglary, gun assaults, and non-major crimes (Branas et al., 2018), offering summer youth employment programs reduce overall violent and property arrests –no crime category disaggregation– (Modestino, 2019), and increasing homeownership rates decrease robberies, burglaries, and thefts (Disney et al., 2023). However, none of these studies can tell whether murder decreased. This situation is understandable as homicides are rare, requiring large sample sizes to detect small changes. However, given its high cost to society, analyzing whether crime decreases and providing specific crime category analyses contributes to having a better understanding of the crimes affected by neighborhood investments. Otherwise, when finding changes in violent crimes, we may be referring mostly to aggravated assaults, the lion's share of this category.

Finally, this research contributes to the promising literature finding that localized investments can promote safer neighborhoods by revitalizing neighborhoods. Equally important, such investments can come from public, non-profit, or private actors. This research suggests that financial institutions, inadvertently, may be contributing to reducing crime by providing mortgages to creditworthy individuals to acquire a property or improve their current one. The effect is larger in minority-prevalent and lower-income neighborhoods, which can be a way to reduce urban inequality. Given the wide geographical presence and large financial asset size of banks, the role of lending in promoting neighborhood revitalization is a key and promising area of research.

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

	Mean (std. dev)		
	2011	2014	2017
Non-Major crimes	222.7 (309.3)	198.3 (251.7)	193.6 (241.3)
Major crimes	142.8 (152.9)	134.2 (158.6)	133.0 (163.4)
Violent	25.9 (28.6)	24.6 (28.2)	26.6 (31.1)
Murder	0.4 (0.8)	0.4 (0.8)	0.4 (1.0)
Robbery	12.2 (14.6)	10.8 (13.3)	10.5 (13.1)
Aggravated assault	13.4 (16.3)	13.4 (17.0)	15.7 (20.5)
Property	116.9 (133.8)	109.6 (140.9)	106.3 (143.9)
Burglary	29.1 (31.6)	22.9 (24.4)	18.9 (20.7)
Theft	73.3 (105.3)	73.6 (117.2)	73.9 (121.5)
Motor vehicle theft	14.5 (15.6)	13.1 (16.0)	13.6 (16.0)
Number of loans	43.7 (66.4)	51.7 (65.8)	60.1 (72.8)
Loan amount (million dollars)	12.1 (26.3)	15.0 (24.9)	19.7 (30.7)
Population (thousands)	3.8 (2.0)	3.9 (2.1)	4.0 (2.2)
White (%)	51.2 (30.3)	51.3 (30.1)	51.0 (29.4)
Black (%)	27.7 (32.4)	27.3 (31.8)	26.8 (31.2)
Hispanic (%)	23.3 (25.4)	23.9 (25.4)	24.2 (25.3)
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 (%)	24.4 (9.0)	24.6 (9.1)	25.4 (9.4)
Age 40-54 (%)	20.3 (5.6)	19.8 (5.3)	19.0 (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 (%)	18.2 (7.1)	18.5 (7.1)	18.0 (7.1)
College+ (%)	37.0 (22.1)	38.5 (22.4)	40.8 (22.6)
Unemployment rate (%)	10.9 (7.3)	11.7 (7.7)	8.5 (6.3)
Family income (thousands)	63.5 (38.2)	65.1 (39.7)	71.9 (43.2)
Poverty rate (%)	16.8 (14.3)	18.0 (14.6)	16.3 (13.6)
Occupied housing units	1,469.6 (793.0)	1,495.7 (826.8)	1,539.1 (872.0)
Vacant housing units	192.4 (176.2)	185.2 (172.2)	177.1 (168.3)

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	0.005**	0.007***	0.007**	0.008**	0.021***	−0.005	−0.007***	−0.002	−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	53,755	53,755	53,755	53,755	53,755	53,755	51,515	53,755	53,457	44,120
B. Fixed effects										
Loan amount	0.005*	0.005*	0.004	0.004	0.011**	0.008*	−0.002	0.011**	−0.0004	0.003
	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.005)	(0.005)	(0.002)
Observations	53,755	53,755	53,755	53,755	53,755	53,755	51,515	53,755	53,457	44,120
C. First differences using the lagged value as IV										
Loan amount	−0.090*	−0.066	−0.025	−0.053***	0.003	−0.023**	−0.001	−0.023***	0.004	−0.007
	(0.051)	(0.050)	(0.043)	(0.015)	(0.018)	(0.011)	(0.001)	(0.008)	(0.007)	(0.116)
Observations	38,061	38,061	38,061	38,061	38,061	38,061	36,461	38,061	37,614	31,467

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, so the estimates are interpretated 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 (all variables are first differenced) instrumenting the loan amount with its lagged value, so the estimates are interpretated 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	0.219^{***}	0.213^{***}
	(0.025)	(0.025)
Mean dep. var.	2.69	2.71
Observations	54,698	53,755
F-statistic	78.8	73.5
Year FE	X	X
Tract FE	X	X
Covariates	-	X

Notes: First stage estimates using ordinary least squares regression of the share-shift instrument of the inner product of the nation wide bank loan growth rates outside of the 27 cities and the bank-tract share on mortages following equation (3). The dependent variables, local mortgages, uses the inverse hyperbolic sine transformation, so technically 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. 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	-0.025^{***}	-0.035^{***}	-0.081^{***}	-0.039^{**}	0.088^{***}	-0.025	0.021	-0.006	-0.061^{***}	-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	-0.116^{**}	-0.165^{***}	-0.378^{***}	-0.183^{*}	0.414^{***}	-0.119	0.095	-0.026	-0.286^{***}	-0.186^{***}
	(0.048)	(0.055)	(0.077)	(0.095)	(0.116)	(0.076)	(0.079)	(0.091)	(0.099)	(0.055)
Mean crime	5.08	4.83	4.32	3.30	2.67	3.30	0.29	2.47	2.65	5.50
Observations	53,755	53,755	53,755	53,755	53,755	53,755	51,515	53,755	53,457	44,120

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, so 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. 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	−0.074**	−0.105***	−0.212***	−0.139**	0.251***	−0.033	−0.057	0.046	−0.168***	−0.072**
	(0.029)	(0.033)	(0.044)	(0.058)	(0.070)	(0.049)	(0.048)	(0.058)	(0.064)	(0.031)
Loan amount*D	−0.136	−0.198**	−0.555***	−0.152	0.552**	−0.264**	0.480**	−0.220	−0.372**	−0.414***
	(0.085)	(0.098)	(0.144)	(0.169)	(0.215)	(0.131)	(0.196)	(0.173)	(0.166)	(0.115)
Mean crime	5.09	4.83	4.32	3.31	2.67	3.31	0.29	2.47	2.66	5.50
Observations	53,978	53,978	53,978	53,978	53,978	53,978	51,738	53,978	53,680	44,120
B. Hispanic population = D										
Loan amount	−0.098**	−0.142***	−0.339***	−0.141	0.355***	−0.103	0.092	−0.036	−0.259***	−0.161***
	(0.046)	(0.052)	(0.074)	(0.089)	(0.109)	(0.073)	(0.076)	(0.086)	(0.095)	(0.056)
Loan amount*D	−0.142**	−0.175**	−0.290**	−0.326**	0.448**	−0.128	0.017	0.067	−0.208	−0.183***
	(0.070)	(0.085)	(0.115)	(0.152)	(0.180)	(0.114)	(0.157)	(0.150)	(0.150)	(0.064)
Mean crime	5.08	4.83	4.32	3.30	2.67	3.30	0.29	2.47	2.65	5.50
Observations	53,755	53,755	53,755	53,755	53,755	53,755	51,515	53,755	53,457	44,120
C. Poverty level = D										
Loan amount	−0.059**	−0.075***	−0.162***	−0.030	0.152***	−0.013	−0.013	0.055	−0.150***	−0.024
	(0.023)	(0.027)	(0.039)	(0.048)	(0.057)	(0.041)	(0.041)	(0.048)	(0.052)	(0.029)
Loan amount*D	−0.417	−0.666*	−1.687***	−1.145**	2.032**	−0.914**	0.841	−0.702	−1.170**	−1.246**
	(0.280)	(0.348)	(0.600)	(0.581)	(0.820)	(0.452)	(0.592)	(0.528)	(0.583)	(0.513)
Mean crime	5.08	4.82	4.31	3.29	2.67	3.30	0.28	2.46	2.66	5.50
Observations	52,897	52,897	52,897	52,897	52,897	52,897	50,657	52,897	52,599	43,273

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. 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	−0.006
	(0.008)	(0.009)
Mean dep. var.	1.13	0.18
Observations	53,720	53,720
B. Home purchase mortgages		
Loan amount	0.018*	−0.023*
	(0.010)	(0.012)
Mean dep. var.	1.14	0.18
Observations	50,667	50,667

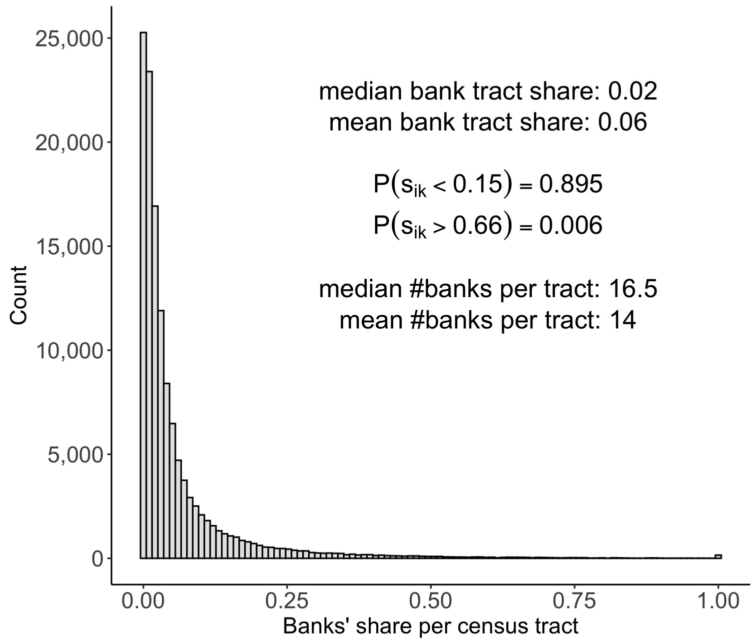
Notes: Second stage least squares (instrumental variable) estimates of mortgages on the number of housing units in the census tract. Panel A uses all mortgages for the instrument and the endogeneous variable, which is the same approach as the main estimates. Panel B uses only mortgages with the purpose 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, so the results are expressed as percent changes ($e^{\beta_1} - 1$). 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	Black	Some college	College+
	(1)	(2)	(3)	(4)
Loan amount	0.008	−0.005	−0.003	−0.001
	(0.010)	(0.008)	(0.006)	(0.007)
Mean dep. var.	0.48	0.26	0.18	0.38
Observations	53,980	53,980	53,978	53,978

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 ($e^{\beta_1} - 1$). Robust standard errors clustered at the census tract level in parentheses. *p<0.1; **p<0.05; ***p<0.01.

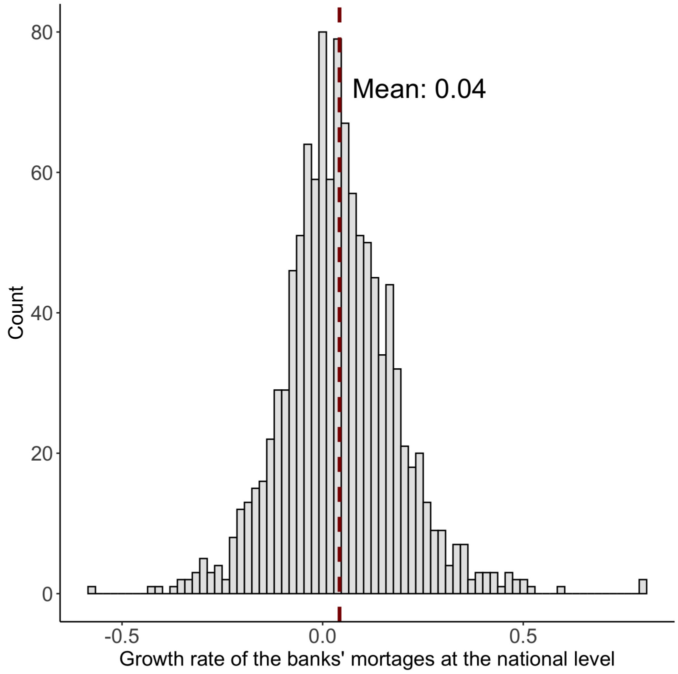
Figure 1: Histogram of banks' mortgage share, 2007



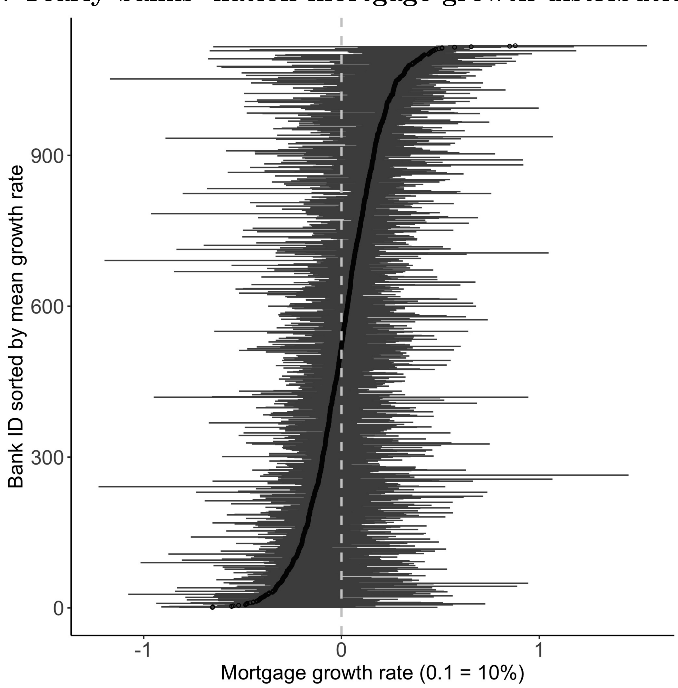
Notes: The figure shows the 2007 banks' share of the mortgage loan amount in the census tracts (s_{ikt_0}) included in the analysis. The results suggest little evidence of market concentration in the sample.

Figure 2: Banks' nation mortgage growth, 2011-2017

A. Average banks' nation mortgage growth



B. Yearly banks' nation mortgage growth distribution



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 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.

ONLINE APPENDIX

A Appendix: Tables and Figures

Table A.1: Alternative instrument: 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	-0.029^{***}	-0.033^{***}	-0.079^{***}	-0.027	0.063^{***}	-0.032^{*}	0.011	-0.010	-0.079^{***}	-0.021^{**}
	(0.010)	(0.011)	(0.013)	(0.020)	(0.023)	(0.017)	(0.018)	(0.022)	(0.021)	(0.009)
B. Second-stage least squares										
Loan amount	-0.142^{***}	-0.161^{***}	-0.380^{***}	-0.129	0.302^{***}	-0.155^{*}	0.052	-0.051	-0.380^{***}	-0.129^{**}
	(0.051)	(0.056)	(0.078)	(0.096)	(0.115)	(0.086)	(0.087)	(0.104)	(0.111)	(0.056)
Mean crime	5.09	4.83	4.32	3.31	2.67	3.29	0.29	2.46	2.64	5.49
Observations	52,797	52,797	52,797	52,797	52,797	52,797	50,606	52,797	52,501	43,197

Notes: These specifications use an alternative Bartik instrument, which was built using only banks with less than 66 percent of the mortgages share-tract in 2007 to reduce concerns that banks with high market concentration could be related to crime, and, hence, bias the results. 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, so the results are expressed as percent changes (e.g., $e^{\beta_1} - 1$). 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. Robust standard errors clustered at the census tract level are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.2: Alternative functional forms: 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)
1) Variables as log(.+1)										
A. Reduced form										
Instrument	-0.025^{***}	-0.034^{***}	-0.073^{***}	-0.042^{**}	0.067^{***}	-0.023^{*}	0.016	-0.006	-0.052^{***}	-0.032^{***}
	(0.009)	(0.010)	(0.012)	(0.017)	(0.019)	(0.014)	(0.013)	(0.016)	(0.016)	(0.008)
B. Second-stage least squares										
Loan amount	-0.137^{**}	-0.188^{***}	-0.402^{***}	-0.229^{**}	0.370^{***}	-0.127^{*}	0.088	-0.036	-0.284^{***}	-0.213^{***}
	(0.054)	(0.061)	(0.081)	(0.095)	(0.110)	(0.077)	(0.072)	(0.089)	(0.095)	(0.062)
Mean crime	4.42	4.17	3.68	2.73	2.16	2.73	0.22	1.99	2.15	4.82
Observations	53,755	53,755	53,755	53,755	53,755	53,755	51,515	53,755	53,457	44,120

Notes: Outcomes using log(.+1), so the results are expressed as percent changes (e.g., $e^{\beta_1} - 1$). Panel A shows the reduced form estimates following equation (4). Panel B presents the second stage least squares (instrumental variable) estimates following equation (5). 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. Robust standard errors clustered at the census tract level are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.3: Alternative dependent variable: Reduced form and 2SLS estimates of mortgages on crime rates

	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	-0.022^{**}	-0.032^{***}	-0.080^{***}	-0.024	0.124^{***}	-0.022	0.017	-0.003	-0.069^{**}	-0.030^{***}
	(0.011)	(0.012)	(0.015)	(0.024)	(0.032)	(0.020)	(0.033)	(0.027)	(0.028)	(0.010)
B. Second-stage least squares										
Loan amount	-0.101^{*}	-0.151^{**}	-0.373^{***}	-0.113	0.579^{***}	-0.103	0.080	-0.013	-0.323^{**}	-0.169^{***}
	(0.053)	(0.061)	(0.085)	(0.113)	(0.157)	(0.097)	(0.150)	(0.127)	(0.141)	(0.065)
Mean crime	6.13	5.88	5.36	4.32	3.64	4.31	0.52	3.40	3.61	6.58
Observations	53,755	53,755	53,755	53,755	53,755	53,755	51,515	53,755	53,457	44,120

Notes: Outcomes use the inverse hyperbolic sine transformation of crimes per 10,000 people rather than crime incidents to account for differential crime risks across census tracts. The results are expressed as percent changes (e.g., $e^{\beta_1} - 1$). Panel A shows the reduced form estimates following equation (4). Panel B presents the second stage least squares (instrumental variable) estimates following equation (5). 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 A.4: Alternative weights: 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	-0.028^{**}	-0.037^{***}	-0.070^{***}	-0.051^{**}	0.070^{***}	-0.030^{*}	0.029	-0.002	-0.078^{***}	-0.035^{***}
	(0.012)	(0.012)	(0.015)	(0.025)	(0.027)	(0.017)	(0.020)	(0.021)	(0.021)	(0.012)
B. Second-stage least squares										
Loan amount	-0.098^{**}	-0.128^{***}	-0.247^{***}	-0.177^{**}	0.245^{***}	-0.104^{*}	0.095	-0.006	-0.273^{***}	-0.158^{***}
	(0.044)	(0.047)	(0.060)	(0.089)	(0.095)	(0.063)	(0.064)	(0.074)	(0.086)	(0.059)
Mean crime	5.22	4.98	4.51	3.43	2.75	3.37	0.29	2.56	2.71	5.67
Observations	53,737	53,737	53,737	53,737	53,737	53,737	51,497	53,737	53,439	44,102

Notes: Reduced form and second stage least squares (instrumental variable) estimates following equation (4) and (5). The observations are weighted by the number of residential house units per census tract. Outcomes use the inverse hyperbolic sine transformation, so the results are expressed as percent changes (e.g., $e^{\beta_1} - 1$). 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. Robust standard errors clustered at the census tract level are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.5: Alternative weights: 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	-0.027^{**}	-0.034^{***}	-0.068^{***}	-0.059^{**}	0.075^{***}	-0.034^{**}	0.034^{*}	-0.016	-0.075^{***}	-0.037^{***}
	(0.011)	(0.012)	(0.015)	(0.025)	(0.027)	(0.017)	(0.020)	(0.022)	(0.020)	(0.013)
B. Second-stage least squares										
Loan amount	-0.091^{**}	-0.116^{***}	-0.230^{***}	-0.200^{**}	0.255^{***}	-0.116^{*}	0.110^{*}	-0.054	-0.255^{***}	-0.167^{***}
	(0.041)	(0.044)	(0.058)	(0.086)	(0.093)	(0.060)	(0.064)	(0.076)	(0.076)	(0.061)
Mean crime	5.13	4.88	4.39	3.36	2.71	3.34	0.29	2.52	2.70	5.65
Observations	53,755	53,755	53,755	53,755	53,755	53,755	51,515	53,755	53,457	44,120

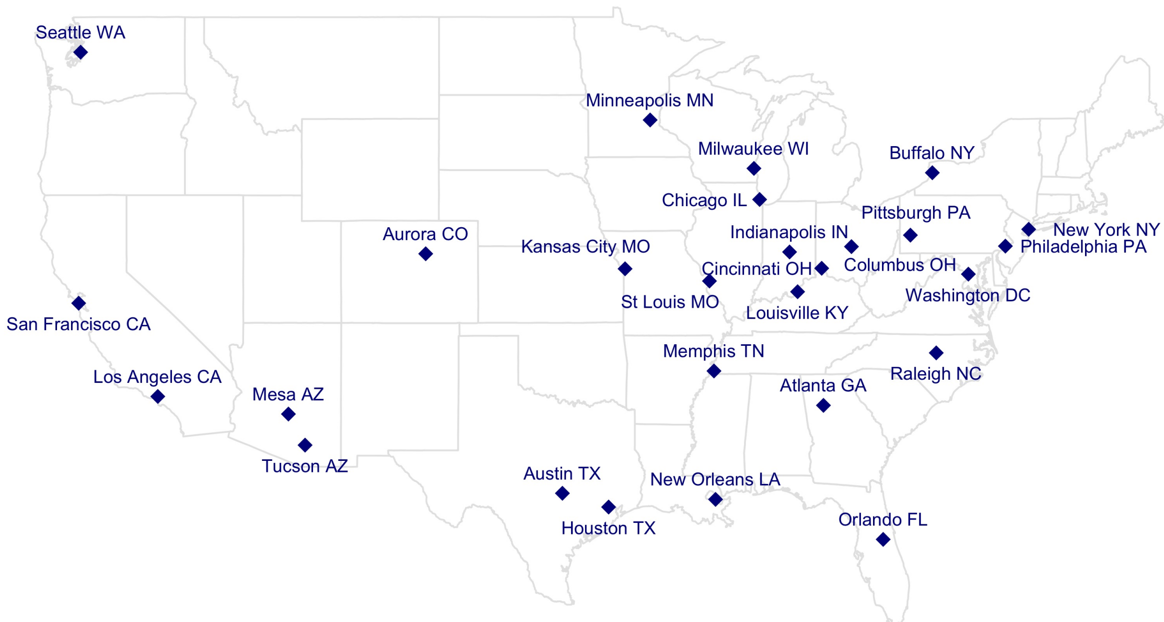
Notes: Reduced form and second stage least squares (instrumental variable) estimates following equation (4) and (5). The observations are weighted by the population in census tract. Outcomes use the inverse hyperbolic sine transformation, so the results are expressed as percent changes (e.g., $e^{\beta_1} - 1$). 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. Robust standard errors clustered at the census tract level are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.6: 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	−0.453*	−0.645**	−1.571***	−0.671	1.676***	−0.628*	0.494	−0.338	−0.969**	−0.797**
	(0.232)	(0.283)	(0.532)	(0.425)	(0.626)	(0.355)	(0.353)	(0.393)	(0.459)	(0.337)
Mortgage*2nd tercile	−0.127**	−0.186**	−0.438***	−0.192*	0.462***	−0.126	0.067	−0.015	−0.333**	−0.200**
	(0.063)	(0.074)	(0.123)	(0.116)	(0.152)	(0.098)	(0.080)	(0.111)	(0.129)	(0.081)
Mortgage*3rd tercile	−0.072**	−0.101**	−0.217***	−0.121*	0.248***	−0.055	0.034	0.009	−0.190***	−0.088*
	(0.034)	(0.040)	(0.070)	(0.063)	(0.087)	(0.055)	(0.045)	(0.062)	(0.072)	(0.045)
$\beta_{tercile1} = \beta_{tercile2}$	0.07	0.04	0.01	0.15	0.02	0.07	0.16	0.30	0.08	0.03
$\beta_{tercile2} = \beta_{tercile3}$	0.13	0.04	0.00	0.31	0.01	0.24	0.52	0.73	0.07	0.01
$\beta_{tercile1} = \beta_{tercile3}$	0.06	0.03	0.00	0.14	0.01	0.06	0.15	0.31	0.05	0.02
Mean crime	5.38	5.02	4.43	3.58	2.97	4.01	0.52	3.05	3.41	5.68
Observations	53,755	53,755	53,755	53,755	53,755	53,755	51,515	53,755	53,457	44,120

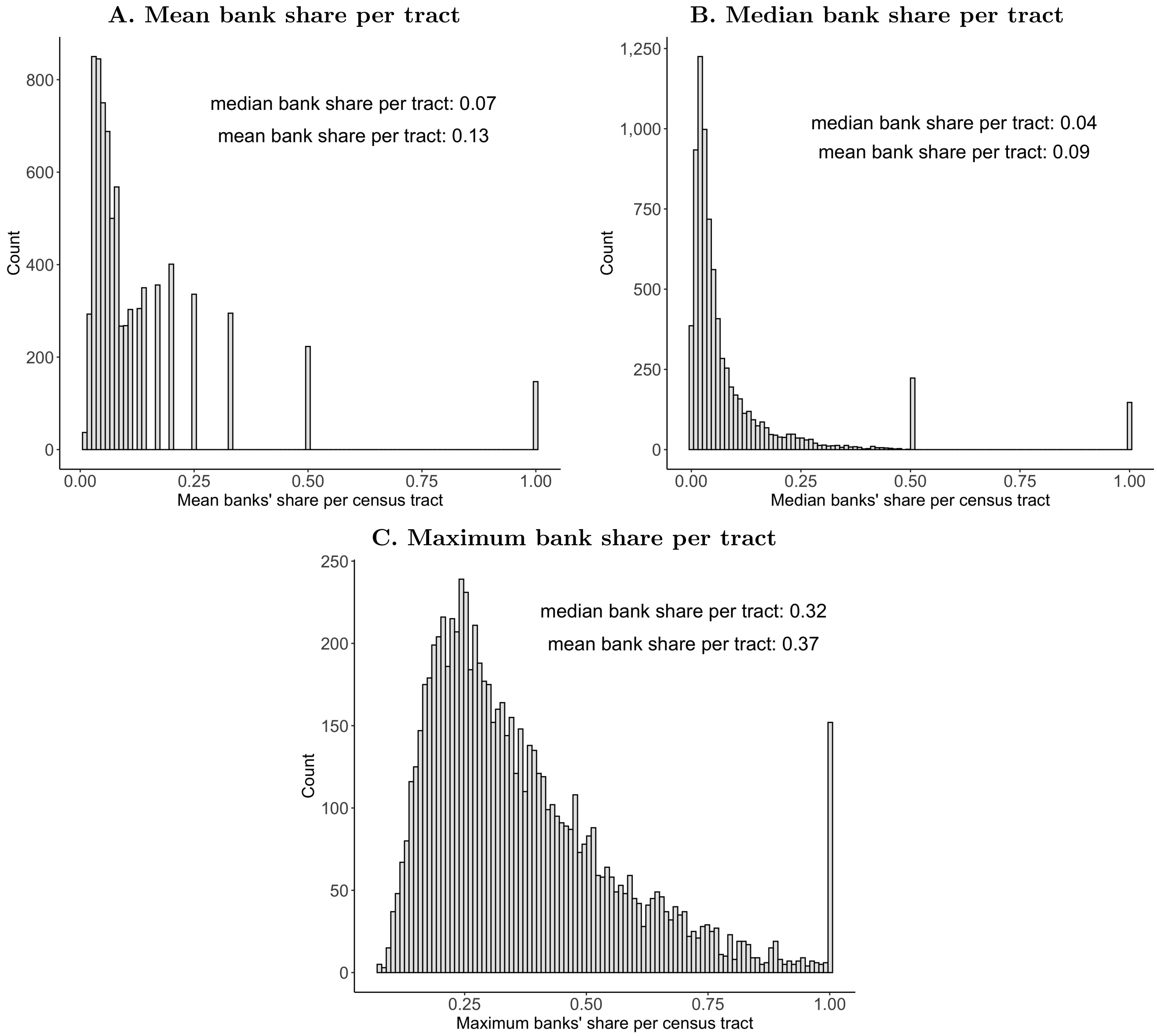
Notes: Second stage least squares (instrumental variable) estimates interacting the loan amount with the tercile group of the average mortgage growth between 2011 and 2017. Specifically, it follows $y_{it} = \gamma_i + \mu_t + \sum_{j=1}^{3} \beta_j \hat{L}_{it} D_i^j + X_{it}\alpha_X + e_{it}$, where 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. Robust standard errors clustered at the census tract level are in parentheses. The bottom rows show the pvalue of the hypothesis testing whether the coefficients across tercile groups are equal. *p<0.1; **p<0.05; ***p<0.01.

Figure A.1: Cities included in the analysis



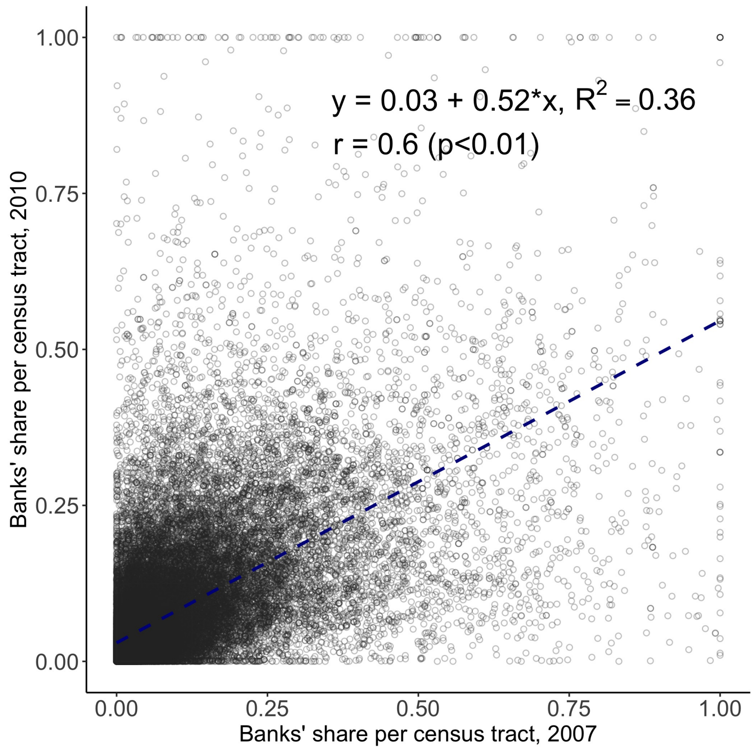
Notes: The map shows the location of the 27 US major cities included in this research. These cities had public crime data that could be aggregated to the census tract-year level.

Figure A.2: Banks' 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. 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.

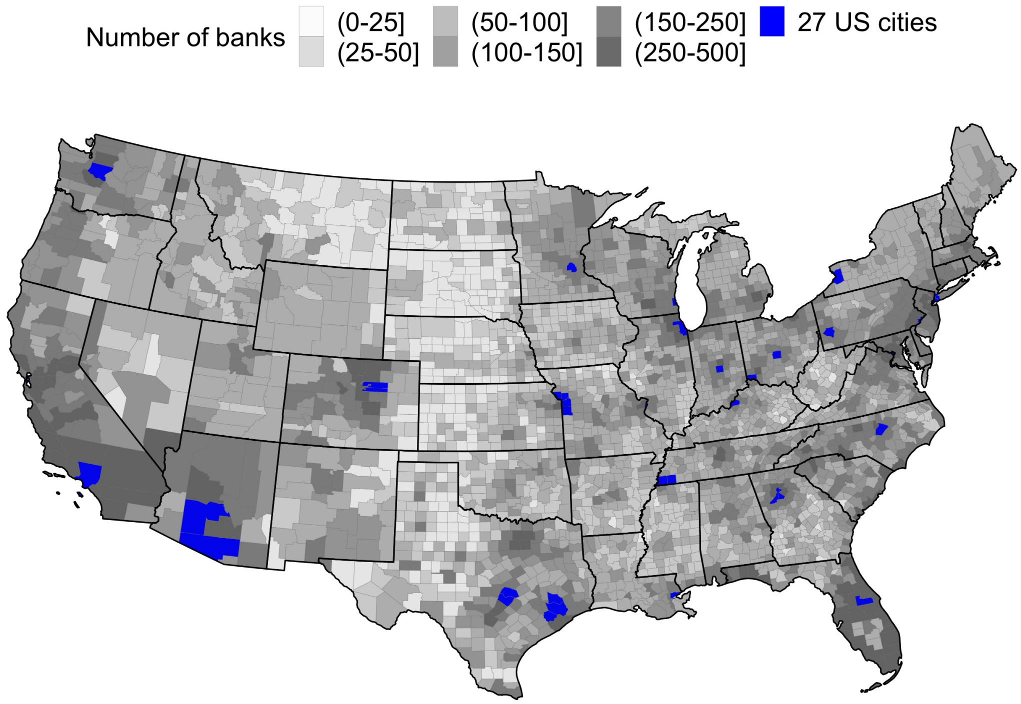
Figure A.3: Correlation of banks' tract shares across time, 2007 vs 2010



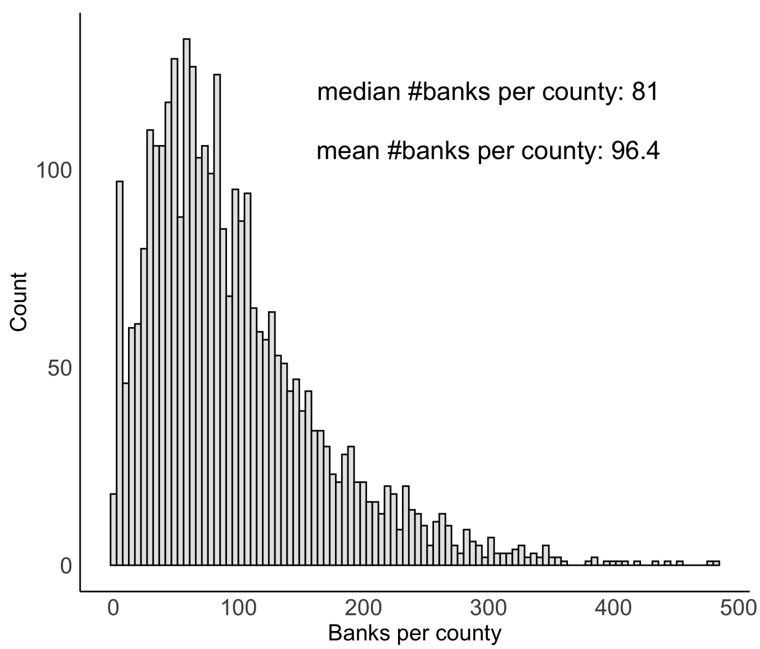
Notes: The figure shows the census tract banks' share of the mortgage loan amount four (2007) and one year (2007) before the study period. While having a large share in 2007 correlates with a high share in 2010, there is considerable unexplained variation in the sample. A best-fit dashed line is drawn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

Figure A.4: Banks' coverage across counties

A. Geographical distribution of banks' across counties



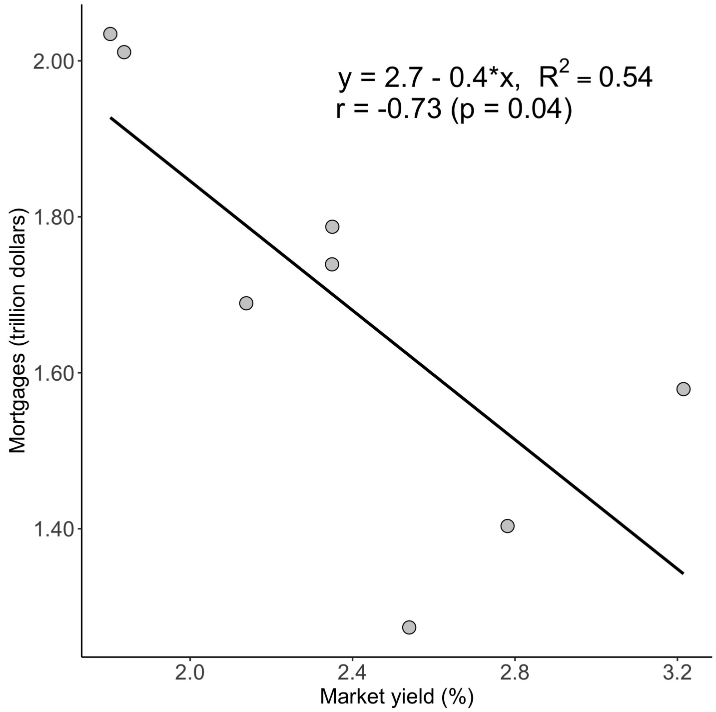
B. Distribution of banks' across counties



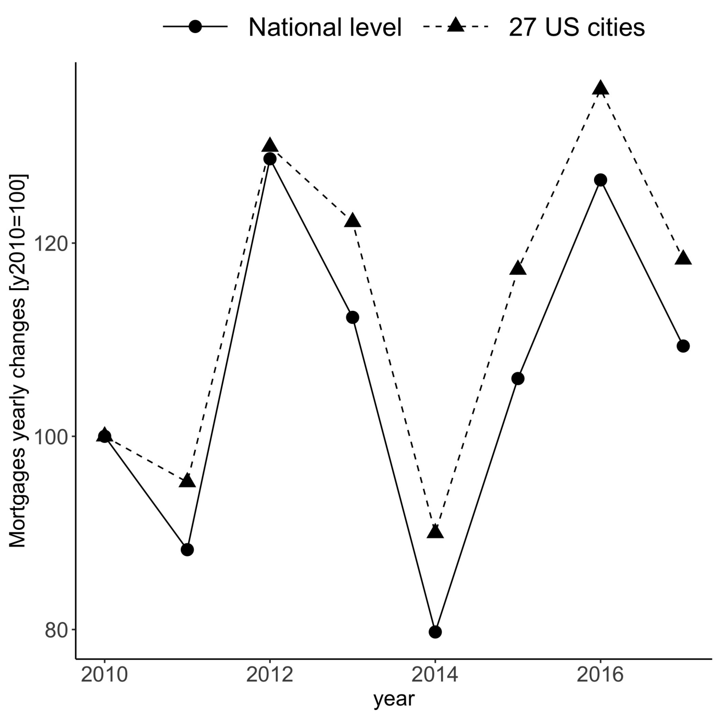
Notes: Panel A shows the number of banks, out of the 1,118 financial institutions used in the instrumental variable, per US county. The blue-colored counties are the ones where the 27 cities included in the analysis are located. While each of the 1,118 do not cover all lower 48 states, jointly, they operate across all 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.5: 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: Panels 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.