Branching Out Inequality: The Impact of Credit Equality Policies

Jacelly Cespedes, Erica Xuewei Jiang, Carlos Parra, and Jinyuan Zhang*

Abstract

We uncover that the Community Reinvestment Act (CRA), a major policy aimed to reduce geographic inequality in credit access, can widen disparities across regions, despite enhancing credit equality within certain regions. This adverse effect arises because banks withdraw branches from economically disadvantaged areas to sidestep the rules. As financial activities shift towards shadow banks, the adverse impact of the CRA regulation is amplified, expanding the set of disadvantaged areas that suffer from branch withdrawals. Using a regression discontinuity design centered on a CRA eligibility threshold, we estimate banks' shadow costs of violating the CRA. We then show that banks with higher costs of CRA violation retract their branches from disadvantaged areas following the expansion of shadow banks. This retraction results in declines in small business lending, financial inclusion, and real economic activity, predominantly in low-income areas with more minority populations. Such dynamics presumably contributed to the worsening cross-region disparities in credit access observed over the recent decade.

*Cespedes is from University of Minnesota, Carlson School of Management. cespe013@umn.edu. Jiang is from University of Southern California, Marshall School of Business. erica.jiang@marshall.usc.edu. Parra is from Pontificia Universidad Católica de Chile. parra.c.carlos.r@gmail.com. Zhang is from the UCLA Anderson School of Management. jinyuan.zhang@anderson.ucla.edu. We thank Kenneth Ahern, Tony Cookson, Gerard Hoberg, Christopher Palmer, Chris Parson, Giorgia Piacentino, Antoinette Schoar, Richard Thakor, Selale Tuzel, Andrew Winton, Anthony Zhang, and the seminar participants at BYU, MIT Sloan, Kansas-City Fed, Minneapolis Fed, University of Minnesota, USC Marshall, Boston Fed, and the conference participants at the University of Minnesota Junior Conference and the HEC McGill conference. *First version: September 2023.*

Promoting equal credit access is crucial for addressing regional inequality in economic opportunities and growth.[1] A prominent type of related government intervention involves leveraging the financial resources of private sector institutions by regulating their lending and investment in underserved areas. The Community Reinvestment Act (CRA) passed in 1977 in the US is a notable example, which mandates banks to serve low-to-moderate income neighborhoods in areas of their operation.[2] Such policies are designed to steer institutions' behavior toward broader social and economic goals. Since private sector institutions are profit-maximizing entities disciplined by market forces, the effectiveness of these policies hinges on institutions' *incentives* and *capacity* to comply. In the last decade, the gap in credit availability in the US has returned to the level observed two decades ago after persistent declines in the early 2000s.[3] This shift coincides with the rapid expansion of less regulated shadow banks, underscoring the necessity for studies on equal credit access regulations that account for these industry dynamics.

To shed light on the ongoing debate, this paper examines the impact of the CRA on banks' branching and lending decisions amid the rise of shadow banks. Our findings suggest that the CRA may potentially distort the allocation of financial services in a manner contrary to the regulation's intended objectives. Specifically, while it benefits underserved neighborhoods in prosperous regions, the CRA can have adverse effects on certain economically disadvantaged areas where banks refrain from establishing branches to avoid CRA requirements. The rise of shadow banks escalates banks' CRA compliance costs, leading to a contraction of bank branches, especially in lower-income regions. As banks retract their branches, these regions experience declines in small business lending, financial inclusion, and real economic activity. Such dynamics presumably contributed to the worsening cross-region disparities in credit access over the recent decade, as depicted in Figure 1 over the recent decade.

We begin by developing a parsimonious model of bank lending under CRA regulations.

[1] See, for example, Chodorow-Reich (2014), Beck et al. (2010) and Chen et al. (2017).

[2] In the US, another prominent government intervention to reduce disparities in credit access is the national borrowing rate policy set by government-sponsored entities (GSEs). Hurst et al. (2016) discusses how the GSEs' pricing rule leads to cross-region transfers. Unlike the CRA, this intervention is subsidized via implicit government guarantees. Other quantity regulations similar to the CRA include India's Priority Sector Lending (PSL), which mandates commercial banks to allocate a specific portion of their lending to sectors vital for broader economic and social progress. In the same spirit, South Africa's National Credit Act is aimed at safeguarding consumers, especially those in vulnerable and historically marginalized communities, ensuring fair and unbiased access to credit.

[3] As illustrated in Figure 1, the GINI index of local mortgage rejection rates and newly originated mortgage credit relative to loan applicants shifted from declining to increasing after the financial crisis.

The CRA mandates that banks provide adequate lending to underserved neighborhoods in each CRA assessment area where their branches operate. Banks weigh the costs of extending lending beyond the optimal level in the underserved neighborhoods, as required by the CRA, against the benefits of maintaining branches to serve the entire area. When the benefits outweigh the costs, banks lend more in the underserved neighborhoods than they would in the absence of CRA regulations. However, if the costs surpass the benefits, banks might opt to shut down branches within the area to bypass CRA regulations. The latter is more likely to occur in areas with a weaker economy. Thus, the CRA could potentially widen cross-region disparities.

There are two important premises of the above framework. First, the shadow cost of CRA violation needs to be material, and thus banks have the incentive to comply. Indeed, failing to comply with CRA regulations hinders banks from opening new branches and participating in mergers and acquisitions, but the shadow cost of CRA violation may not be material if banks are not constrained by such enforcement. Second, banks must receive lower risk-adjusted returns in the under-served neighborhood to satisfy CRA requirements, which implies that complying with the CRA is costly for banks.

We begin our empirical analysis by estimating the shadow cost of CRA violation. This allows us to test the first model premise as well as to obtain helpful variation for examining the trade-off as predicted by the model. Our estimation leverages on the CRA's adoption of the 80% Median Family Income (MFI) threshold to designate underserved census tracts. Census tracts with MFI less than 80% of the MFI of the surrounding geographic area are classified as underserved, or low- and median-income (LMI) neighborhoods. We implement a regression discontinuity (RD) design that compares lending in neighborhoods just above and below this income threshold, allowing for the identification of the shadow cost of CRA violation for each bank based on differences in lending behavior.

Comparing census tracts around the 80% MFI threshold, we find a 2% increase in the mortgage supplied by banks *with branches* to LMI census tracts compared to the amount supplied to non-LMI tracts. Importantly, the estimated shadow costs of CRA violation vary significantly across banks and are positively associated with bank expansion efforts, including merger activities and branch development. This indicates that banks with strategic growth objectives encounter greater costs when they violate CRA rules, making them more inclined to ensure compliance.

Utilizing the same RD design, we validate the second model premise by examining how CRA regulation affects risk-adjusted prices. Should loan prices increase concurrently with volume in underserved neighborhoods, it would suggest higher profit margins for loans in these regions, challenging the notion that compliance with CRA regulations imposes financial burdens on banks. Contrary to this, our findings reveal that risk-adjusted mortgage rates are lower in census tracts with MFI just below the 80% threshold compared to those just above. These results align with the model premise that CRA regulation compresses profit margins on loans to underserved neighborhoods.

We next empirically examine the extent to which CRA compliance costs lead to negative effects. As our model shows, banks with a higher shadow cost of CRA violation need to lend more to underserved neighborhoods if they set up branches. However, lending to underserved neighborhoods can be costly, and thus, these banks are less likely to set up branches and tend to be the first to close branches as CRA compliance costs increase. Empirically, exploiting purely cross-sectional variation in banks' shadow costs of CRA violation may lead to biases caused by its correlation with other bank characteristics. To overcome this challenge, we exploit the rapid expansion of shadow banks in the residential mortgage market after the financial crisis (Buchak et al., 2018a). We view this transformation as a negative to the demand for bank credit, thereby increasing their CRA compliance costs.

To measure local exposure to the national surge in shadow banking, we construct a Bartik instrument, utilizing data on local shadow bank market shares from 2005 to 2008. This allows us to explore how banks with varying degrees of CRA-related shadow costs adjust their branching and lending behaviors in response to increases in local shadow bank market share. We include stringent county-by-year and bank-by-year fixed effects to control for any time-varying unobservables at the local and bank level.

Our research shows that banks with above-median CRA violation costs, compared to banks with below-median CRA violation costs, shut down an additional 2.2% of their branches and are 3.9% more likely to fully vacate their local branch presence in response to a 30% increase in the local market dominance of shadow banks. This reduction in branch presence is accompanied by a decline in mortgage credit availability, demonstrated by decreases in both lending volume and approval rates, as well as a deterioration in loan quality, reflected in heightened withdrawal rates. Moreover, these adverse impacts extend to small business lending, a sector where branch access is vital. Our data reveal that for banks with high CRA violation costs, a 30% increase in the shadow bank market share results in a 13% larger cutback in lending volume than that observed in banks with low CRA violation costs.

Importantly, we find that above negative impacts of CRA regulations are predominantly concentrated in regions with lower income per capita and more minority populations. At the market level, the negative impacts on small business lending persist. This underscores that market forces fail to pick up the slack in lending as banks with high CRA violation costs retract from the market.

Our analysis so far shows that while banks with high CRA violation costs indeed escalate lending in underserved neighborhoods, they simultaneously curtail lending in poor and minority regions. To comprehensively assess the CRA's net impact and to determine the significance of its potential negative consequences, we estimate the previously introduced model and decompose the effects. Our estimation identifies the marginal county from which banks choose to exit in response to the escalating CRA compliance costs due to the expansion of shadow banks. We find that counties in the bottom 44 percentiles, ranked by local per capita income, bear the adverse effects of the CRA. In these counties, bank lending declines by 76% in underserved neighborhoods and by 33% in non-LMI neighborhoods, compared to a theoretical benchmark without CRA regulations. Conversely, underserved neighborhoods in the top 56 percentiles of counties experience a 104% surge in lending, reaping the benefits of the CRA. These result in a net effect of a 3.4% reduction in overall lending volume.

A more concerning adverse impact of the CRA lies in its unintended consequences in widening disparity in credit access. As we have established above, the rise of shadow banks makes it costlier for banks to comply with the CRA, shifting some areas from benefiting to suffering from the CRA as banks close branches to bypass the regulation. Finally, we show that such disparities are observed empirically over the past decade.

We estimate the CRA treatment intensity using a similar RD design as before at the MSA level and define areas with the above-median estimated values as *CRA binding areas*. This measure captures the distribution of banks with varying levels of shadow costs of CRA violation and differences in local economic fundamentals. The estimation suggests that in CRA binding areas, CRA requirements significantly improve lending by banks with branches to underserved census tracts relative to non-underserved census tracts around the 80% threshold. We show that these areas tend to have weaker economic fundamentals, as reflected in GDP and per capita income.

We find that, compared to non-CRA binding areas, CRA binding areas experience more bank branch closures, with more zip codes turning into branch deserts (without any branch), as shadow banks expand in local mortgage markets. In the wake of branch closures, there is a noticeable decline in financial inclusion, a contraction in small business lending, and a reduction in local business establishments. This suggests that the CRA regulation is likely to distort the allocation of financial services in a manner dis-aligned with its intended objectives.

Related Literature Our paper contributes to the debate about the effect of the CRA regulation. Previous research has generated diverse findings regarding its impact on credit markets. Several papers find a CRA-induced increase in the overall supply of credit in residential mortgages (Bhutta, 2011; Ding and Nakamura, 2017; Lee and Bostic, 2020) and small business loans (Ding et al., 2018; Chakraborty et al., 2020). In contrast, Dahl et al. (2000) and Conway et al. (2023) do not find evidence of increased credit supply. Moreover, Ding and Nakamura (2021) and Brevoort (2022) document the substitution effect between loan origination and purchases induced by the CRA.[4] However, the research discussed thus far focuses on analyzing the impacts of the CRA *within* an area—specifically, whether the CRA promotes increased lending to underserved neighborhoods in comparison to non-underserved neighborhoods. We contribute to this literature by providing the first evidence that the CRA can lead to *cross-region* disparities in credit access.

Cespedes et al. (2023), the closest paper to ours, find that banks near the new size threshold in the 1995 CRA reform strategically reduced their asset growth to avoid increased regulatory burdens, which negatively impacted lending and the real economy. Similar to this paper, we study banks' strategic behavior to bypass the regulation and uncover the unintended consequences. We differ from this paper in several ways. First, we focus on banks' strategic behaviors across regions in their branching decisions. Second, we explore how the impacts of the CRA is modulated by the evolving banking landscape, offering a broader perspective on the regulatory and economic dynamics at play. Finally, we provide an economic framework that distinguishes the concepts of within- versus cross-region disparities and quantify the net effect of the CRA.

Our paper also contributes to the literature that studies the consequences of transfor-

[4] Although not closely related to the focus of our paper, the literature also examines the effect of the CRA regulation on credit riskiness. Using different methodologies, Agarwal et al. (2012) and Saadi (2020) find higher origination rates and defaults due to the CRA. In contrast, Ringo (2023), Ghent et al. (2015) and Avery and Brevoort (2015) find no evidence of increased risk-taking due to the CRA.

mative shifts in the banking sector, such as the rapid expansion of shadow banks (Buchak et al., 2018b; Gopal and Schnabl, 2022; Hamdi et al., 2023; Begley and Srinivasan, 2022; Jiang, 2023; Gete and Reher, 2021) and technological disruption (Chen et al., 2019; Goldstein et al., 2019; Fuster et al., 2019; Berg et al., 2022). In particular, our study relates to the literature that evaluates the effectiveness of regulations and policies that target the banking sector, as shadow banks play an increasingly important role in the modern economy. Previous research has shown that the substitution of traditional banking services by shadow banks affects monetary policy transmission (Buchak et al., 2018a; Agarwal et al., 2023; Xiao, 2020) and capital regulation (Corbae and D'Erasmo, 2021; Lee et al., 2023). We add to this literature by highlighting that when combined with the growth of shadow banks, some important bank regulations, such as the CRA, could result in unintended consequences. Moreover, despite the rising market share of shadow banks in various credit markets, they cannot pick up the slack in bank lending.

Finally, we contribute to the literature on the significance of geographic proximity, distance, and the role of branches in shaping credit allocation. Traditional banking businesses are local, and their branches are crucial in promoting financial inclusion and local economic development.[5] Advances in financial technology have transformed banking to provide digital alternatives to access banking services. Nevertheless, recent literature confirms the importance of branches in facilitating the provision of banking services in the digital era (Jiang et al., 2022; Sakong and Zentefis, 2022; Nguyen, 2019; Fonseca and Matray, 2022).

1 The Community Reinvestment Act

1.1 History, Objective, and Ongoing Political Debate

The Community Reinvestment Act (CRA) was enacted in 1977. At the time, the U.S. Congress recognized that banks bear a persistent and proactive duty to address the financial requirements of their local communities. The primary goal of the CRA is to encourage depository institutions to meet the credit needs of all community segments, particularly low- and median-income (LMI) areas, where the banks operate. This legislative action

[5] See, for example, Petersen and Rajan (2002); Beck et al. (2010); Célerier and Matray (2019); Stein and Yannelis (2020); Brown et al. (2019); Jayaratne and Strahan (1996); Huang (2008); Allen et al. (2021); Bruhn and Love (2014) and Allen et al. (2021).

was grounded in earlier laws governing bank charters, which mandate that banks must prove their deposit facilities cater to the convenience and necessities of the communities they serve, encompassing both credit and deposit services. Notably, the practice of "draining resources" was prevalent, where banks would often have branches in underprivileged neighborhoods, accepting deposits from residents but refraining from lending in those areas. Consequently, regulators aimed to counter this "draining" phenomenon through the CRA, ensuring that banks actively reinvest at least part of their funds in the communities where they operate and accept deposits (White, 2020).

The CRA has undergone significant changes since its enactment. One notable revision was implemented in 1995, with a subsequent reform taking place in 2005, which aimed to provide clear guidance on evaluating CRA performance and improve enforcement by emphasizing performance, clarity, and objectivity. Moreover, since 2022, the agencies overseeing the CRA have been jointly working on a new CRA reform proposal that incorporates substantial changes in how assessment areas are defined and implements more quantitative metrics for evaluations and compliance.

Ever since the revision in 1995, the following core content of the CRA regulation has remained unchanged. The primary categories of loans eligible under the CRA regulation include mortgages and small business loans, with both originated and purchased loans contributing to CRA ratings. CRA evaluations are conducted by bank regulators.[6] The CRA regulation applies to all FDIC-insured depository institutions, such as commercial banks and thrifts, but does not require compliance from credit unions or non-depository institutions (i.e., shadow banks). The act mandates that banks lend to all the LMI census tracts within their assessment areas. Assessment areas for a bank are defined as the geographic areas where the bank has branches and deposit-taking ATMs, which are often delimited by metropolitan statistical areas (MSAs). LMI census tracts are defined as areas with median family incomes (MFI) less than 80% of the MFI of the surrounding geographic area, typically an MSA or non-metro area of the state if it is outside an MSA (Code of Federal Regulations Title 12, Section 25.12). Figure 3 provides examples of the tract eligibility status, specifically the LMI census tract designations, for Orange County in California and Philadelphia County in Pennsylvania.

[6] The evaluations are done by the Board of Governors of the Federal Reserve System (FRB) for state bank members, by the Federal Deposit Insurance Corporation (FDIC) for non-member state-chartered banks, and by the Office of the Comptroller of the Currency (OCC) for national banks.

1.2 CRA Exam and the Relevance for Banks

To comply with the CRA regulation, banks undergo a comprehensive examination involving lending, investment, and service tests. The lending test, which is a major component of the CRA evaluation, focuses primarily on evaluating loans reported in HMDA and CRA disclosure statements, mainly mortgages and small business loans.[7] Both originated and purchased loans to LMI areas contribute to a bank's CRA assessment. Key aspects assessed in the lending test include the number and total amount of loans, the geographic distribution of loans, the proportion and dispersion of lending, and the number and amount of loans classified by geography (distinguishing between LMI and non-LMI areas).

The assessments of bank lending, investment, and service collectively contribute to the CRA examination rating system, which comprises four tiers: Outstanding, Satisfactory, Needs to Improve, and Substantial Non-compliance. The last two ratings indicate non-compliance. Between 2005 and 2008, 87% of assessed banks obtained a satisfactory rating, whereas 12% obtained an outstanding rating. Institutions failing to comply with the CRA regulation may encounter restrictions on branch expansion, participation in mergers and acquisitions, more frequent assessments (potentially every 12 months), and heightened public scrutiny due to publicly available ratings. For example, Chen et al. (2023) finds that following negative CRA ratings, banks experience a decline in deposit growth.

2 Model

In this section, we present a model of bank lending that takes into account the presence of CRA regulation. We simplify the model to include only the key components necessary for studying the costs and benefits of the CRA regulation. This model also serves as motivation for the empirical design.

[7] 12 CFR 345.28 illustrates how important the lending test is for the overall CRA rating. For example, a bank that receives an "outstanding" rating on the lending test receives an assigned rating of at least "satisfactory." In addition, no bank may receive an assigned rating of "satisfactory" or higher unless it receives a rating of at least "low satisfactory" on the lending test.

2.1 Setup

We focus on an assessment area that comprises two neighborhoods: the underserved neighborhood (with subscription $i = 1$) and the non-underserved neighborhood (with subscription $i = 2$). A bank provides credit while facing a downward-sloping demand curve in each of these neighborhoods:[8]

$$r_i(L_i, b) = \alpha + \alpha_i - \beta L_i + \gamma b, \tag{1}$$

where L_i represents the loan volume supplied by the bank in neighborhood i, while b indicates whether the bank operates a branch in the assessment area. $\alpha + \alpha_i$, β, and γ are demand curve parameters. α represents the average loan demand in the assessment area. α_i is neighborhood-specific adjustment to loan demand, with $\alpha_1 < 0$ and $\alpha_2 > 0$. β corresponds to demand elasticity.[9] According to the literature, demand elasticity is closely related to the area's economic fundamentals, where a smaller β typically reflects a stronger local economic fundamental.[10] $\gamma > 0$ captures borrowers' preference for local branches, making them willing to pay a premium for the convenience offered by the branch.

The bank chooses its lending volume in each of the two neighborhoods (L_i) and decides whether to open branches ($b \in \{1, 0\}$) to maximize its total profit:

$$\max_{L_1, L_2, b} \quad \pi(L_1, L_2, b) = \underbrace{r_1(L_1, b)L_1 + r_2(L_2, b)L_2}_{\text{Lending Profit}} - \underbrace{\delta(\bar{L} - L_1) \times \mathbb{1}(b > 0)}_{\text{Shadow Cost of CRA}}. \tag{2}$$

The first term represents the profit from lending, while the second term corresponds to the shadow cost associated with CRA regulation. As discussed in Section 1, the operation of branches in an area is a key determinant for whether a bank's lending in that area is subject to CRA assessment. If a bank operates branches in an area, the CRA assesses whether the bank provides a sufficient amount of lending ($\bar{L}$) in the underserved neighborhood of that area. Conditional on having a branch in the area, if the lending amount is less than the CRA threshold (i.e., $L_1 < \bar{L}$), the bank incurs a per-unit cost of δ. This cost δ can be viewed

[8]This setup is isomorphic to a monopolistic competition, in which banks offer differentiated products. The monopolistic competition allows banks to extract rents to cover fixed costs.

[9]Demand elasticity is derived as $-\frac{1}{\beta}\frac{r}{L_i}$. A smaller β reflects a higher demand elasticity or a higher interest rate sensitivity.

[10]Literature shows that demand elasticity is correlated with local demographics, such as income and house prices. For example, Andersen et al. (2020) find that high-income borrowers' refinance behavior is less responsive to changes in interest rates, and Buchak et al. (2018a) find that the mortgage demand of homeowners of more expensive houses is less sensitive to interest rates.

as the bank's *shadow cost of CRA violation*.[11] In our following analysis, we focus on the parameter regime where $\bar{L} > L_1^*$, which we refer to as the *CRA binding* area.

The first-order condition yields the following optimal lending strategy:

$$L_1^* = \begin{cases} \frac{\alpha+\alpha_1+\gamma+\delta}{2\beta} & \text{if } b = 1 \\ \frac{\alpha+\alpha_1}{2\beta} & \text{if } b = 0, \end{cases} \qquad L_2^* = \begin{cases} \frac{\alpha+\alpha_2+\gamma}{2\beta} & \text{if } b = 1 \\ \frac{\alpha+\alpha_2}{2\beta} & \text{if } b = 0 \end{cases} \tag{3}$$

Defining $\Delta\pi \equiv \pi(L_1^*, L_2^*, 1) - \pi(L_1^*, L_2^*, 0)$ as the difference between the profit when the bank has a branch versus the profit when the bank does not have a branch:

$$\Delta\pi = \frac{(2\alpha + \alpha_1 + \alpha_2)\gamma + \gamma^2}{2\beta} - \delta(\bar{L} - \frac{\alpha + \alpha_1 + \gamma}{2\beta} - \frac{\delta}{4\beta}). \tag{4}$$

The optimal branching strategy is as follows:

$$b^* = \begin{cases} 1 & \text{if } \Delta\pi > 0 \\ 0 & \text{if } \Delta\pi \leq 0. \end{cases} \tag{5}$$

2.2 The Effect of the CRA Regulation

To understand the impact of the CRA regulation, we consider a counterfactual scenario without it, i.e., setting $\delta = 0$ in the baseline model. The optimal lending and branching decisions are as follows:

$$L_1^{*'} = \begin{cases} \frac{\alpha+\alpha_1+\gamma}{2\beta} & \text{if } b = 1 \\ \frac{\alpha+\alpha_1}{2\beta} & \text{if } b = 0, \end{cases} \qquad L_2^{*'} = \begin{cases} \frac{\alpha+\alpha_2+\gamma}{2\beta} & \text{if } b = 1 \\ \frac{\alpha+\alpha_2}{2\beta} & \text{if } b = 0, \end{cases} \qquad b^{*'} = \begin{cases} 1 & \text{if } \Delta\pi' > 0 \\ 0 & \text{if } \Delta\pi' \leq 0, \end{cases}$$

where $\Delta\pi' = \frac{(2\alpha+\alpha_1+\alpha_2)\gamma+\gamma^2}{2\beta}$. The differences between this counterfactual and the baseline indicate the effects of the CRA regulation on bank branching and lending decisions.

We start with the trade-off faced by the bank in its branching decision. Given that

[11] Banks may have a particularly high incentive to comply with CRA regulation when anticipating participation in M&As and opening new branches, or when seeking to avoid costs associated with frequent CRA exams if failing to comply, or when facing higher reputation concerns and hassles from community groups. If banks possess a stronger incentive to comply with CRA regulation, we consider these banks to have a higher cost of CRA violation, denoted as a higher δ.

customers value branches, establishing branches allows the bank to charge higher markups in both the underserved and the non-underserved neighborhoods, earning larger variable profits.[12] However, when the local fundamental is weak, the bank may have to extend lending beyond the profit-maximization level absent the CRA regulation to avoid violating the CRA requirement, which reduces the bank's profit. This *regulatory cost* is derived as follows:

$$\underbrace{\Delta\pi' - \Delta\pi}_{\text{Regulatory cost}} = \underbrace{\delta}_{\text{Shadow cost of CRA violation}} \times \underbrace{(\bar{L} - \frac{\alpha + \alpha_1 + \gamma}{2\beta} - \frac{\delta}{4\beta})}_{\text{Deviation from required lending}}. \tag{6}$$

The regulatory cost is comprised of two components: shadow cost of CRA violation, δ, and the deviation from the required lending. It is evident that when δ equals zero, the regulatory cost disappears. Hence, δ *emerges as the key parameter driving the variation in regulatory cost.* As δ increases, the regulatory cost also increases. The latter term is linked to the loan demand α and the economic fundamental β of the assessment area. Specifically, in areas with a strong fundamental and high loan demand (i.e., a higher value of $\frac{\alpha}{\beta}$), the associated CRA regulatory cost is lower, for any given δ.

In CRA binding areas where $\bar{L} > L_1^*$, the regulatory cost is positive.[13] When this regulatory burden is substantial, such that $\Delta\pi' - \Delta\pi > \Delta\pi'$, the bank closes its local branch. Branch closures directly impact banks' lending outcomes. The overall impact of the CRA regulation on bank lending thus depends on whether the regulatory cost is sufficiently high to lead to branch closure, as characterized below:

$$L_1^* - L_1^{*'} = \begin{cases} \frac{\delta}{2\beta} & \text{if } \Delta\pi' - \Delta\pi < \Delta\pi' \\ \frac{-\gamma}{2\beta} & \text{if } \Delta\pi' - \Delta\pi > \Delta\pi', \end{cases} \qquad L_2^* - L_2^{*'} = \begin{cases} 0 & \text{if } \Delta\pi' - \Delta\pi < \Delta\pi' \\ \frac{-\gamma}{2\beta} & \text{if } \Delta\pi' - \Delta\pi > \Delta\pi'. \end{cases} \tag{7}$$

The following Lemmas 1, 2 and 3 below summarize the main predictions of the model, concerning the effects of CRA regulation. Lemma 1 focuses on individual banks' behaviors and emphasizes the role of banks' shadow cost of CRA violation (i.e., δ). Lemma 2 points out a paradox of the CRA regulation by focusing on β, namely that it fosters equal credit in economically strong areas while potentially curtailing lending in economically weak areas

[12] In our simplified model, we do not include a variable or fixed cost of operating branches and hence, $\Delta\pi'$ is always positive. The results remain qualitatively the same even when considering the costs of operating branches.

[13] In CRA binding areas, we have $\bar{L} > L_1^* = \frac{\alpha+\alpha_1+\gamma+\delta}{2\beta} > \frac{\alpha+\alpha_1+\gamma+\frac{1}{2}\delta}{2\beta}$. Thus, $\Delta\pi' - \Delta\pi = \delta(\bar{L} - \frac{\alpha+\alpha_1+\gamma+\frac{1}{2}\delta}{2\beta}) > 0$.

that would benefit most from the CRA's intent. Lemma 3 discusses the impact of CRA regulation amid the rise of shadow banks.

LEMMA 1. *CRA regulation imposes an economic burden on banks, denoted as $\Delta\pi' - \Delta\pi$. When the regulatory cost becomes sufficiently high, banks close branches and reduce lending. This effect is more pronounced for banks with higher costs of CRA violations; that is, $\frac{\partial(\Delta\pi' - \Delta\pi)}{\partial\delta} > 0$.*

LEMMA 2. *Given a positive δ, the regulatory cost is higher in economically disadvantaged areas; that is, $\frac{\partial(\Delta\pi' - \Delta\pi)}{\partial\beta} > 0$.*

- *In economically strong areas where the regulatory cost of the CRA is sufficiently low to not lead to branch closure, underserved neighborhoods receive more lending under CRA regulation than they would without it; that is, $\Delta\pi' - \Delta\pi < \Delta\pi'$, resulting in $L_1^* - L_1^{*'} = \frac{\delta}{2\beta} > 0$).*

- *In economically weak areas where the regulatory cost of CRA is sufficiently high to lead to branch closure, all neighborhoods experience a reduction in lending under CRA relative to the no-CRA benchmark; that is, $\Delta\pi' - \Delta\pi > \Delta\pi'$, leading to $L_j^* - L_j^{*'} = -\frac{\gamma}{2\beta} < 0$).*

LEMMA 3. *The decline of demand for bank lending (i.e., α decreases) compresses the range of $\frac{1}{\beta}$ values under which the CRA leads to positive effect.*

Figure 2 graphically illustrates the model predictions by plotting lending (y-axis) against the economic fundamental ($\frac{1}{\beta}$, x-axis). Panels A and B hold the same all other parameter values except for the level of shadow cost of CRA violation (δ). Panels B and C hold the same as all other parameter values except for the level of demand (α). In each panel, we plot the lending in the underserved neighborhood, with (L_1^*) and without ($L_1^{*'}$) the CRA, and the lending in the non-underserved neighborhood, with (L_2^*) and without ($L_2^{*'}$) the CRA.

In all panels, when $\frac{1}{\beta}$ is high, the lending to the underserved neighborhood is higher under the CRA regulation, as suggested by the positive difference between L_1^* and $L_1^{*'}$. In other words, in areas with strong economic fundamentals, the CRA increases lending to underserved neighborhoods, reducing lending disparities between neighborhoods. However, when $\frac{1}{\beta}$ is low, the costs associated with the CRA rise. Upon reaching a critical threshold, the bank closes branches and curtails lending in both neighborhoods. As shown in the shaded area of both panels, lending in a world without the CRA is higher than lending with it. This result underscores the unintended negative aspect of CRA, where it could inadvertently limit bank lending to economically disadvantaged areas.

By comparing the differences in L_1^* and $L_1^{*'}$ across panels A and B, it becomes evident that a higher δ amplifies the positive effect of the CRA regulation, but it concurrently narrows the range of $\frac{1}{\beta}$ necessary for sustaining the positive effect. Specifically, as δ rises, the minimal value of $\frac{1}{\beta}$ needed for upholding a positive effect of CRA increases, lessening its efficacy. Furthermore, as illustrated by comparing panels B and (c), a decrease in loan demand (α) compresses the range of $\frac{1}{\beta}$ values under which the CRA regulation leads to a positive effect. Thus, shocks to the demand for bank loans, such as the rise of shadow banks, could intensify the adverse consequences of the CRA, further compromising banking access in underprivileged areas.

In conclusion, the above discussion underscores a significant *paradox* of the CRA: it promotes credit equality in wealthier areas, yet this comes at the expense of poorer regions, which consequently experience diminished banking access.

3 Data

Our main analysis uses bank regulatory datasets about lending, branches, and financial statements. We use the Home Mortgage Disclosure Act (HMDA) data to construct shadow bank market shares and the total originated and purchased mortgages in specific census tracts for individual lending institutions. The HMDA data contains application-level information, such as loan amount and borrower location, for nearly all U.S. mortgage applications, linked to the originating institutions. For each financial institution, it also collects information about purchased mortgages.[14] In addition, we obtain bank branch-related data from the Summary of Deposits (SOD), financial information about banks from bank call reports, and small business lending data from the Community Reinvestment Act (CRA) dataset.

We obtain mortgage pricing data from the CoreLogic Loan-Level Market Analytics (LLMA). The dataset provides information about mortgage and borrower characteristics, such as interest rate, credit score, loan-to-value, debt-to-income, documentation type, and

[14]Purchase mortgages also contribute to CRA ratings.

product type.[15] To compare loan prices, we restrict our sample to a set of standardized loans with full documentation: 30-year fixed-rate mortgages with full documentation and without missing values in interest rate, FICO score, loan-to-value ratio, or debt-to-income ratio.[16]

We use census tract-level demographic data from the Federal Financial Institutions Examination Council (FFIEC) to identify LMI census tracts as well as to construct pertinent controls. Importantly, Median Family Income (MFI) provided in this dataset is the one used by regulators to delimit LMI census tracts. Finally, we compile data on the number of firms from the Census's Business Dynamics Statistics (BDS). Our dataset also includes local covariates obtained from the 2000 Decennial Census.

Our estimation of the shadow costs of CRA violation uses samples from 2005, a year marked by a significant CRA revision, to 2008, prior to the rapid expansion of shadow banks.[17] Our analysis of the impact of the CRA regulation focuses on the period from 2011 to 2017, coinciding with the rise of shadow banks. Table 1 provides summary statistics for key variables. Our sample exhibits a right-skewed bank size distribution with a mean asset value of \$7 billion and a median value of \$510 million; the average bank in our sample maintains 4.72 branches per county.

4 The Shadow Cost of CRA Violation

There are two important premises of the theoretical framework. First, the shadow cost of CRA violation needs to be significantly positive (i.e., $\delta > 0$), and thus banks have the incentive to comply. Indeed, failing to comply with the CRA regulation hinders banks from opening new branches and participating in mergers and acquisitions, but the cost may not be material if banks are not constrained by such enforcement. Second, banks receive lower risk-adjusted returns in the underserved neighborhoods to satisfy the CRA requirement, which implies that complying with CRA regulation is costly for banks.

Our empirical analysis starts with estimating the shadow cost of CRA violation (δ) for each bank and discusses how the shadow cost is correlated with bank characteristics. The

[15] This dataset does not contain lender identity in any form.

[16] We expand the sample to include all loans for analysis of portfolio riskiness in the appendix.

[17] The 2005 CRA revision significantly altered the geographic scope of CRA-eligible communities. Additionally, it reclassified the categories of small and large banks, introduced a new category of financial institutions known as 'intermediate small banks,' and revised the standards and reporting requirements for different institution categories.

estimation allows us to test the first model premise as well as to obtain helpful variation for examining the effects of the CRA as predicted by the model. We then provide evidence for the second premise by examining how the CRA regulation affects risk-adjusted prices.

4.1 Estimating the Shadow Cost of CRA Violation

As Section 2 illustrates, the shadow cost of CRA violation is captured by the difference between a bank's equilibrium lending under the CRA regulation ($L_1^*|_{b=1}$) and its equilibrium lending in a world without the CRA regulation ($L_1^{*'}|_{b=1}$). However, simultaneously observing bank lending in a world with and without CRA regulation is not feasible.

To overcome this empirical challenge, we exploit the income discontinuities in the CRA regulation, which allows us to identify δ by comparing lending in the neighborhoods around the income threshold. Specifically, according to Equation (3),

$$L_1^*|_{b=1} - L_2^*|_{b=1} = \frac{\alpha_1 - \alpha_2 + \delta}{2\beta}. \tag{8}$$

If two neighborhoods have similar fundamental characteristics and loan demand, i.e., $\alpha_1 = \alpha_2$, but one is subject to CRA oversight and the other is not, then

$$L_1^*|_{b=1} - L_2^*|_{b=1} = \frac{\delta}{2\beta}. \tag{9}$$

As Section 1 describes, the CRA sets discontinuous designation of census tracts at the 80% MFI threshold. Census tracts around the 80% MFI threshold presumably have similar fundamentals but different CRA eligibility. Accordingly, we employ a Regression Discontinuity (RD) design to empirically estimate δ_b for each bank:

$$\log(\text{Loans})_{b,i,t} = \hat{\delta}_b \mathbb{1}(\text{LMI}_{i,t}) + \kappa_1(\text{MFI}_{i,t} - 80\%) + \kappa_2 \mathbb{1}(\text{LMI}_{i,t}) \times (\text{MFI}_{i,t} - 80\%) + \gamma_{m,t} + \epsilon_{b,i,t}, \tag{10}$$

where b denotes a bank, i denotes a census tract, m denotes an assessment area, and t denotes a year. The dependent variable is the logarithm of total lending (originated plus purchased home-purchase loans) by bank b in census tract i during year t. According to Regulation 12 CFR 25.41, we define an assessment area as an MSA if the census tract is located within an MSA and as a county if the census tract is located outside of an MSA.

$\mathbb{1}(\text{LMI}_{i,t})$ is an indicator for an LMI census tract with MFI less than 80%. $(\text{MFI}_{i,t} - 80\%)$ is the running variable representing the distance between the census tract's MFI and the 80% MFI threshold.[18] $\gamma_{m,t}$ is assessment area by year fixed effects.

For each bank b, we focus on its lending in places where it has branches, as guided by Equation (9). The estimation starts in 2005, coinciding with a CRA reform that year, and concludes prior to the rise of shadow banks in 2008. To account for differences in β across assessment areas, we use income per capita (PCI_m for assessment area m) to proxy for $\frac{1}{\beta}$ and weight each assessment area by $\frac{PCI_{US}}{PCI_m}$. To augment statistical power, our analysis is confined to banks that have at least 50 census tract-year observations in the sample from 2005 to 2008. The estimated $\hat{\delta}_b$ captures bank b's willingness to lend beyond the optimal level to comply with the CRA regulation, or the shadow cost of CRA violation for bank b.

Identifying Assumption, Design Validity, and Placebo The key identifying assumption of the RD design is that tracts with MFI around the 80% threshold share similar underlying characteristics. We perform three sets of tests to check the validity of the RD design. First, Table A1 provides a standard balance test using the 1990 Census (i.e., the census conducted before the introduction of the threshold in 1995), which shows no evidence of discontinuities at the 80% cutoff for various demographic variables.[19] Second, we find no evidence for population or loan demand flowing to the census tracts with MFI right below the 80% cutoff over time. Figure A1 shows no sorting of census tracts around the 80% MFI threshold (Cattaneo et al., 2020). Table A2 shows no statistically significant jumps in population, demographics, or loan demand around the threshold using 2010 data. Finally, we conduct placebo tests with alternative MFI thresholds—60% and 120%—as shown in Tables A3 and A4. These tests reveal that banks do not display different lending behaviors at these alternative thresholds, in contrast to the distinct lending patterns observed at the 80% MFI threshold mandated by the CRA regulation.

[18] The estimation approach employs local linear regression, following Hahn et al. (2001), Imbens and Lemieux (2008), and Gelman and Imbens (2019).

[19] If the variation in the treatment near the cutoff is approximately randomized, then all baseline characteristics determined *before* the assignment variable is realized should have a similar distribution just above and below the cutoff.

4.2 Estimation Results and Discussion

Table 2 displays the results of the pooled regression analysis. The specification aligns with Equation (10), modified to include bank fixed effects due to the use of a comprehensive sample encompassing all banks for the estimation. Following Imbens and Kalyanaraman (2012), we identify the optimal bandwidth with minimized mean square error, which ranges from 9.6% to 22%. To ensure robustness, we employ three distinct bandwidths in our local polynomial regression estimates (±13%, ±15%, and ±17%). The estimates suggest that banks' mortgage supply increases by 2.0%-2.1% in the LMI census tracts with MFI just below the 80% threshold compared to those just above. The estimates are robust when including market-by-year fixed effects.

We then estimate $\hat{\delta}_b$ for each bank using Specification (10). Table 1 presents the summary statistics of the estimated $\hat{\delta}_b$ across banks. The average value of $\hat{\delta}_b$ obtained by estimating Equation (10) separately for each individual bank is about 4%. Importantly, the estimated shadow cost of CRA violation differs by banks. As shown in Table 1, the standard deviation of $\hat{\delta}_b$ is about 0.57, suggesting that banks with one standard deviation higher $\hat{\delta}_b$ supply 57% more mortgages beyond what they would lend without the CRA regulation. We classify banks with above-median $\hat{\delta}_b$ as banks with *high* $\hat{\delta}$. Panels A and B of Figure 4 illustrate a marked difference in lending around the 80% MFI threshold only for banks with high $\hat{\delta}$.

Figure 5 aims to understand the determinants of the shadow cost of CRA violation by regressing an indicator for high $\hat{\delta}_b$ on various bank-level variables. This figure shows a significant positive correlation between receiving a satisfactory or outstanding CRA rating and *high* $\hat{\delta}$. Furthermore, there are positive correlations between our measure of CRA violation cost and an indicator for whether a bank engaged in any mergers and acquisitions (M&A) along with branch growth rate from 2005 to 2008. The findings are consistent with the idea that since failing to satisfy the CRA increases regulatory hurdles to conducting M&A or branch opening or closures, banks with growth plans are subject to higher costs of CRA violation and thus are more inclined to comply with the CRA regulation. In contrast, ROA, loan portfolio performance, and bank profitability are not correlated with our measure of CRA violation cost.

Finally, *high* $\hat{\delta}$ banks do not appear to serve different market segments compared to *high* $\hat{\delta}$ banks. We computed the share of FHA mortgages, the share of non-white borrowers, the share of female borrowers, and the average income of borrowers for each bank using HMDA. None of these variables strongly correlates with $\hat{\delta}$.

4.3 CRA Regulation and Risk-Adjusted Prices

Does the CRA regulation lower the profit margins on loans to underserved neighborhoods? We examine risk-adjusted loan rates to address this question. After showing an increase in lending volume in LMI neighborhoods, a corresponding rise in loan rates, after adjusting for loan default risk, would suggest higher profit margins on loans to LMI regions, violating the model assumption that CRA compliance is costly for banks.[20]

We exploit the same CRA discontinuity and estimate the following loan-level specification using the CoreLogic LLMA data from 2005 to 2008:[21]

$$r_i = \kappa_0 \mathbb{1}(\text{LMI}_i) + \kappa_1(\text{MFI}_i - 80\%) + \kappa_2 \mathbb{1}(\text{LMI}_i) \times (\text{MFI}_i - 80\%) + X_{i,t}\Gamma + \epsilon_i. \tag{11}$$

r_i is the mortgage rate. $X_{i,t}$ is a saturated set of controls to approximate default risk, including credit score, loan-to-value, debt-to-income, their squared terms, monthly-level origination date fixed effects, loan type (i.e., conventional, FHA/VA, and RHS loans)-by-year fixed effects, and assessment area-by-year fixed effects. Since the most detailed geographic information available in CoreLogic LLMA is at the zip code level, we aggregate MFI from the census tract level to the zip code level by calculating the average, weighted by the proportion of residential and business addresses. To compare loan prices, we restrict our sample to a set of standardized loans with full documentation. Specifically, we keep 30-year fixed rate mortgages with full documentation and drop loans missing data for interest rate, FICO score, loan-to-value ratio, or debt-to-income ratio.

Table 3 shows the results. Like before, we identify the optimal bandwidth with minimized mean square error, which ranges from 7% to 13%. To ensure robustness, we employ three distinct bandwidths in our local polynomial regression estimates: ±15%, ±13%, and ±10%. The outcome variable in columns 1, 3, and 5 is the raw mortgage rate. The outcome variable

[20] Another supporting evidence that complying with the CRA is costly for banks comes from Cespedes et al. (2023), who show that banks are incentivized to bunch at the small bank threshold to be subject to a more streamlined CRA examination.

[21] Specification (11) is different from the pooled regression in the previous section because HMDA did not provide rate-related information, and we need to switch to the CoreLogic LLMA, which does not provide lender identity.

in columns 2, 4, and 6 is the residualized mortgage rate estimated using the full sample of standardized loans with full documentation from 2005 to 2008 (i.e., not restricted to loans within the bandwidth).[22]

The estimates across columns consistently and robustly suggest that the risk-adjusted mortgage rates are lower in the census tract with MFI just below the 80% threshold compared to those just above. For example, the residualized mortgage rates in the census tract with MFI between 70% and 80% are 2.2 basis points lower than the rates in the census tracts with MFI between 80% to 90% (column 6). The results are consistent with the model premise that the CRA regulation lowers the profit margins on loans to under-served neighborhoods.

Riskiness of Bank Loan Portfolio Our model abstracts away from more complicated aspects of bank lending to focus on the basic economic concepts of price and quantity. In practice, banks also decide on the risk level of the investment, which affects their returns beyond quantity and price. To account for risk differences in driving mortgage rates, our above analysis uses risk-adjusted mortgage rates. The findings suggest banks lower the rate for a given risk level to expand lending to comply with the CRA regulation. Another possible practice is to expand credit provision by lowering the lending standard. While this alternative practice would generate the same set of predictions,[23] it would have additional implications for financial stability. However, in Table A5, we do not find supporting evidence for banks lowering the lending standard because of the CRA regulation.[24]

5 The Adverse Impact of the CRA

We next empirically examine the extent to which CRA compliance costs in the current economy lead to branch closures and subsequently adversely impact credit accessibility.

[22]We calculate residuals of the raw mortgage rate regressed on origination year-month, loan type, loan default risk measures (i.e., FICO, ltv, dti, and their squared terms), and three-way interactions between these three sets of covariates. Since we already residualized the mortgage rates, we do not include default risk measures as controls in these columns.

[23]There are various reasons why banks might not lend to riskier borrowers in the absence of the CRA, such as adverse selection, regulatory constraints, and securitization restrictions. In all these cases, if a bank lowered the lending standard in response to the CRA, the return on investment would decline, e.g., because of higher loan default rates or increased difficulty in securitization, which in turn might induce branch closures.

[24]We measure the risk of a loan using an indicator for whether the loan is a Balloon mortgage, an indicator for whether the loan application has full documentation, the credit score of the borrower, and the loan-to-value ratio of the loan, where the last two metrics are conditional on the loan having full documentation, and thus borrower credit score and loan-to-value ratio are recorded.

5.1 Empirical Design

As Equation (6) indicates, there are two components that affect the economic burden imposed by the CRA: bank-level cost of CRA violation (δ) and fundamental demand for bank credit (α and β). Empirically, exploiting purely cross-sectional variation in δ may lead to biases caused by correlation between δ and other bank unobserved characteristics. To overcome this challenge, we exploit time-series shocks to the fundamental demand for bank credit (i.e., changes in α or β) and examine whether banks with higher δ are the first to close branches as indicated by Lemma 1.[25]

The expansion of shadow banks stands out as the most significant transformation in the mortgage market landscape in recent decades.[26] We interpret such a transformative shift as a negative shock to the demand for bank mortgage loans (i.e., a lower α) and compare the changes in branching and lending decisions of banks with different estimated δ as the local areas are exposed to such shocks:

$$\Delta Y_{b,c,m,t} = \kappa\big(\text{SBank Shock}_{m,t} \times \text{High } \hat{\delta}_b\big) + \mu_{b,t} + \nu_{c,m,t} + \epsilon_{b,c,m,t}. \tag{12}$$

$\Delta Y_{b,c,m,t}$ is the change of bank b's branching or lending in county c in year t relative to 2010. Subscript m denotes the assessment area that county c belongs to. The testing sample spans from 2011 to 2017, a period of time witnessing rapid shadow bank growth (Buchak et al., 2018b). We measure outcome variables at the county level because the geographic scope of a county remains consistent throughout the sample period, whereas the geographic scope of assessment areas—usually at the MSA level—changes over time.[27]

SBank Shock$_{m,t}$ is the assessment area m's exposure to the national growth of shadow banks from 2010 to year t, which we will define shortly after. High $\hat{\delta}_b$ is an indicator for whether the estimated $\hat{\delta}_b$ for bank b is above the median value among all banks. As described

[25] An example can be used to clarify this idea. Let us assume that the average demand for bank loans experiences a shock, which causes α_{pre} to shift to α_{post}. Then, assuming other factors stay the same, the change in regulatory cost in Equation (6) can be stated as follows: $(\Delta\pi'_{post} - \Delta\pi_{post}) - (\Delta\pi'_{pre} - \Delta\pi_{pre}) = \delta\frac{\alpha_{pre}-\alpha_{post}}{2\beta}$. A decline in average demand, as indicated by $\alpha_{\text{pre}} > \alpha_{\text{post}}$, leads to an increase in regulatory costs. As established in Lemma 1, sufficiently high regulatory costs can trigger branch closures and reductions in lending, and this effect is more pronounced for banks with higher shadow costs of CRA violation.

[26] The expansion of shadow banks can be attributed to various factors, including technological advancements that expedite application processing and regulatory arbitrage opportunities (Buchak et al., 2018b; Fuster et al., 2019).

[27] For example, some census tracts may have been part of one MSA during the earlier years of our sample period but become part of a different MSA in later years. If we were to construct the outcome variable at assessment areas, we would mistakenly introduce changes in the total number of branches due to such changing geographic scopes of the assessment areas.

in Section 4.1, $\hat{\delta}_b$ is estimated using data from 2005-2008, so that the estimates are not contaminated by contemporaneous bank actions. We show in Figure A2 that $\hat{\delta}_b$ is relatively persistent and remains a valid predictor for the shadow cost of CRA violation during the analysis period. Finally, the inclusion of county-year fixed effects, $\nu_{c,m,t}$, absorbs variation caused by regional differences in economic fundamentals. We also include bank-year fixed effects $\mu_{b,t}$ to remove variation due to bank characteristics. Therefore, our identification is mainly based on variation across banks with different levels of $\hat{\delta}_b$ under time-varying regulatory costs imposed by shadow bank shocks.

To construct local exposure to the national growth of shadow banks, we find historical shadow bank market share in assessment area m during 2005-2008 ($s_{m,0508}$) and multiply it by the cumulative national shadow bank growth rate since 2010 ($\frac{S_t}{S_{10}}$):

$$\text{SBank Shock}_{m,t} = s_{m,0508} \times \frac{S_t}{S_{10}} \tag{13}$$

where $s_{m,0508} = \frac{\text{Sbank Volume}_{m,0508}}{\text{Total Volume}_{m,0508}}$. In constructing the national shadow bank growth rate, we exclude the focal assessment area to address the finite sample bias inherent in using own-observation data: $S_t = \frac{\sum_{m'} \text{Sbank Voulme}_{m',t}}{\sum_{m'} \text{Total Volume}_{m',t}}$.

Our measure of local exposure to national shadow bank growth features the idea of a Bartik instrument. Therefore, it relies on the assumption that $s_{m,0508}$ are not correlated with the various outcomes we study, conditional on observables (Goldsmith-Pinkham et al., 2020).[28] Table A6 shows that shadow bank market shares from 2005 to 2008 are not strongly correlated with pre-treatment local characteristics, including our estimated CRA treatment intensity.[29]

5.2 Impact on Banks' Branching Decisions

We begin by examining the impact of the CRA regulation on banks' branching decisions as shadow banks grow in the residential mortgage market. Table 4 presents the results.

[28]In the framework proposed by Goldsmith-Pinkham et al. (2020), the identification assumption relies on the exogeneity of shares. Borusyak et al. (2022) show that identification can be achieved via quasi-random allocation of shocks.

[29]We introduce the market level estimation in Section 7.1. In short, we estimate CRA treatment intensity in each assessment area and classify an area as a CRA Binding Area if the estimate is above the median among all assessment areas.

Columns 2 and 5 correspond to specification (12), while columns 1 and 4 use a less saturated specification. Results across these columns consistently suggest that banks with high shadow cost of CRA violation ("high δ bank" hereinafter) are the first to close branches as shadow banks expand. Quantitatively, in response to a 30% increase in shadow bank market share in a county, high δ banks are 3.9% more likely to withdraw their entire local branch network than low δ banks in the same county (column 2).[30] In terms of the number of branches, high δ banks close 2.2% more branches than low δ banks (column 5). In columns 3 and 6, we show that the results are robust when comparing banks with similar sizes by adding bank asset size in 2010 interacted with the shadow bank shock as a control.

Our findings corroborate the model predictions, implying that banks face a trade-off between the costs associated with CRA regulation and the benefits of maintaining a branch presence in a particular area. When confronted with a decline in demand attributable to the rise of shadow banks, banks with higher shadow costs of CRA violations tend to withdraw their branches from the local market.

5.3 Impact on Bank Lending

We next examine the effect on lending to shed light on the potential real impact of the mechanism we identified in the previous section. We focus on two primary categories of lending targeted by the CRA, mortgage and small business lending, by estimating specification 12 for various lending-related outcome variables. Table 5 presents the results of specification 12, with Panel A for mortgage lending and Panel B for small business lending.

Mortgage Lending. Conceptually, the effect on mortgages is unambiguous: as banks close branches to sidestep the increased compliance cost amid the expansion of shadow banks, mortgage supply would decline if having a local branch could facilitate mortgage provision. Yet, as technology advances, branches become less important for mortgage supply. Thus, the extent to which the branch closure channel affects mortgage lending is an empirical question.

[30] The magnitude of the impact is calculated using the formula $(\exp(-0.134)-1)\times 100\% = -13\%$, which corresponds to the impact of a 100% increase in shadow bank share. In this calculation, -0.134 is the estimated coefficient in column 2 of Table 4. We apply the same formula to interpret the coefficients in all future specifications with dependent variables on a logarithmic scale. Building on the findings from Buchak et al. (2018a), which observed a roughly 30% increase in the market share of shadow banks between 2011 and 2017, we accordingly adjust the effect size to -3.9%, calculated as $13\% * 0.3$.

Panel A demonstrates, through various outcome variables, that the negative impact of the CRA on bank branches coincided with a decrease in the supply of mortgage credit. As the local shadow bank market share increases by 30%, high δ banks reduce the total amount of originated and purchased mortgage loans by 14.5% more than low δ banks (column 1). The relative reduction of loan origination (column 2) is more than twice larger than that of loan purchase (column 3): relative to low δ banks, high δ banks reduce loan origination by 23% while reducing loan purchase by 15.8% in response to a 30% increase in the local shadow bank market share. Moreover, the application rejection rates at high δ banks increase by 1% (column 4), and the withdrawal rate of approved applications increase by 1.3% (column 5), compared to those at low δ banks. Consequently, the net origination rate among all mortgage applications at high δ banks declines by 1.7% more than that at low δ banks (column 6). Overall, the results suggest that as high δ banks close more local branches to avoid heightened CRA regulatory compliance costs due to the rise of shadow banks, their supply of mortgage credit declines in terms of both quantity, as reflected in lending volume and rejection rates, and quality, as reflected in withdrawal rates.

A possible confounding story that explains our findings is that shadow banks more directly compete with high δ banks, which forces them to close branches as their mortgage profits decline. For instance, if high δ banks happen to originate more FHA mortgages or lend more to low-income borrowers like shadow banks, they may lose more business to shadow banks as shadow banks expand. However, we do not find evidence consistent with this alternative story: as shown in Figure 5, there is no significant difference in the loan portfolios or customer demographics between high δ and low δ banks. This evidence suggests that the growth of shadow banks alone cannot fully account for our results, reinforcing the specific impact of the CRA on banks' operations.

Small Business Lending. Unlike the unambiguous prediction for mortgages, the effect on small business lending could be either positive or negative. On the one hand, the CRA may lead to a reduction in small business lending owing to its adverse effect on branch closures amid the rise of shadow banks (*branch closure channel*). Since relationship lending is prevalent in small business lending, and branches remain a crucial instrument for it, this would suggest that a reduction in branches is likely to negatively impact small business lending (Nguyen, 2019). On the other hand, as mortgage demand for bank credit declines, banks facing higher CRA violation costs might expand lending to small businesses to meet the CRA requirement. This *substitution channel* predicts a potentially positive effect on small business lending.

Results in Panel B suggest that the CRA regulation leads to a reduction in bank small business lending as shadow banks expand, indicating that the *branch closure channel* dominates the *substitution channel*. As the shadow bank market share increases by 30%, high δ banks reduce small business lending by 13% in terms of dollar volume (column 1) and by 8.6% in terms of loan counts (column 3), compared to low δ banks. Comparable effects are observed in loans to firms with revenue under \$1 million (columns 2 and 4).

5.4 Regional Heterogeneity

We then investigate the impact of the CRA regulation across assessment areas with varying fundamental characteristics. We focus on income and race, for two reasons. First, areas with lower income and a larger population of racial minorities tend to be associated with weaker economic fundamentals, which allows us to test Lemma 2. Second, the initial motivation for creating the CRA was to address the issue of redlining, which tends to target the poorest communities and communities of color.[31] Analyzing the heterogeneous effects along these two dimensions sheds light on whether the regulation distorts the allocation of financial services in a manner aligned with its intended objectives.

We categorize counties into sub-groups based on average income per capita and share of minority population. Panels A and B of Figure 6 present the estimated effect on bank branching decisions (κ in specification (12)) for each of the four county subsamples classified based on income per capita and minority population share in 2010: low-income and high racial minority share, low-income and low racial minority share, high-income and high racial minority share, and high-income and low racial minority share.[32] The results suggest that the effect of CRA regulation on bank branches is predominantly observed in economically disadvantaged areas and in those with a higher proportion of the minority population. In low-income counties with a high racial minority share, high δ banks close about 7.8% more

[31] https://ncrc.org/the-purpose-and-design-of-the-community-reinvestment-act-cra-an-examination-of-the-1977-hearings-and-passage-of-the-cra/

[32] High and low are defined based on whether the values are in the top quartile among all counties. Detailed definitions can be found in the figure note.

branches than low δ banks, as the shadow bank market share increases by 30%. In contrast, in high-income counties or counties with a low racial minority share, the difference in branch closures between the two types of banks is much smaller or statistically insignificant.

The findings in Sections 5.2 and 5.3 suggest that the increased CRA regulatory compliance costs from the rise of shadow banks negatively impact credit supply through branch closures. This implies that in the wake of branch closures, there would be a noticeable regional heterogeneity in lending contraction as well. Panels (c)-(d) of Figure 6 empirically show that this is indeed the case. In low-income counties with a high racial minority share, compared to low δ banks, high δ banks reduce small business lending by 19% (panel c) and reduce mortgage origination by 27.5% (panel d), and their mortgage rejection rates increase by 6.6% while net origination rates decline by 5%, as the shadow bank market share increases by 30%. In contrast, in high-income counties or counties with a low racial minority share, the difference in lending between the two types of banks is much smaller or statistically insignificant.

5.5 Aggregate Effect on Regional Lending

The preceding bank-county analysis focuses on the decisions of individual banks and overlooks market-level adjustments. The observed effects on the branching decisions of singular banks might not translate to significant impacts on the regional economy if low δ banks or new market entrants, like non-bank lenders who are not subject to CRA regulations, pick up the slack in lending as high δ banks close branches. We next evaluate the effect on the regional aggregate supply of credit.

We estimate the following specification using county-level data from 2011 to 2017:

$$\begin{aligned}\Delta Y_{c,m,t} = {}& \kappa_1(\text{SBank Shock}_{m,t} \times \text{High} \sum_b w_b \hat{\delta}_b) + \kappa_2(\text{SBank Shock}_{m,t} \times X_c^{2010}) \\ & + \kappa_3 \text{SBank Shock}_{m,t} + \kappa_4 \text{High} \sum_b w_b \hat{\delta}_b + \kappa_6 \Delta X_{c,t-1} + \mu_{c,m} + \nu_t + \epsilon_{c,m,t},\end{aligned} \tag{14}$$

$\Delta Y_{c,t}$ is the cumulative change in one of the county aggregate lending-related outcomes since 2010. SBank Shock$_{m,t}$ has been previously defined in Section 5.1. $\sum_b w_b \hat{\delta}_b$ is the branch-weighted bank-level estimated δ. Counties with above median $\sum_b w_b \hat{\delta}_b$ are classified as high $\sum_b w_b \hat{\hat{\delta}}_b$. $\Delta X_{c,t-1}$ include the dynamic versions of the following controls: income per capita, population, GDP, housing index, and local average bank size ("Dynamic controls"), constructed as the cumulative changes in these values from 2010 to year $t-1$. $\mu_{c,m}$ and ν_t are county fixed effects and year fixed effects, respectively.

Table 6 presents the effects on small business lending. Columns 1 and 2 report the results of total small business lending. Columns 3 and 4 report the results of lending to small businesses with revenue less than \$ 1 million. We observe a consistently negative impact of increasing CRA regulatory costs on local small business lending across these columns. In comparison to counties dominated by low δ banks, those with a higher concentration of high δ banks exhibit a reduction in small business lending ranging from 6.8% (column 2) to 11% (column 4), as the shadow bank market share increases by 30%. These results support the narrative that relationship lending and local branches play crucial roles in providing small business loans, and hence, individual banks are less substitutable for each other.

Unlike small business lending, mortgage lending is less information-intensive, and thus, lenders are more substitutable. As we report in Table A7, we do not observe a notable effect on market-level mortgage lending volume or overall mortgage rejection rate, despite significant lending contraction at high δ banks established in Section 5.3. This indicates that other banks or non-bank lending institutions are stepping in to pick up the slack in lending from high δ banks. However, these institutions do not appear to fully replicate the crucial role of bank branches in facilitating loan origination: the overall withdrawal rates increase, and the overall origination rates decline in counties dominanted by high δ banks as shadow banks expand.

6 The Net Effect of the CRA

Our empirical analysis so far provides evidence for the two-sided impacts of the CRA on credit accessibility: on the one hand, it improves credit access in underserved neighborhoods within prosperous areas; on the other hand, it simultaneously curtails the supply of credit in economically disadvantaged areas, where banks avoid establishing branches to circumvent the CRA obligations. This dichotomy calls for a comprehensive evaluation of the CRA's impact on bank lending. In particular, to what extent should we be concerned about the adverse impact of the CRA, as we compare it to the magnitude of the positive impact?

To this end, we estimate the model outlined in Section 2 to quantify and decompose the net effect of the CRA. We find the counties that are negatively (or positively) influenced by the CRA, quantify the aggregate CRA-induced decline (or increase) in bank lending in these counties, and compute the net effect of the CRA. Furthermore, we conduct a counterfactual analysis to find the percentage of counties that shifted from benefiting to suffering from the CRA as the shadow banks expanded after the financial crisis.

6.1 Estimation

Our estimation proceeds in two steps. We first estimate the four pivotal demand and supply parameters by assessing the relationship between lending and local economic conditions. We then leverage the reduced-form analysis in Section 5 to pinpoint the marginal county that banks are likely to withdraw from in response to the increase in CRA compliance costs.

Equation (3) describes the relationship between lending and local economic fundamentals ($\frac{1}{\beta}$) in LMI and non-LMI neighborhoods, respectively, under the conditions of branch presence versus absence. We estimate the four expressions in Equation (3) to obtain values of the pivotal parameters in our model: $\alpha+\alpha_1$, $\alpha+\alpha_2$, γ, and δ. As shown in Equation (3), when $b=0$, $L_1 = \frac{\alpha+\alpha_1}{2\beta}$ and $L_2 = \frac{\alpha+\alpha_2}{2\beta}$. Thus, the relationship between the lending to LMI (or non-LMI) neighborhoods provided by banks without any branches in the local market and local economic fundamental ($\frac{1}{\beta}$) pins down $\alpha+\alpha_1$ (or $\alpha+\alpha_2$):

$$\frac{\partial L_1(b=0)}{\partial \frac{1}{\beta}} = \alpha+\alpha_1,\ \frac{\partial L_2(b=0)}{\partial \frac{1}{\beta}} = \alpha+\alpha_2.$$

Then, when banks have branches in the local market, the relationship between their lending to LMI, or non-LMI, neighborhoods and local economic fundamentals is given by

$$\frac{\partial L_1(b=1)}{\partial \frac{1}{\beta}} = \alpha+\alpha_1+\gamma+\delta,\ \frac{\partial L_2(b=1)}{\partial \frac{1}{\beta}} = \alpha+\alpha_2+\gamma$$

Therefore, the difference between $\frac{\partial L_2(b=1)}{\partial \frac{1}{\beta}}$ and $\frac{\partial L_2(b=0)}{\partial \frac{1}{\beta}}$ identifies γ. Given the estimated γ, the difference between $\frac{\partial L_1(b=1)}{\partial \frac{1}{\beta}}$ and $\frac{\partial L_1(b=0)}{\partial \frac{1}{\beta}}$ identifies δ.

Following the above procedures, we estimate Equation (3) using bank-county level data from 2011 to 2017 to obtain the four parameters. We use county-level per capita income (PCI) in 2010 to proxy for the local economic fundamental ($\frac{1}{\beta}$). We then estimate the following specification separately for LMI and non-LMI neighborhoods:

$$\begin{aligned}\log(\text{SBL} + \text{Mortgage})_{b,c,m,t} = &\kappa_1\Big(\log \text{PCI}_c^{2010} \times \text{I}(\text{Branch=1})_{b,c,m,t}\Big) + \kappa_2 \log \text{PCI}_c^{2010} \\ &+ \nu_{b,t} + \mu_{s,t} + \epsilon_{b,c,m,t},\end{aligned} \tag{15}$$

$\log(\text{SBL} + \text{Mortgage})_{b,c,m,t}$ is the log of bank b's small business lending and originated and purchased mortgage in county c in year t. $\text{I}(\text{Branch=1})_{b,c,m,t}$ is an indicator for whether bank b has at least one branch in county c in year t. $\log \text{PCI}_c^{2010}$ is our proxy for $\frac{1}{\beta}$, which is the log of per capita income in 2010 in county c. $\nu_{b,t}$ and $\mu_{s,t}$ are bank-year and state-year fixed effects, respectively. The estimated κ_2 using the non-LMI, $\kappa_2^{\text{non-lmi}}$, corresponds to $\frac{\partial L_2(b=0)}{\partial \frac{1}{\beta}}$, which indicates the value of $\alpha + \alpha_2$. The estimated $\kappa_1^{\text{non-lmi}}$ corresponds to the difference between $\frac{\partial L_2(b=1)}{\partial \frac{1}{\beta}}$ and $\frac{\partial L_2(b=0)}{\partial \frac{1}{\beta}}$, which equates to $\frac{\gamma}{2}$. Similarly, from the estimates using the LMI sample, we deduce the values of $\alpha + \alpha_1$ and δ.

Next, we identify the marginal county from which banks choose to exit in response to the escalating CRA compliance costs due to the expansion of shadow banks. As illustrated in Equation (3), a bank's branch closure leads to a reduction in lending by $\frac{\gamma+\delta}{2\beta}$ within LMI neighborhoods and by $\frac{\gamma}{2\beta}$ in non-LMI areas. With the estimated γ and λ, we can obtain the critical value of $(\frac{1}{\beta})^*$ if we know the impact of CRA-induced branch closures and their subsequent effect on lending. This critical value indicates the threshold at which banks are induced to withdraw from a county owing to CRA requirements.

We estimate the following specification to quantify the changes in lending triggered by the CRA-induced changes in branch presence, separately for LMI and non-LMI neighborhoods:

$$\Delta \log(\text{SBL} + \text{Mortgage})_{b,c,t} = \kappa_3\Big(\log \text{PCI}_{c,2010} \times \overline{\Delta\text{I}(\text{Branch=1})}_{b,c,t}\Big) + \nu_{b,t} + \mu_{c,t} + \epsilon_{b,c,t}, \tag{16}$$

where $\overline{\Delta\text{I}(\text{Branch=1})}_{b,c,t}$ is the predicted change in branch presence induced by the CRA regulation, as detailed in column (3) of Table 4. Finally, we obtain the critical value $(\frac{1}{\beta})^*$ using the estimated κ_3^{lmi} and $\kappa_3^{\text{non-lmi}}$, γ, and δ:

$$(\frac{1}{\beta})^* = \frac{2(\kappa_3^{\text{lmi}} + \kappa_3^{\text{non-lmi}})}{2\gamma + \beta}$$

Estimation Results. Panel A of Table 7 presents the estimation results. columns 1 and 2 indicate a positive correlation between bank lending and the robustness of local economic fundamentals, a connection that becomes stronger in the presence of local bank branches. The positive coefficients on $\overline{\Delta \text{I(Branch=1)}}_{b,c,t}$ in columns 3 and 4 corroborate the model's prediction that banks increase their lending in counties where they have a branch presence, particularly emphasizing a more pronounced effect in LMI neighborhoods. Panel B reports the model parameters estimated based on Panel A. The parameter $\alpha + \alpha_2$ exceeds $\alpha + \alpha_1$, indicating a higher overall lending demand in non-LMI neighborhoods.

The analysis identifies the marginal county with a log CPI of 10.375, placing it in the 44th percentile among the sampled counties. Leveraging these parameters, we calculate the threshold $\bar{L}$ at which $\Delta\pi$ equals zero (Equation 4), the condition where banks are indifferent between maintaining or withdrawing branch operations.

6.2 Net Effect of the CRA and the Rise of Shadow Banks

Net Effect. Panels A and B in Figure 7 depict the estimated relationship between bank lending and local economic conditions in LMI and non-LMI neighborhoods, respectively. The blue shaded area denotes the decline in lending attributed to the CRA ($\Delta^{\text{lmi}}_{neg}, \Delta^{\text{non-lmi}}_{neg}$), whereas the red region indicates the additional lending prompted by the CRA ($\Delta^{\text{lmi}}_{pos}, \Delta^{\text{non-lmi}}_{pos}$). To quantify these impacts, we aggregate the lending volume according to the density distribution of county log(PCI) for LMI neighborhoods, and analogously for non-LMI neighborhoods, as follows:[33]

$$\Delta^{\text{lmi}}_{neg} = \int_{\underline{\log \text{PCI}}}^{10.375} \frac{\gamma}{2} \log \text{PCI}\, d\big(\log \text{PCI}\big), \quad \Delta^{\text{lmi}}_{pos} = \int_{10.375}^{\overline{\log \text{PCI}}} \frac{\delta}{2} \log \text{PCI}\, d\big(\log \text{PCI}\big) \tag{17}$$

Panel C in Table 7 outlines the findings. The total CRA-driven lending reduction through the branch closure channel is marked at 76% in LMI neighborhoods and 33% in non-LMI neighborhoods, calculated against a hypothetical baseline without the CRA. Conversely, in those prosperous regions above the critical value for maintaining bank branches, the CRA is associated with a substantial, 104%, increase in lending in LMI neighborhoods. Overall, the net effect of the CRA across regions is a 3.4% reduction in overall lending volume, suggesting

[33] $\Delta^{\text{non-lmi}}_{neg}$ is the same as $\Delta^{\text{lmi}}_{neg}$, whereas $\Delta^{\text{non-lmi}}_{pos}$ is 0.

that its adverse effects surpass its positive contributions.

Counterfactual. We simulate a counterfactual in which the demand for bank credit increases by 30%, which corresponds to the period before the expansion of shadow banks. Panels (c) and (d) of Figure 7 depict the counterfactual effects of the CRA. Before the rise of shadow banks, only 1% of counties experience a CRA-induced withdrawal of bank branches; and the CRA's impact is notably positive, facilitating a 30% increase in overall credit availability.

7 Real Implications: Widened Geographic Disparities

We have established that the rise of shadow banks makes it costlier for banks to comply with the CRA, shifting some areas from benefiting to suffering from the CRA as banks close branches to bypass the regulation. A more concerning adverse impact of the CRA lies in its unintended consequences in widening disparity in credit access. In this section, we study the implications for the real economy and the geographic disparities that stem from the CRA.

7.1 Measuring CRA Treatment Intensity for an Area

As our model suggests, the regional variation in the intensity of CRA treatment comes from two sources: the distribution of banks with varying levels of shadow costs of CRA violation and differences in local economic fundamentals. To quantify the treatment intensity of the CRA, or the degree of CRA bindingness, across different assessment areas, we employ a similar RD design to the one introduced in Section 4.1. Specifically, for each assessment area, we estimate the following specification using the aggregate amount of newly originated home purchase loans by banks:

$$\begin{aligned}\log(\text{Loans})_{i,m,t} = \hat{\eta}_m \mathbb{1}(\text{LMI}_{i,m,t}) + \kappa_1(\text{MFI}_{i,m,t} - 80\%) \\ + \kappa_2 \mathbb{1}(\text{LMI}_{i,m,t}) \times (\text{MFI}_{i,m,t} - 80\%) + \nu_t + \epsilon_{i,m,t},\end{aligned} \tag{18}$$

where i denotes a census tract, m denotes an assessment area, and t denotes a year. $\hat{\eta}_m$ captures the extent to which lending under the CRA regulation exceeds the equilibrium lending volume that would exist in the absence of the CRA. This estimation accounts for both the shadow costs of CRA violation among banks operating in the area, as well as the local economic fundamentals (i.e., $\frac{\delta}{2\beta}$ in Equation 9).

As shown in Table 1, the standard deviation of $\hat{\eta}_m$ is 1.72, suggesting a large variation in the CRA treatment intensity across assessment areas. We define areas where CRA requirements significantly affect lending outcomes as *CRA binding areas*, which correspond to markets with $\hat{\eta}_m$ above the median. Panel A of Figure 8 illustrates the regions with low and high levels of CRA bindingness across the US. Consistent with the model prediction, Panel B shows that CRA binding areas tend to have weaker economic fundamentals than non-CRA binding areas: lower GDP and lower income per capita. This finding underscores the benefit of the CRA in promoting credit access equality *within regions*, narrowing the gap between LMI and non-LMI neighborhoods. However, this benefit is accompanied by widened *cross-regional* disparities, which we show in the following section.

7.2 Branch Desert, Financial Inclusion, and Real Implications

With the estimated treatment intensity of the CRA, we proceed to estimate the real implications of the mechanisms established in Section 5:[34]

$$\begin{aligned}\Delta Y_{c,m,t} = {} & \kappa_1(\text{SBank Shock}_{m,t} \times \text{CRA Binding Area}_m) + \kappa_2(\text{SBank Shock}_{m,t} \times X_c^{2010}) \\ & + \kappa_3\text{SBank Shock}_{m,t} + \kappa_4\text{CRA Binding Area}_m + \kappa_5 X_c^{2010} + \kappa_6\Delta X_{c,t-1} + \mu_s + \nu_t + \epsilon_{c,m,t},\end{aligned} \tag{19}$$

where CRA Binding Area_m equals 1 if the estimated effect of CRA regulation on bank lending in market m ($\hat{\eta}_m$) is above the median among all markets in 2005-2008, and other variables have been defined in Section 5.5. The specification incorporates time-invariant and lagged time-varying county controls as well as state fixed effects to eliminate many potential confounding factors. The inclusion of state fixed effects allows us to compare counties within the same state. To mitigate the concern that other local characteristics could drive our findings, we include a broad array of static and dynamic local controls. Table 8 presents the results for a set of county-level outcome variables, which we describe below.

[34] The geographical association between MSA and county FIPS codes can change over time due to the redefinition of MSA regions. Given that the SOD database only logs the most current MSA code, there's a potential risk of inaccurately allocating the number of branches to specific regions owing to modifications in MSA codes. To circumvent such errors in assignments, our assessment is conducted at the county level.

Branch Desert. Columns 1 and 2 show that the CRA binding areas experience more bank branch closures, with more zip codes turning into branch deserts (without any branch), as shadow banks expand in local mortgage markets. The CRA binding areas experience 2.2% more branch closures relative to the non-CRA binding areas as the shadow bank market share increases by 30% (column 1). The branch closures expand the branch desert—the share of zip codes without any bank branches—by 2 percentage-points in the CRA binding areas than the non-CRA binding areas (columns 2).

Financial Inclusion. In the wake of branch closures, there is a noticeable decline in financial inclusion: the underbanked rate among low-income population—the marginal users of banking services—rises significantly in the CRA binding areas relative to that in the non-CRA binding areas as shadow banks expand in the local market. As shown in column 3, the underbanked rate increases by 13.9 percentage-points among the low-income population in the CRA binding area, compared to the non-CRA binding areas, when the shadow bank market share increases by 30%.

Small Business Lending. Meanwhile, there is a contraction in small business lending, as shown in columns 4 and 5. A 30% rise in the shadow bank market share in the local mortgage market is associated with an additional 5.7% decrease in small business loans within the CRA binding areas, relative to the non-CRA binding areas. The contraction is more severe in the government subsidized loans to small businesses: the amount of revolving credit subsidized by the Small Business Administrative 7(a) Loan Program reduces by 15.3% in the CRA binding areas, compared to the non-CRA binding areas, following a 30% increase in the shadow bank market share.

Business Establishments. As lending is geographically segmented (Petersen and Rajan, 2002; Becker, 2007), a decrease in local credit supply could hinder local business growth. In the last column, we present the results of the number of business establishments obtained from the Business Dynamics Statistics provided by the U.S. Census Bureau. A 30% increase in the shadow bank market share in mortgage origination is associated with a 1% decrease in the number of establishments in a CRA binding area relative to a non-CRA binding area. The results are consistent with the narrative that the regulatory expenses imposed by the CRA increase cross-region disparities in economic development in the aftermath of the emergence of shadow banks.

Taken together, the results in this section suggest that the rise of shadow banks makes it costlier for banks to comply with the CRA regulation, leading to a regime shift in some areas. These areas transition from benefiting to suffering under the CRA as banks close branches to bypass the regulation. Consequently, both underserved neighborhoods and non-underserved neighborhoods experience credit reduction, with the impact being more severe in underserved neighborhoods that previously benefited from subsidies. Market forces do not make up for the reduced subsidized bank credit, resulting in real consequences. Importantly, these regime shifts are more likely to happen in the CRA binding areas, precisely the economically disadvantaged regions that the CRA regulation aims to support.

8 Conclusion

The CRA was enacted in 1977 to mitigate regional disparities in credit access, particularly in underserved communities. However, as the landscape of financial intermediation evolves, the CRA's impact on both banks and communities has come under scrutiny. Our paper contributes to a deeper understanding of the CRA's role in shaping the behavior of banks and its consequences for communities in the context of the changing financial environment—the rise of shadow banks.

We find that banks with higher costs of CRA violation tend to close branches to bypass the CRA regulation as shadow banks expand, especially in economically disadvantaged regions. This withdrawal of traditional banks has significant repercussions, including a substantial decline in small business lending. This, in turn, results in business downturns. These findings underscore a paradox inherent in the CRA regulation, which is further intensified by the growth of shadow banks: while the CRA promotes equal credit access in economically robust areas, its regulation adversely affects economically disadvantaged regions where banks shut down branches to bypass it. Consequently, this potentially exacerbates the inequality of credit access between economically advantaged and disadvantaged areas. The results emphasize the need for nuanced policy considerations concerning the interaction between CRA compliance and the evolving financial landscape.

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Figure 1. Inequality in Credit Access

The figure depicts the time-series variation of the Gini coefficient, derived from three distinct metrics: mortgage rejection rates, the ratio of mortgage lending to application count, and the ratio of mortgage lending to population size. Data for these metrics are obtained from the Home Mortgage Disclosure Act (HMDA) at the census tract-year level, enabling the annual computation of the Gini coefficient across all census tracts.

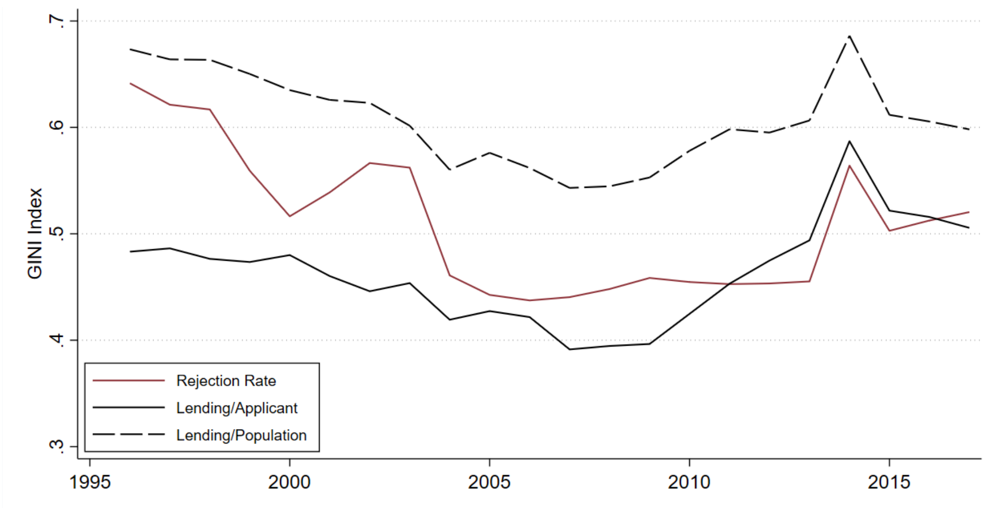
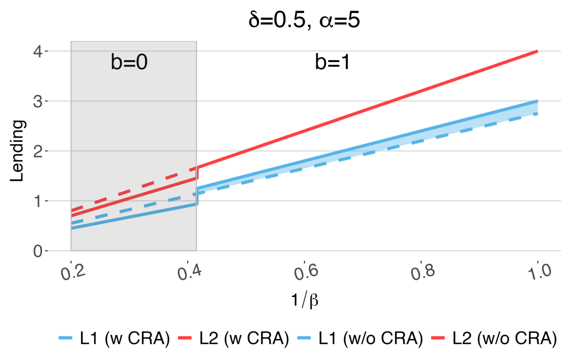
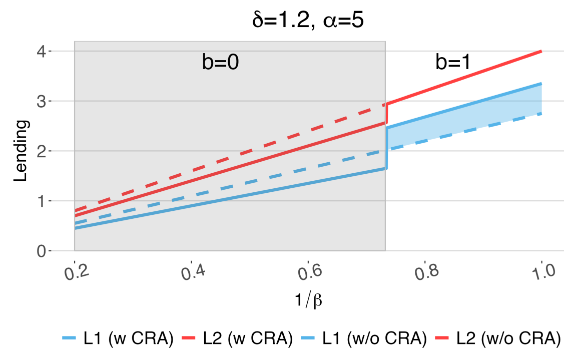


Figure 2. Model Illustration

This figure graphically illustrates the model predictions by plotting lending (y-axis) against economic fundamentals ($\frac{1}{\beta}$, x-axis). Panels (a) and (b) hold the same as all other parameter values except for the level of shadow cost of CRA violation (δ). Panels (b) (c) hold the same as all other parameter values except for the level of demand (α). In each panel, we plot the lending in the underserved neighborhood, with (L_1^*) and without ($L_1^{*'}$) the CRA, and the lending in the non-underserved neighborhood, with (L_2^*) and without ($L_2^{*'}$) the CRA. The shaded area indicates regions where the bank does not open a branch ($b = 0$). Parameters: $\alpha_1 = -0.5$, $\alpha_2 = 2$, $\gamma = 1$, and $\bar{L} = 6.5$.



(a)



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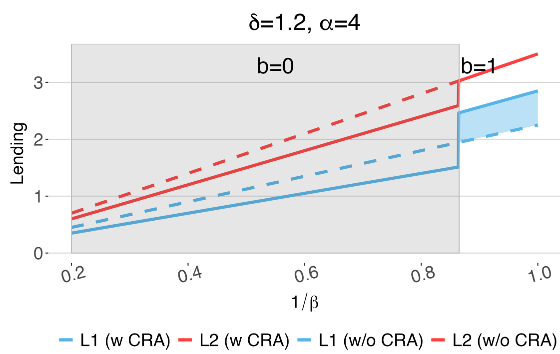
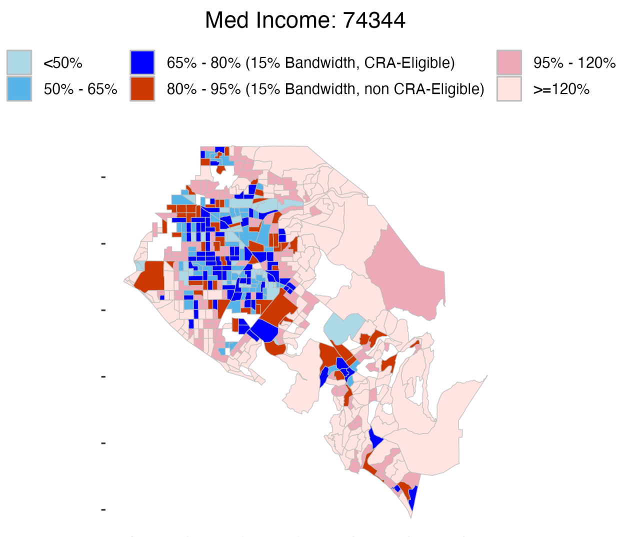


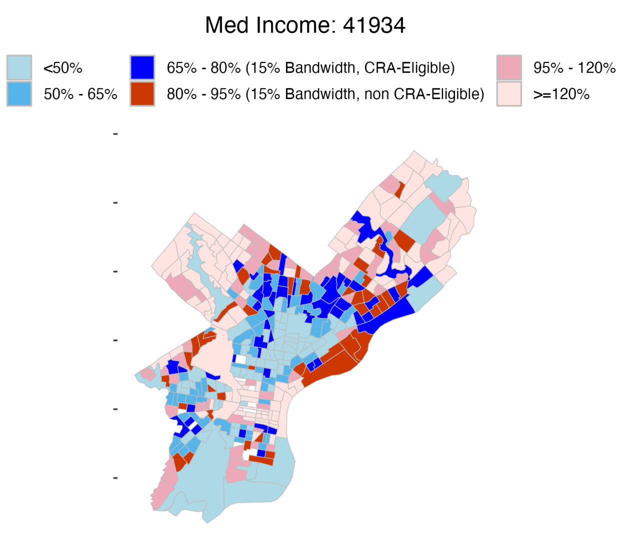
(c)

Figure 3. Examples of Tract Income and CRA Eligibility Areas

The figure plots census tract income maps of Orange County in California and Philadelphia County in Pennsylvania in 2016. The colors represent areas with different Median Family Income (MFI) levels. Blue tracts fall below the 80% cutoff and correspond to CRA-eligible tracts, while red tracts exceed the 80% cutoff. Orange County is within the top 10% quantile for MFI among counties with a population exceeding 100,000, whereas Philadelphia's MFI falls below the bottom 10% quantile in the same population category.



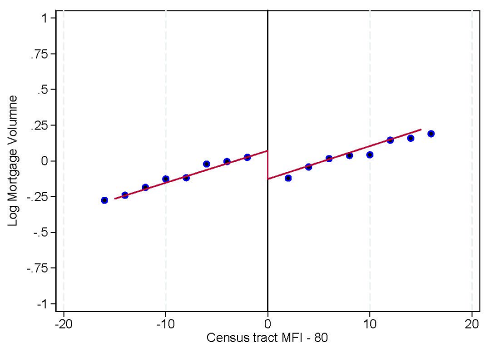
(a) Orange County



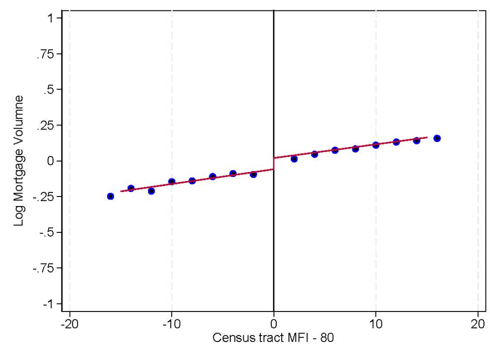
(b) Philadelphia County

Figure 4. Discontinuity Around the CRA Eligibility Threshold: Loan Volume and Price

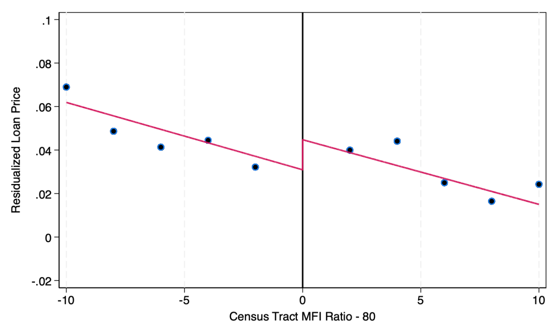
This figure depicts the discontinuity of lending volume and loan prices around the 80% median family income (MFI) threshold. The y-axis in panels (a) and (b) correspond to the logarithm of total lending, which includes both originated and purchased home-purchase loans. The y-axis in panel (c) corresponds to interest rates. The x-axis indicates the distance from the 80% MFI threshold. Panels (a) and (b) correspond to column 4 in Table 2, in which Panel (a) uses the subsample of banks with $\hat{\delta}$ above the median, and Panel (b) uses the subsample of banks with $\hat{\delta}$ below the median. Panel (c) corresponds to column 6 in Table 3. All specifications account for differential slopes on each side of the cutoff. Each dot represents the sample average of the dependent variable within a specific bin. Solid lines represent non-parametric fits from local linear regressions.



(a) Total Lending for High $\hat{\delta}$



(b) Total Lending for non-High $\hat{\delta}$



(c) Loan Pricing for Full Sample

Figure 5. The Shadow Cost of CRA Violation and Bank Characteristics

This figure presents estimates about the relation between the shadow cost of CRA violation and bank characteristics. Each estimate corresponds to a regression of $High, \hat{\delta}$, an indicator variable for whether the estimated shadow cost of the CRA violation for bank b ($\hat{\delta}_b$) is above median among all banks, on each covariate. CRA passing rating corresponds to the average of an indicator variable for whether the bank obtained at least a "Satisfactory" CRA rating between 2005 and 2008. Merger is an indicator variable for whether the bank was involved in any merger or acquisition between 2005 and 2008. Branch growth corresponds to the total number of branches in 2008 relative to the number of branches by the end of 2004. Assets correspond to the mean total assets measured between 2005 and 2008. ROA corresponds to the mean of the return on assets between 2005 and 2008. Charge-off ratio comprises the mean of total loans and leases charge-off divided by year-end loan values between 2005 and 2008. Non-performing ratio corresponds to the mean of the sum of non-accruing loans and leases, along with loans that are more than 90 days late, divided by year-end loan values between 2005 and 2008. Profitability is defined as the mean of the ratio of net interest income to year-end loan values between 2005 and 2008. Branch intensity is the mean of the ratio of number of branches to total deposits for each bank between 2005 and 2008. % FHA mortgages is the average share of FHA loans in the mortgage market between 2005 and 2008. % Non-white borrowers is the average of the non-white indicator in the mortgage market for each bank between 2005 and 2008. % Female borrowers is the average of the female indicator in the mortgage market for each bank between 2005 and 2008. ln(income) borrowers is the log of the average income of borrowers in the mortgage market for each bank between 2005 and 2008. Variables are standardized to have unit variance and winsorized at the 1% level.

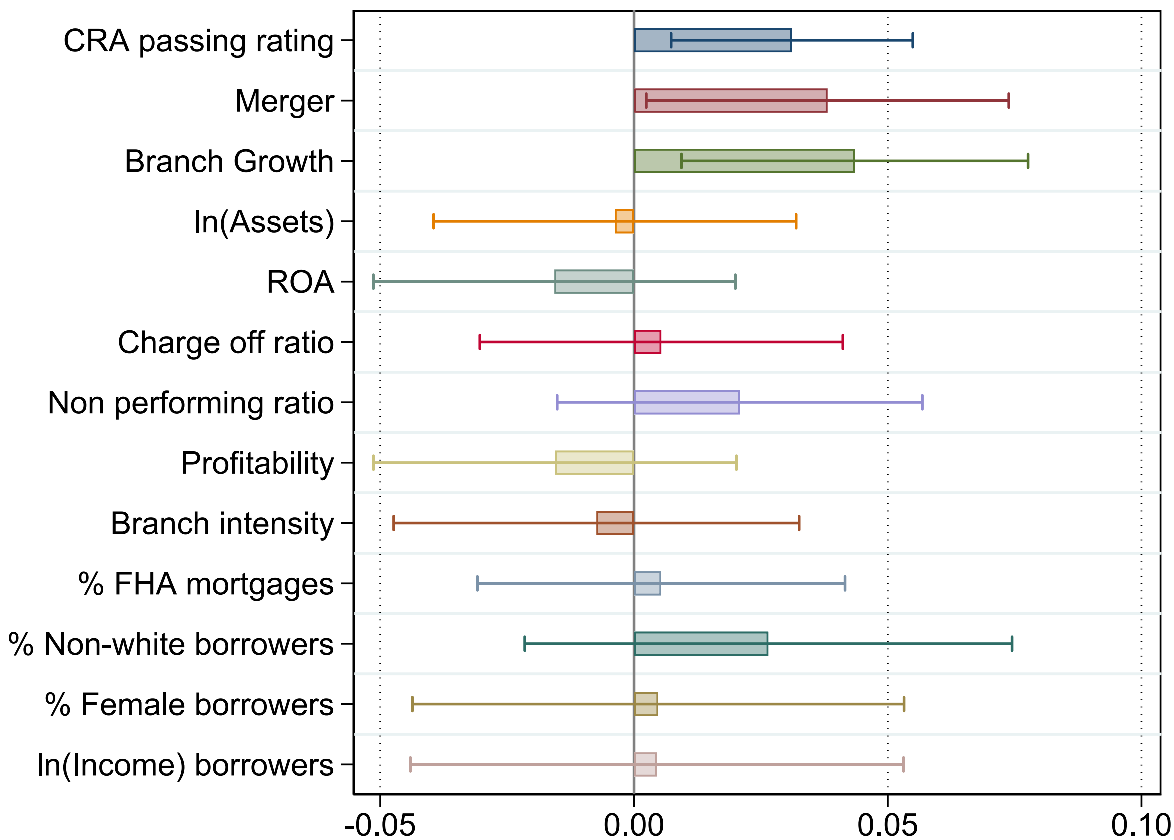
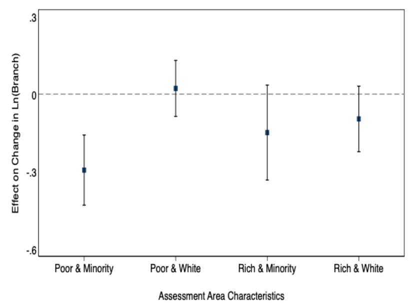
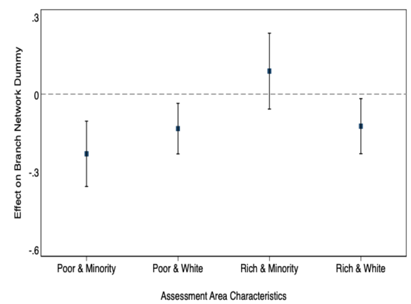


Figure 6. Regional Heterogeneity of the CRA Effects

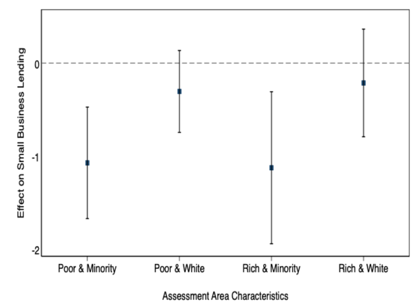
This figure illustrates the impact of the CRA regulation on banks' branching and lending decisions across counties with varying demographic characteristics amid the rise of shadow banks in the residential mortgage market during 2011-2017. In each panel, we plot the estimated β in specification (12) using each of the four county subsamples: low-income and high share of racial minority population ("Poor & Minority"), low-income and low share of racial minority population ("Poor & White"), high-income and high share of racial minority population ("Rich & Minority"), and high-income and low share of racial minority population ("Rich & White"). The bars indicate the 95% confidence intervals. Counties are categorized based on income per capita and minority population share. High-income counties are defined as counties with 2010 income per capita in the top quantile among all counties, while all other counties are classified as low-income counties. Counties with high share of racial minority population are defined as counties with minority population share in the top quantile in 2010, and the rest of the counties are classified as low share of racial minority population. The dependent variables are defined in Table 4 and 5.



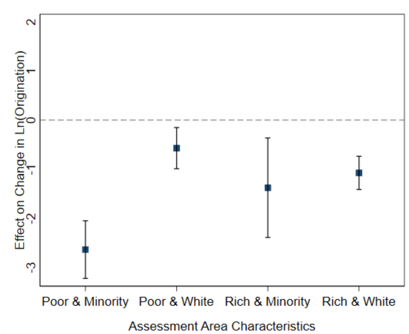
(a) Ln(Branch)



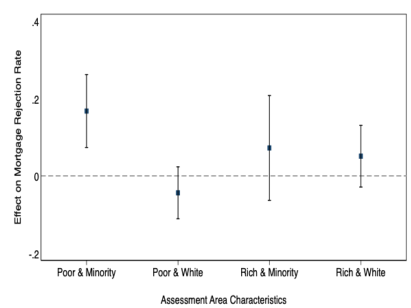
(b) Local Branch Existence



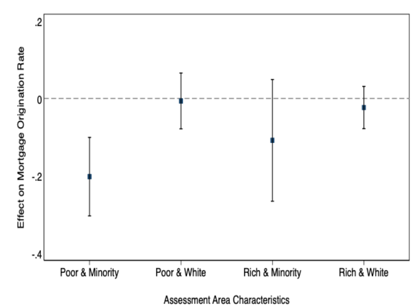
(c) Small Business lending



(d) Mortgage Lending Volume



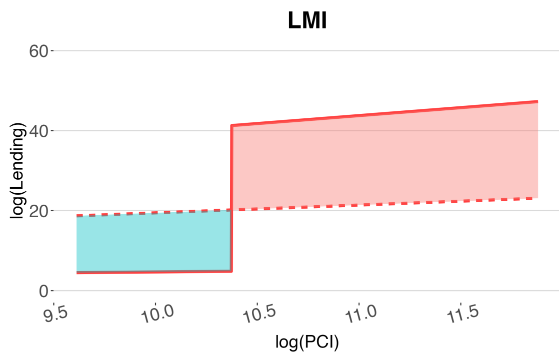
(e) Mortgage Rejection Rate



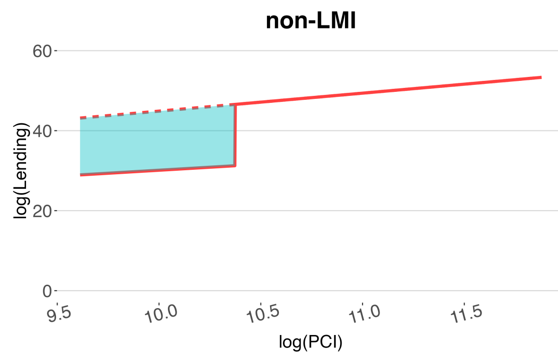
(f) Net Origination Rate

Figure 7. Net Effect — Quantification

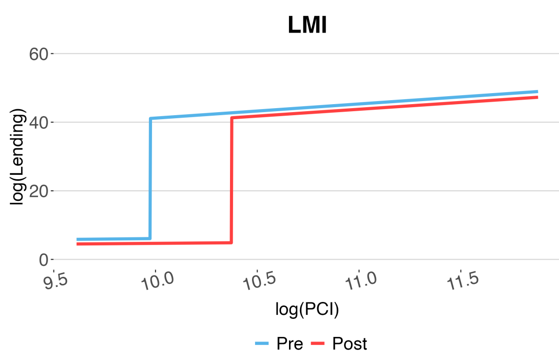
The figure presents the relationship between lending activities and the logarithm of per capita income (PCI), serving as a proxy for $\frac{1}{\beta}$. Utilizing the parameters extracted from Table 7, the red lines chart this relationship. Meanwhile, the blue lines visualize a hypothetical scenario in which the parameter α increases by 30%, mirroring the lending landscape before the rise of shadow banking. Specifically, Panels (a) and (c) delve into LMI neighborhoods, whereas Panels (b) and (d) explore non-LMI neighborhoods. The solid lines delineate the relationship under CRA, and the dashed lines depict the theoretical relationship in the absence of CRA. The blue region highlights the reduction in lending attributed to CRA regulations, whereas the red region highlights the additional credit provided as a result of CRA.



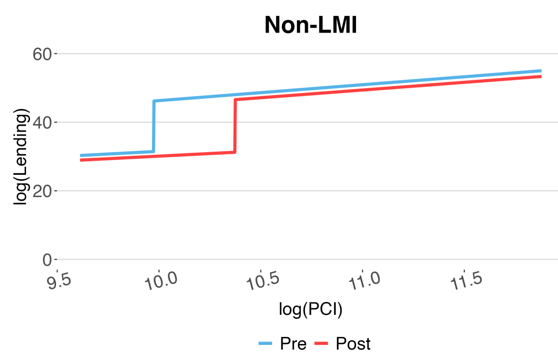
(a)



(b)



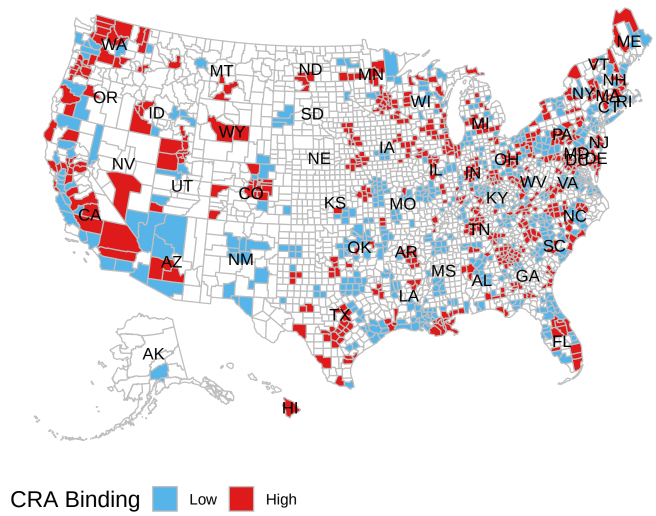
(c)



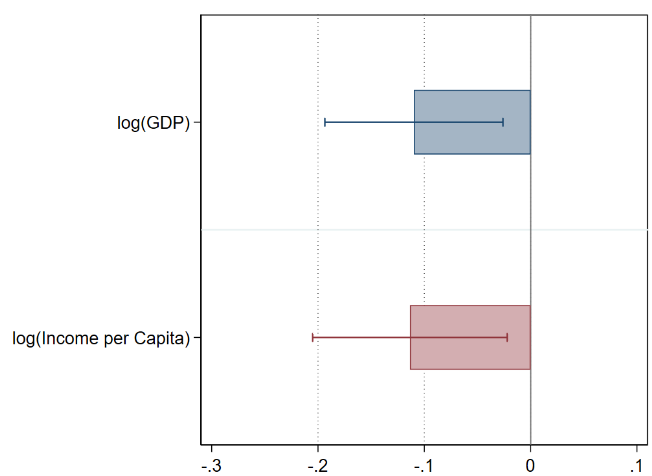
(d)

Figure 8. CRA Regulation Binding Areas

Panel A displays the map of CRA binding areas. We estimate the effect of the CRA regulation on an MSA region using the total lending of branching banks in each census tract-year during 2005-2008, following the same specification as presented in Table 8. An MSA region is classified as a CRA binding area ("high" in the map) if the estimated η_m is above the median among all MSAs, and it is classified as a non-CRA binding area otherwise ("low" in the map). Panel B compares economic conditions between CRA binding and non-CRA binding areas. The figure plots the estimated coefficients of various outcome variables regressed on a CRA binding dummy using data from 2005-2008. All outcome variables are standardized to have unit variance.



(a)



(b)

Table 1 Summary Statistics

This table presents the summary statistics of the final samples. Bank Characteristics are collected from year-end Call Reports and correspond to the average over the period from 2005 to 2008. Bank and local level outcomes are sourced from HMDA, Summary of Deposits, and CRA from 2011 to 2017. SBL stands for small business lending. The unit of observation is a bank in Panel A, a bank-county-year in Panel B, a loan in Panel C, a county-year in Panel D, and a bank in Panel E.

	N	Mean	SD	p25	Median	p75
Panel A: Bank Characteristics						
Assets (M)	753	6,690.52	54,610.69	288.80	509.88	1,155.63
ROA	753	0.01	0.01	0.01	0.01	0.01
Charge-off ratio	753	0.00	0.00	0.00	0.00	0.00
Non-performing ratio	753	0.01	0.01	0.00	0.01	0.01
Profitability	753	0.08	0.01	0.07	0.08	0.09
Number mergers	753	0.66	1.30	0.00	0.00	1.00
Branch growth	753	0.45	1.61	0.00	0.18	0.44
Panel B: Bank Level Outcomes						
Branches	89,176	4.72	9.71	1.00	2.00	4.00
SBL (volume)	190,349	10,151.00	43,446.00	152.00	902.00	4,206.00
SBL (count)	190,349	3,538.00	16,492.00	0.00	170.00	1,624.00
SBL revenue <$1 Million (volume)	190,349	155.80	1,030.00	2.00	10.00	60.00
SBL revenue <$1 Million (count)	190,349	90.97	703.30	0.00	4.00	26.00
Panel C: CoreLogic LLMA Sample						
Interest rate	535,689	6.41	0.60	6.00	6.38	6.75
Credit score	1,365,736	680.10	73.99	626.00	679.00	741.00
Loan-to-Value	1,605,417	86.83	14.13	80.00	90.00	98.69
Balloon	3,592,891	0.02	0.14	0.00	0.00	0.00
Full documentation	2,551,012	0.63	0.48	0.00	1.00	1.00
Panel D: Local Level Outcomes						
Number of branches	8,604	55.97	107	11	24	56
Branch per 1000 population	8,604	0.32	0.14	0.24	0.30	0.38
SBL (volume)	8,604	299,525	780,798	23,389	85,821	267,944
SBL (count)	8,604	107,358	256,965	10,032	34,639	106,423
SBL revenue < $1 Million (volume)	8,604	7,504	22,418	692	1,992	6,015
SBL revenue < $1 Million (count)	8,604	3,644	11,270	336	947	2,838
Number of establishments	8,604	4,500	10,742	565.5	1,545	4,045
Number of employees	8,604	81,437	206,245	7,247	23,113	68,115
Panel E: Shadow Cost CRA Violation and Shadow Banks						
$\hat{\delta}$	753	0.04	0.57	-0.26	0.03	0.35
$\hat{\eta}$	553	-0.11	1.72	-0.67	0.08	0.43
Shadow bank market share	108,172	0.35	0.156	0.23	0.34	0.46

Table 2 Banks' Shadow Cost of CRA Violation

This table presents estimates of the regression discontinuity (RD) analysis results regarding the banks' shadow cost of CRA violations. The dependent variable across all columns is the logarithm of total lending (both originated and purchased home-purchase loans) by bank b in census tract i during year t. The running variable of the RD design is the ratio of the median family income (MFI) in a census tract to the median MFI in the surrounding metropolitan statistical area (MSA), or to the statewide non-metropolitan median family income if located outside an MSA. The key variable of interest, $\mathbb{1}(\text{LMI}_{i,t})$, indicates whether the census tract is designated as a Low- and Moderate-Income (LMI) area, defined as tracts where the running variable falls below 80%. Specifically, we estimate the following RD design using bank-census tract-year level total lending volume from 2005 to 2008:

$$\log(\text{Loans})_{b,i,t} = \hat{\delta}\mathbb{1}(\text{LMI}_{i,t}) + \kappa_1(\text{MFI}_{i,t} - 80\%) + \kappa_2\mathbb{1}(\text{LMI}_{i,t}) \times (\text{MFI}_{i,t} - 80\%) + \mu_b + \nu_{m,t} + \epsilon_{b,i,t}$$

The optimal bandwidth with minimized mean square error, following Imbens and Kalyanaraman (2012), is between 9.6% and 22%. To demonstrate robustness, we use three distinct bandwidths for estimating local polynomial regression. Columns 1 and 2 focus on census tracts within a 17% bandwidth, where the ratio of a census tract's MFI to the median MFI of the region varies from (80%-17%) to (80%+17%). Columns 3 and 4, along with 5 and 6, analyze tracts within narrower bandwidths of 15% and 13%, respectively. In accordance with Regulation 12 CFR 25.41, an assessment area is defined as an MSA if the census tract lies within an MSA and as a county if located outside an MSA. Observations are weighted by $\frac{PCI_m}{PCI_{US}}$ to account for differences in elasticity across assessment areas. Standard errors are clustered at county-year. Numbers in parentheses represent standard errors.*, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	[-17,+17]		[-15,+15]		[-13,+13]	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(LMI)	0.020**	0.020**	0.021**	0.021**	0.021*	0.021*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
MFI-80	0.015***	0.015***	0.015***	0.015***	0.016***	0.016***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\mathbb{1}$(LMI)×(MFI-80)	-0.001	-0.001	0.000	0.000	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓	
Assessment Area FE	✓		✓		✓	
Assessment Area×Year FE		✓		✓		✓
Adjusted R^2	0.397	0.397	0.395	0.395	0.394	0.394
Observations	360,992	360,269	312,572	311,838	266,077	265,334

Table 3 CRA Effect on Loan Pricing

This table presents the results of the regression discontinuity (RD) analysis on banks' loan pricing. Since the loan pricing data records only zip code information, we aggregate census tract median family income (MFI) to zip code level by taking the average, weighted by the proportion of residential and business addresses. The running variable for the RD design is the ratio of the MFI in a zip code to either the median MFI in the surrounding metropolitan statistical area (MSA) or to the statewide non-metropolitan median family income, if the zip code is located outside an MSA. The key variable of interest, denoted as $\mathbb{1}(\text{LMI}_{i,t})$, indicates whether the borrower resides in a zip code where the running variable is below 80%. Specifically, we estimate the following RD design using CoreLogic LLMA loan-level data from 2005 to 2008:

$$Y_i = \kappa_0 \mathbb{1}(\text{LMI}_i) + \kappa_1(\text{MFI}_i - 80\%) + \kappa_2 \mathbb{1}(\text{LMI}_i) \times (\text{MFI}_i - 80\%) + X_i\Gamma + \mu_{c,t} + \epsilon_i$$

The optimal bandwidth with minimized mean square error, following Imbens and Kalyanaraman (2012), is between 7% to 13%. To demonstrate robustness, we use three distinct bandwidths for estimating local polynomial regression. Columns 1 and 2 use a sample of zip codes within the bandwidth of 15%, i.e., zip codes MFI to region's median MFI ratio is between (80%-15%) and (80%+15%). Columns 3 and 4 (5 and 6) use a sample of zip codes within the bandwidth of 13% (10%). To compare loan prices, we restrict our sample to a set of standardized loans with full documentation. Specifically, we keep 30-year fixed-rate mortgages with full documentation and drop loans with missing data for interest rate, FICO score, loan-to-value ratio, or debt-to-income ratio. We also remove outliers at 1/99th percentiles of interest rates and loan-to-value ratios. The outcome variable in columns 1, 3, and 5 is the raw mortgage rate. In these columns, we include a saturated set of default-risk measures (i.e., FICO, LTV, DTI, and their squared terms), monthly-level origination date fixed effects, loan type (i.e., conventional, FHA/VA, and RHS loans)-by-year fixed effects, and CBSA-by-year fixed effects. The outcome variable in columns 2, 4, and 6 is the residualized mortgage rate estimated using the full sample of standardized loans with full documentation from 2005 to 2008 (i.e., not restricted to loans within the bandwidth). Specifically, we calculate residuals of the raw mortgage rate regressed on origination year-month, loan type, loan default risk measures (i.e., FICO, LTV, DTI, and their squared terms), and three-way interactions among these three sets of covariates. Since we already residualized the mortgage rates, we do not include default risk measures as controls in these columns. Neither do we include origination-date nor loan type-by-year fixed effects. Note that our results are robust to including these controls. Standard errors are clustered at county-year. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	[-15,+15]		[-13,+13]		[-10,+10]	
	(1)	(2)	(3)	(4)	(5)	(6)
	Raw Rate	Residualized Rate	Raw Rate	Residualized Rate	Raw Rate	Residualized Rate
$\mathbb{1}$(LMI)	-0.010**	-0.011**	-0.011*	-0.012**	-0.022***	-0.022***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
MFI-80	-0.002***	-0.002***	-0.003***	-0.002***	-0.004***	-0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\mathbb{1}$(LMI)×(MFI-80)	-0.002**	-0.001**	-0.001	-0.001	-0.002	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Assessment Area×Year FE	✓	✓	✓	✓	✓	✓
Loan Type×Year FE	✓		✓		✓	
Origination Date FE	✓		✓		✓	
Default-Risk Controls	✓		✓		✓	
Adjusted R^2	0.317	0.051	0.316	0.052	0.314	0.054
Observations	535,541	535,543	458,985	458,987	345,653	345,655

Table 4 Shadow Cost of CRA and Branch Closure

This table presents bank-county-level regression results about the effects of CRA regulation on banks' branching decisions amid the rise of shadow banks in the residential mortgage market during 2011-2017:

$$\Delta Y_{b,c,m,t} = \kappa_1 \text{SBank Shock}_{m,t} \times \text{High } \hat{\delta}_b + \kappa_2 \text{SBank Shock}_{m,t} \times \text{Assets}_{b,2010} + \mu_{b,t} + \nu_{c,m,t} + \epsilon_{b,c,m,t}.$$

The variable Y denotes either a binary indicator of the presence of branches or the logarithmic count of the branches that bank b operates within county c in year t. Δ captures the cumulative change observed from the year 2010 up to year t. SBank Shock$_{m,t}$ represents the shift-share instrument, calculated as the product of the average shadow bank shares observed in the focal assessment area m from 2005 to 2008 with the cumulative national growth rate of shadow banks, excluding the focal assessment area. Assets$_{b,2010}$ is the total asset size in 2010. High $\hat{\delta}_b$ is an indicator for whether the estimated shadow cost of the CRA regulation for bank b ($\hat{\delta}_b$) is above median among all banks. The estimation procedure is described in Section 4.1. In estimating the shadow cost of CRA regulation, we employ a 15% bandwidth to estimate local polynomials. Standard errors are clustered at county-year. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	Δ I(Branch=1)			Δ log(1+Branch)		
	(1)	(2)	(3)	(4)	(5)	(6)
SBank Shock $\times$ High $\hat{\delta}_b$	-0.084***	-0.134***	-0.112***	-0.073**	-0.077**	-0.057*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
SBank Shock $\times$ Assets$_{2010}$			0.017***			0.015**
			(0.01)			(0.01)
SBank Shock	0.249***			0.337***		
	(0.02)			(0.02)		
Bank FE	✓			✓		
Year FE	✓			✓		
Bank $\times$ Year FE		✓	✓		✓	✓
County $\times$ Year FE		✓	✓		✓	✓
Adjusted R^2	0.200	0.280	0.280	0.271	0.286	0.286
Observations	98,204	94,468	94,468	97,743	94,468	94,468

Table 5 Shadow Cost of the CRA and Lending

This table presents results about the effects of the CRA regulation on banks' mortgage lending and small business lending amid the rise of shadow banks in the residential mortgage market during 2011-2017:

$$\Delta Y_{b,c,m,t} = \kappa_1 \text{SBank Shock}_{m,t} \times \text{High } \hat{\delta}_b + \kappa_2 \text{SBank Shock}_{m,t} \times \text{Assets}_{b,2010} + \mu_{b,t} + \nu_{c,m,t} + \epsilon_{b,c,m,t}.$$

$Y_{b,c,m,t}$ is the bank-county-year level outcome variable. $\Delta Y_{b,c,m,t}$ captures the cumulative change observed from the year 2010 up to year t. The SBank Shock$_{m,t}$ represents the shift-share instrument, calculated as the product of the average shadow bank shares observed in the focal assessment area m from 2005 to 2008 with the cumulative national growth rate of shadow banks, excluding the focal assessment area. Assets$_{b,2010}$ is the total asset size in 2010. High $\hat{\delta}_b$ is an indicator for whether the estimated shadow cost of the CRA regulation for bank b ($\hat{\delta}_b$) is above the median among all banks. Panel A's outcome variables are the log of total mortgage volume in column 1, originated loans in column 2, purchased loans in column 3, and mortgage rejection, withdrawal, and origination rates in columns 4 to 6. In Panel B, the outcome is the log of small business lending (SBL) volume or count by bank b in county c for year t, with even columns for total SBL and odd columns for SBL to firms with annual revenue below 1 million dollars. Standard errors are clustered at county-year. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Mortgage Lending

	Δlog(Orig. &Pur.) (1)	Δlog(Orig.) (2)	Δlog(Pur.) (3)	ΔRejection Rate (4)	ΔWithdrawal Rate (5)	ΔOrigination Rate (6)
SBank Shock × High $\hat{\delta}_b$	-0.661***	-1.478***	-0.746***	0.034*	0.042***	-0.054**
	(0.10)	(0.13)	(0.11)	(0.02)	(0.01)	(0.02)
SBank Shock × Assets$_{2010}$	-0.032	-0.059**	0.155***	0.001	0.006**	-0.005
	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
Bank×Year FE	✓	✓	✓	✓	✓	✓
County×Year FE	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.270	0.216	0.638	0.086	0.092	0.089
Observations	210,048	210,048	210,048	179,926	162,914	179,926

Panel B: Small Business Lending

	Δlog(Dollar Volume)		Δlog(Loan Count)	
	Total Lending (1)	Revenue <1 Million (2)	Total Lending (3)	Revenue <1 Million (4)
SBank Shock × High $\hat{\delta}_b$	-0.569***	-0.320**	-0.348***	-0.236***
	(0.10)	(0.13)	(0.06)	(0.08)
SBank Shock × Assets$_{2010}$	0.095***	0.101***	0.164***	0.251***
	(0.02)	(0.03)	(0.01)	(0.02)
Bank× Year FE	✓	✓	✓	✓
County× Year FE	✓	✓	✓	✓
Adjusted R^2	0.116	0.152	0.472	0.491
Observations	136,565	87,122	136,573	87,123

Table 6 Effect on Local Small Business Lending

This table presents the results of local small business lending:

$$\Delta Y_{c,m,t} = \kappa_1(\text{SBank Shock}_{m,t} \times \text{High}\sum_b w_b\hat{\delta}_b) + \kappa_2(\text{SBank Shock}_{m,t} \times X_c^{2010})$$
$$+ \kappa_3\text{SBank Shock}_{m,t} + \kappa_4\text{High}\sum_b w_b\hat{\delta}_b + \kappa_6\Delta X_{c,t-1} + \mu_{c,m} + \nu_t + \epsilon_{c,m,t},$$

$\Delta Y_{c,m,t}$ is the cumulative log change of county-level small business lending from 2010 to year t. Columns 1 and 2 report the total small business lending. Columns 3 and 4 report the lending to businesses with annual revenue below 1 million dollars. SBank Shock$_{m,t}$ is assessment area m's exposure to the national growth of shadow banks from 2010 to year t, calculated as the average shadow bank shares observed in assessment area m from 2005 to 2008 multiplied by the cumulative national growth rate of shadow banks, excluding the focal assessment area. $\sum_b w_b\hat{\delta}_b$ represents the aggregated shadow cost of CRA violation in a county, calculated by weighting the estimated $\hat{\delta}_b$ of individual banks using their branch share within the county as of 2010. Counties with aggregated costs above the median are classified as high $\sum_b w_b\hat{\delta}_b$. $\Delta X_{c,t-1}$ are lagged dynamic controls, consisting of cumulative changes in the logarithmic values of income per capita, population, GDP, and housing index, starting from 2010. Observations are weighted by county population size. Standard errors are clustered at the county level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	Δlog(Small Business Lending) Total		Δlog(Small Business Lending) Revenue <1 Million	
	(1)	(2)	(3)	(4)
SBank Shock × High $\sum_b w_b\hat{\delta}_b$	-0.551***	-0.262*	-1.172***	-0.444**
	(0.21)	(0.15)	(0.33)	(0.22)
SBank Shock	2.954***	-0.891	4.528***	-22.481***
	(0.35)	(3.85)	(0.47)	(6.39)
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Dynamic Controls		✓		✓
Adjusted R^2	0.764	0.802	0.796	0.826
Observations	17,880	12,765	17,765	12,737

Table 7 Model Estimation

This table presents the parameters estimated for Equation (3) utilizing a balanced sample of bank-county-year data, focusing on counties where banks provided credit between 2011 and 2017. Our analysis begins by estimating the changes in lending induced by the CRA, encompassing both small business lending and the originated and purchased mortgage loans. We first estimate the relationship between bank lending and local PCI, by separately examining LMI and non-LMI neighborhoods across counties:

$$\log(\text{SBL} + \text{Mortgage})_{b,c,t} = \kappa_1 \log \text{PCI}_{c,2010} \times \text{I}(\text{Branch=1})_{b,c,t} + \kappa_2 \log \text{PCI}_{c,2010} + \nu_{b,t} + \mu_{s,t} + \epsilon_{b,c,t},$$

Then, we utilize the instrumented branch presence changes in column (3) of Table 4 to assess alterations in lending, separately for LMI and non-LMI neighborhoods across counties (columns 3 and 4). Panel B elucidates the back-out parameters connected to Equation (3) from parameters reported in Panel A. Panel C presents percentage lending change in LMI and non-LMI neighborhoods, compared to the benchmark case without CRA regulation. Standard errors are clustered at county-year. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Estimation Results

	Log(SBL + Mortgage)		ΔLog(SBL + Mortgage)	
	LMI	Non-LMI	LMI	Non-LMI
	(1)	(2)	(3)	(4)
$\log(\text{PCI}_{c,2010})$	0.468***	3.011***		
	(0.06)	(0.07)		
$\log(\text{PCI}_{c,2010}) \times \text{I}(\text{Branch=1})_{b,c,t}$	3.513***	1.478***		
	(0.19)	(0.09)		
$\overline{\Delta \text{I}(\text{Branch=1})}_{b,c,t}$			33.798***	17.987**
			(4.66)	(7.06)
Bank× Year FE ✓	✓	✓	✓	✓
State× Year FE	✓	✓		
County× Year FE			✓	✓
Adjusted R^2	0.358	0.422		
Observations	737,130	737,130	737,130	737,130
Cragg-Donald Wald F statistic			29.274	29.274

Panel B: Parameters

$\alpha + \alpha_1$	$\alpha + \alpha_2$	γ	δ	$(\frac{1}{\beta})^*$	$\bar{L}$
0.936	6.022	2.956	4.066	10.375	89.212

Panel C: Quantification

	% Lending Change in LMI	% Lending Change in Non-LMI
Below $(\frac{1}{\beta})^*$	-76%	-33%
Above $(\frac{1}{\beta})^*$	104%	0%

Table 8 Widened Cross-Region Disparities

This table presents county-level results of the CRA-induced widened cross-region disparities amid the rise of shadow banks in the residential mortgage market during 2011-2017:

$$\Delta Y_{c,m,t} = \kappa_1(\text{SBank Shock}_{m,t} \times \text{CRA Binding Area}_m) + \kappa_2(\text{SBank Shock}_{m,t} \times X_c^{2010}) + \kappa_3\text{SBank Shock}_{m,t} + \kappa_4\text{CRA Binding Area}_m + \kappa_5 X_c^{2010} + \kappa_6\Delta X_{c,t-1} + \mu_s + \nu_t + \epsilon_{c,m,t},$$

$\Delta Y_{c,m,t}$ is the cumulative change of county-level outcome variables from 2010 to year t. SBank Shock$_{m,t}$ is assessment area m's exposure to the national growth of shadow banks from 2010 to year t, calculated as the average shadow bank shares observed in assessment area m from 2005 to 2008 multiplied by the cumulative national growth rate of shadow banks, excluding the focal assessment area. CRA Binding Area$_m$ is an indicator for whether the estimated CRA treatment intensity in assessment area m is above the median among all assessment areas. The estimation procedure is described in Section 7.1. X_c^{2010} are static controls, including logarithmic measures of income per capita, population, and GDP, all recorded in 2010. $\Delta X_{c,t-1}$ are lagged dynamic controls, consisting of the cumulative changes in the logarithmic values of per capita income, population, and GDP, starting from 2010. The outcome variables in column 1 is the log change of total number of branches; in column 2 is the change in the proportion of the population living in branch desert, defined as zip codes without any branches; in column 3 is the change of the underbanked population — those who are unbanked or have used non-bank financial services in the past 12 months — among individuals with annual incomes below \$50,000, as reported in the FDIC Survey of Household Use of Banking and Financial Services; in column 4 is the log change of the small business lending volume; in column 5 is the log change of the total number of SBA 7(a) revolving loans; in column 6 is the log change of the number of business establishments with over 20 employees (column 6). Observations are weighted by county population size. Standard errors are clustered at the county level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	Δlog(1+Branch)	ΔBank Desert	ΔFinancial Inclusion	Δlog(Small Business Loans)	Δlog(SBA 7(a) Revolving Credit)	Δlog(Business Establishments)
	(1)	(2)	(3)	(4)	(5)	(6)
SBank Shock ×CRA Binding Area	-0.075**	0.064*	0.381**	-0.211*	-0.715**	-0.035**
	(0.04)	(0.04)	(0.15)	(0.11)	(0.33)	(0.02)
CRA Binding Area	0.020**	-0.015*	-0.132**	0.064*	0.224**	0.009*
	(0.01)	(0.01)	(0.05)	(0.03)	(0.09)	(0.00)
SBank Shock	-2.099*	-0.044	-9.695**	-2.042	15.700	-0.349
	(1.15)	(1.40)	(3.90)	(2.83)	(10.01)	(0.71)
State FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Static Controls	✓	✓	✓	✓	✓	✓
Dynamic Controls	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.374	0.156	0.094	0.530	0.316	0.738
Observations	8,380	8,302	935	8,398	4,848	8,131

Appendix for Online Publication

Figure A1. Histograms and Densities of the Running Variable

The figure depicts the density of census tracts around the MFI 80% threshold for the period 2005-2008. Each bar represents the number of census tracts in each 1% bin. The histogram uses the test for breaks in the density of the running variable proposed in Cattaneo et al. (2020) and uses the code discussed in Cattaneo et al. (2018). The $p - value$ for the test is presented in the figure caption.

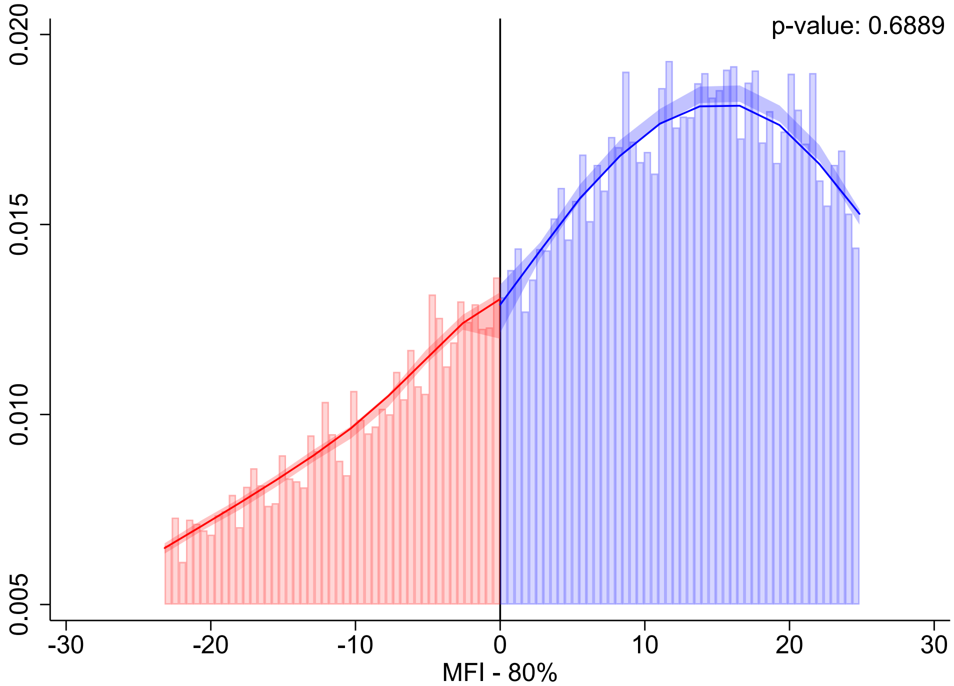


Figure A2. Shadow Cost of CRA Violation Estimation Persistence

This figure shows how persistent the estimated shadow costs of CRA violation are over time. We repeat the estimation procedure described in Section 4.1 using data from 2010 to 2013. We then separately sort the estimates based on 2005-2008 data and the estimates based on 2010-2013 data into four quartiles. The left side of the figure indicates banks' rankings before the financial crisis, and the right side of the figure indicates banks' rankings after the financial crisis. The lines indicate how rankings change from before to after the financial crisis. The larger numbers on either side indicate rankings (i.e., quartiles 1, 2, 3, or 4), and the smaller numbers next to rankings indicate the number of banks in each category. For example, there are 41 banks with estimated shadow costs in the top quartile among 2005-2008 estimates which still fall into the top quartile in 2010-2013.

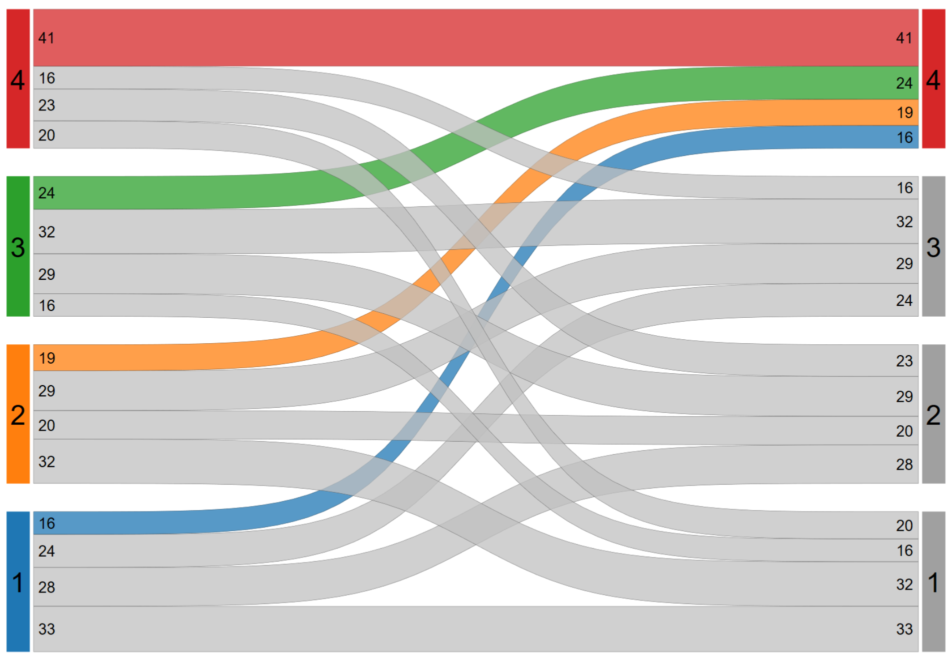


Figure A3. Quantification Illustration

This figure graphically illustrates the relationship between lending (y-axis) and economic fundamentals ($\frac{1}{\beta}$, x-axis) for LMI and non-LMI neighborhoods.

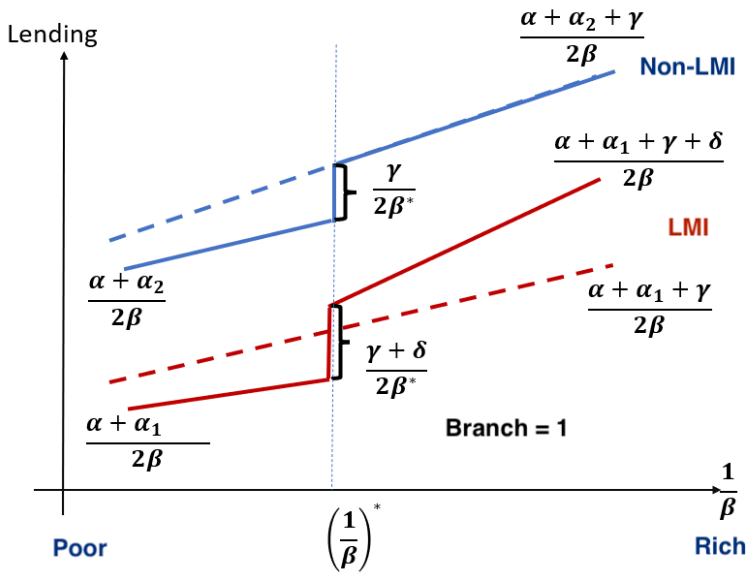


Table A1 Test of Discontinuities in Covariates before the Threshold Implementation

This table presents the results of a test of the balance of local covariates around the 80% MFI threshold. Outcome variables are at the census tract level and come from the 1990 Census. We present the estimated κ_0 for different dependent variables for the following RD design using:

$$Y_i = \kappa_0 \mathbb{1}(\text{LMI}_i) + \kappa_1(\text{MFI}_i - 80\%) + \kappa_2 \mathbb{1}(\text{LMI}_i) \times (\text{MFI}_i - 80\%) + \nu_c + \epsilon_i$$

LMI is defined as census tracts whose median family income (MFI) is below 80% of the median census tract MFI in the surrounding metropolitan statistical area (MSA) or statewide non-metropolitan median family income, if a person or geography is located outside an MSA. The running variable of the RD design is census tract MFI to region's median MFI ratio. We estimate a non-parametric RD specification, in which we control for the census tract MFI as a percentage of the region's median MFI, relative to 80%, and its interaction with the LMI indicator. The non-parametric RD specification allows for different slopes on two sides of the 80% threshold. Column 1 uses a sample of census tracts within the bandwidth of 17%, i.e., census tract MFI to region's median MFI ratio is between (80%-17%) and (80%+17%). Column 2 uses a sample of census tracts within the bandwidth of 15%. Column 3 uses a sample of census tracts within the bandwidth of 13%. Standard errors are clustered at the assessment area level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	[-17,17]	[-15,15]	[-13,13]
	(1)	(2)	(3)
% Vacancy	0.003	0.005	0.003
	(0.005)	(0.006)	(0.006)
Num. rooms	0.018	0.027	0.026
	(0.043)	(0.049)	(0.051)
ln(Rent)	0.003	0.003	-0.012
	(0.013)	(0.014)	(0.013)
ln(Home value)	0.013	0.006	-0.000
	(0.019)	(0.020)	(0.022)
ln(Population)	-0.026	-0.019	-0.011
	(0.054)	(0.054)	(0.060)
% Black	-0.023	-0.020	-0.015
	(0.016)	(0.016)	(0.018)
% Non-white	-0.026	-0.023	-0.018
	(0.016)	(0.016)	(0.018)
Age	-0.086	-0.040	-0.088
	(0.452)	(0.446)	(0.465)
% Social Security inc.	0.009	0.011	0.010
	(0.008)	(0.008)	(0.008)
ln(Inc. per capita)	0.000	-0.003	-0.014
	(0.021)	(0.021)	(0.023)
% Employed	0.001	-0.003	-0.003
	(0.007)	(0.007)	(0.007)
% Renters	-0.009	-0.008	-0.004
	(0.013)	(0.014)	(0.014)
% College degree	0.003	0.003	0.002
	(0.008)	(0.008)	(0.008)
ln(Loan applications)	-0.004	0.002	0.014
	(0.033)	(0.033)	(0.035)
ln(Count loan applications)	-0.002	0.000	0.009
	(0.026)	(0.028)	(0.028)

Table A2 Test of Discontinuities in Covariates within Sample Period

This table presents the results of a discontinuity test around the 80% MFI threshold. Outcome variables are at the census tract level and come from the 2010 Census. We present the estimated κ_0 for different dependent variables for the following RD design using:

$$Y_i = \kappa_0 \mathbb{1}(\text{LMI}_i) + \kappa_1(\text{MFI}_i - 80\%) + \kappa_2 \mathbb{1}(\text{LMI}_i) \times (\text{MFI}_i - 80\%) + \nu_c + \epsilon_i$$

LMI is defined as census tracts whose median family income (MFI) is below 80% of the median census tract MFI in the surrounding metropolitan statistical area (MSA) or statewide non-metropolitan median family income, if a person or geography is located outside an MSA. The running variable of the RD design is census tract MFI to region's median MFI ratio. We estimate a non-parametric RD specification, in which we control for the census tract MFI as a percentage of the region's median MFI, relative to 80%, and its interaction with the LMI indicator. The non-parametric RD specification allows for different slopes on two sides of the 80% threshold. Column 1 uses a sample of census tracts within the bandwidth of 17%, i.e., census tract MFI to region's median MFI ratio is between (80%-17%) and (80%+17%). Column 2 uses a sample of census tracts within the bandwidth of 15%. Column 3 uses a sample of census tracts within the bandwidth of 13%. Standard errors are clustered at the assessment area level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	[-17,17]	[-15,15]	[-13,13]
	(1)	(2)	(3)
ln(Rent)	-0.008	-0.005	-0.006
	(0.012)	(0.013)	(0.015)
ln(Home value)	0.026	0.030	0.021
	(0.028)	(0.030)	(0.034)
ln(Population)	0.004	0.006	0.009
	(0.012)	(0.013)	(0.014)
% Black	-0.000	-0.000	-0.001
	(0.004)	(0.005)	(0.005)
% Non-white	-0.001	-0.001	-0.001
	(0.005)	(0.005)	(0.005)
Age	0.200	0.217	0.138
	(0.163)	(0.172)	(0.197)
ln(Loan applications)	0.004	-0.005	-0.021
	(0.026)	(0.027)	(0.029)
ln(Count loan applications)	-0.002	-0.009	-0.022
	(0.022)	(0.023)	(0.025)

Table A3 Placebo Tests RD Design in Table 2

This table replicates RD design in Table 2 using 120% (in Panel A) and 60% (in Panel B) of the median census tract MFI as placebo cutoff thresholds. All specifications are the same other than the definition of the treatment cutoffs. Standard errors are clustered at the assessment area-year level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Placebo test with 120% as the cutoff

	[-17,+17]		[-15,+15]		[-13,+13]	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(MFI<120)	0.004	0.004	0.007	0.007	0.012	0.011
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
MFI-120	0.010***	0.010***	0.009***	0.009***	0.010***	0.010***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\mathbb{1}$(MFI<120)×(MFI-120)	0.004***	0.004***	0.006***	0.006***	0.007***	0.007***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓	
Assessment Area FE	✓		✓		✓	
Assessment Area×Year FE		✓		✓		✓
Adjusted R^2	0.417	0.420	0.420	0.422	0.420	0.421
Observations	314850	314327	271968	271464	231021	230562

Panel B: Placebo test with 60% as the cutoff

	[-17,+17]		[-15,+15]		[-13,+13]	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(MFI<60)	0.004	0.003	0.005	0.004	0.003	0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
MFI-60	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\mathbb{1}$(MFI<60)×(MFI-60)	-0.006***	-0.006***	-0.005***	-0.005***	-0.006***	-0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓	
Assessment Area FE	✓		✓		✓	
Assessment Area×Year FE		✓		✓		✓
Adjusted R^2	0.396	0.399	0.396	0.399	0.397	0.400
Observations	166176	165644	141663	141183	118762	118303

Table A4 Placebo Tests RD Design in Table 3

This table replicates RD design in table 3 using 120% (in Panel A) and 60% (in Panel B) of the median zip code MFI as placebo cutoffs. All specifications are the same other than the definition of the treatment cutoffs. Standard errors are clustered at the CBSA-year level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Placebo test with 120% as the cutoff

	[-15,+15]		[-13,+13]		[-10,+10]	
	(1)	(2)	(3)	(4)	(5)	(6)
	Raw Rate	Residualized Rate	Raw Rate	Residualized Rate	Raw Rate	Residualized Rate
$\mathbb{1}$(MFI<120)	0.002	0.002	0.002	0.002	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
MFI-120	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\mathbb{1}$(MFI<120)×(MFI-100)	0.000	0.000	0.001	0.001	0.001	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Assessment Area×Year FE	✓	✓	✓	✓	✓	✓
Loan Type×Year FE	✓		✓		✓	
Origination Date FE	✓		✓		✓	
Adjusted R^2	0.365	0.040	0.366	0.039	0.365	0.039
Observations	606125	606127	511668	511670	394898	394900

Panel B: Placebo test with 60% as the cutoff

	[-15,+15]		[-13,+13]		[-10,+10]	
	(1)	(2)	(3)	(4)	(5)	(6)
	Raw Rate	Residualized Rate	Raw Rate	Residualized Rate	Raw Rate	Residualized Rate
$\mathbb{1}$(MFI<60)	0.004	-0.001	0.015	0.012	0.018	0.013
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
MFI-60	-0.001	-0.002*	0.001	0.001	0.003*	0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\mathbb{1}$(MFI<60)×(MFI-60)	-0.003	-0.002	-0.005**	-0.005**	-0.009***	-0.008***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Assessment Area×Year FE	✓	✓	✓	✓	✓	✓
Loan Type×Year FE	✓		✓		✓	
Origination Date FE	✓		✓		✓	
Adjusted R^2	0.287	0.078	0.288	0.082	0.286	0.082
Observations	157281	157281	130466	130466	98433	98434

Table A5 CRA Effect on Lending Standard

This table presents the regression discontinuity (RD) results of banks' lending standards. The key explanatory variable of interest is $\mathbb{1}(\text{LMI}_{i,t})$, which is an indicator of whether the borrower lives in a zip code with an average census tract-level median family income (MFI) below 80% of the median census tract MFI in the surrounding metropolitan statistical area (MSA) or statewide non-metropolitan median family income, if the zip code is outside an MSA. The running variable of the RD design is zip code MFI to region's median MFI ratio. We estimate a non-parametric RD specification, in which we control for the zip code MFI as a percentage of the region's median MFI, relative to 80%, and its interaction with the LMI indicator. The non-parametric RD specification allows for different slopes on two sides of the 80% threshold. Specifically, we estimate the following RD design using CoreLogic LLMA loan-level data from 2005 to 2008:

$$Y_i = \hat{\delta}\mathbb{1}(\text{LMI}_i) + \kappa_1(\text{MFI}_i - 80\%) + \kappa_2\mathbb{1}(\text{LMI}_i) \times (\text{MFI}_i - 80\%) + \nu_{c,t} + \epsilon_i$$

Columns 1-4 use a sample of zip codes within the bandwidth of 15%, i.e., zip codes MFI to region's median MFI ratio is between (80%-15%) and (80%+15%). Columns 5-8 use a sample of census tracts within the bandwidth of 13%. The outcome variable in columns 1 and 5 is an indicator of whether a loan is a Balloon mortgage, which is a major Alternative Mortgage Product (AMP) classified in the literature. The outcome variable in columns 2 and 6 is an indicator of whether the loan application has full documentation. In these two columns, we remove loans whose documentation types are unknown. In columns 3 and 7, the outcome variable is the FICO score; and in columns 4 and 8, the outcome variable is the original loan-to-value ratio. In these columns, we restrict to loans with full documentation. In all columns, we include CBSA-year fixed effects, and standard errors are clustered at the assessment area-year level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	[-15,+15]				[-13,+13]			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Balloon	Full Doc	FICO	LTV	Balloon	Full Doc	FICO	LTV
$\mathbb{1}$(LMI)	0.001	-0.004	-1.098	0.105	0.000	-0.002	-0.810	0.159
	(0.00)	(0.00)	(0.83)	(0.12)	(0.00)	(0.00)	(1.01)	(0.14)
MFI-80	-0.000	-0.001***	0.387***	-0.043***	-0.000	-0.001**	0.396***	-0.035***
	(0.00)	(0.00)	(0.05)	(0.01)	(0.00)	(0.00)	(0.07)	(0.01)
$\mathbb{1}$(LMI)×(MFI-80)	-0.000**	-0.000	0.088	-0.008	-0.000**	-0.000	0.139	-0.013
	(0.00)	(0.00)	(0.11)	(0.02)	(0.00)	(0.00)	(0.15)	(0.02)
Assessment Area×Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.017	0.071	0.076	0.104	0.017	0.073	0.076	0.106
Observations	3,592,844	2,550,953	1,365,646	1,605,347	3,078,752	2,190,752	1,170,958	1,376,244

Table A6 Relationship between Average Shadow Bank Shares from 2005 to 2008 and Market Characteristics

This table presents estimates from regressions of the average shadow bank shares observed in the focal county m from 2005 to 2008 on market-level covariates, with population weighting applied. Each estimate corresponds to a separate regression. Variables have been normalized. Robust standard errors are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)
	Shadow bank share 2005-2008	
ln(Population)	0.024***	0.011***
	(0.01)	(0.00)
Black share	-0.005	0.000
	(0.01)	(0.01)
Renter share	0.004***	0.002***
	(0.00)	(0.00)
Mean age	-0.025**	-0.009
	(0.01)	(0.01)
Rural share	-0.019***	-0.003
	(0.01)	(0.00)
College share	-0.004	0.009
	(0.01)	(0.01)
High school share	-0.005	0.003
	(0.01)	(0.00)
Poverty share	0.011	0.003
	(0.01)	(0.01)
Public assistance share	0.012	0.005
	(0.01)	(0.01)
ln(Income per capita)	0.003	-0.001
	(0.00)	(0.00)
Worked share	-0.011	-0.000
	(0.01)	(0.01)
Rooms	-0.023*	-0.006
	(0.01)	(0.008)
ln(Median rent)	0.019***	0.000
	(0.01)	(0.00)
ln(Median value)	0.015**	0.001
	(0.01)	(0.00)
Mortgage Herfindahl	-0.043***	-0.034***
	(0.01)	(0.01)
FHA share	-0.001	0.013***
	(0.01)	(0.00)
CRA binding area	-0.002	0.002
	(0.01)	(0.01)
State FE	N	Y

Table A7 Effect on Local Mortgage Loans

This table presents the results of local mortgage loans:

$$\Delta Y_{c,m,t} = \kappa_1(\text{SBank Shock}_{m,t} \times \text{High}\sum_b w_b\hat{\delta}_b) + \kappa_2\text{SBank Shock}_{m,t} + \kappa_3\text{High}\sum_b w_b\hat{\delta}_b + \mu_{c,m} + \nu_t + \epsilon_{c,m,t},$$

$\Delta Y_{c,m,t}$ is the cumulative log change of county-level mortgage outcomes from 2010 to year t. The outcome variables are the log change of total originated mortgage loans in column 1, the change of mortgage rejection rate in column 2, the change of withdrawal rate in column 3, and the change of origination rate in column 4. SBank Shock$_{m,t}$ is assessment area m's exposure to the national growth of shadow banks from 2010 to year t, calculated as the average shadow bank shares observed in assessment area m from 2005 to 2008 multiplied by the cumulative national growth rate of shadow banks, excluding the focal assessment area. $\sum_b w_b\hat{\delta}_b$ represents the aggregated shadow cost of CRA violation in a county, calculated by weighting the estimated $\hat{\delta}_b$ of individual banks using their branch share within the county as of 2010. Counties with the aggregated costs above the median are classified as high $\sum_b w_b\hat{\delta}_b$. Observations are weighted by county population size. Standard errors are clustered at the county level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	(1) Δlog(Origination)	(2) ΔRejection Rate	(3) ΔWithdrawal Rate	(4) ΔOrigination Rate
SBank Shock × High $\sum_b w_b\hat{\delta}_b$	0.250	0.018	0.028*	-0.045*
	(0.21)	(0.02)	(0.02)	(0.03)
SBank Shock	1.733***	0.025	0.074***	-0.067*
	(0.23)	(0.03)	(0.02)	(0.03)
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Adjusted R^2	0.883	0.617	0.595	0.689
Observations	17,880	12,765	17,765	12,737