Branching Out Inequality:
The Impact of Credit Equality Policies

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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 is amplified, expanding the set of disadvantaged areas suffering 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, business establishments, and employment, predominantly in low-income neighborhoods within these disadvantaged regions. Such dynamics could contribute to the worsening cross-region disparities in credit access observed over the recent decade.

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Addressing CRA responsibilities ... imposes costs on financial institutions. It appears that, at least in some instances, the CRA has served as a catalyst, inducing banks to enter underserved markets that they might otherwise have ignored.

—Ben Bernanke Speech in 2007

Promoting equal credit access is crucial for addressing regional inequality in economic opportunities and growth. 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.[1] 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.[2] 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

[1] In the US, another prominent government intervention to reduce disparities in credit access is the national borrowing rate policy set by the 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.

[2] 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.

branches, especially in lower-income regions. As banks retract their branches, these regions experience declines in small business lending, business establishments, and employment. Such dynamics presumably contributed to the worsening cross-regional disparities in credit access depicted in Figure 1 over the recent decade.

We begin by developing a parsimonious model of bank lending under the CRA regulation. The CRA mandates banks to provide adequate lending to underserved neighborhoods in a CRA assessment area where their branches operate. Banks weigh the cost of extending lending beyond the optimal level in the underserved neighborhood, as required by the CRA, against the benefits of maintaining branches to serve the area. Should the benefits outweigh the costs, banks lend more in underserved neighborhoods beyond what they would in the absence of the CRA. However, if the costs surpass the benefits, banks might opt to shut down all branches within the area to bypass the CRA regulation. The latter is more likely to occur in an area with weaker economies. Thus, the CRA regulation presents a paradox: it fosters equal credit opportunity in economically strong areas, while potentially curtailing lending in economically weak areas that would benefit most from the CRA's intent.

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 the CRA 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 the CRA requirement, which implies that complying with the CRA is costly for banks.

We begin our empirical analysis by estimating the cost of CRA violation, which allows us to test the model premise as well as to obtain helpful variation for examining the trade-off as predicted by the model. Our estimation leverages the CRA's use of the 80% Median Family Income (MFI) threshold to designate underserved census tracts (Conway et al., 2023). We implement a Regression Discontinuity (RD) design that compares lending in neighborhoods just below and above this income threshold, allowing for the identification of the shadow cost of CRA violation for each bank based on differences in lending behavior.

Leveraging this design, we find a 2% increase in banks' mortgage supply in LMI census tracts compared to non-LMI tracts around this threshold. Importantly, the estimated shadow costs of CRA violation significantly vary across banks, which correlates with measures of bank expansion activities, such as mergers and branch growth. 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.

Relying on the same RD design, we confirm the second model promise by examining how the CRA regulation affects risk-adjusted prices. In particular, having shown that the lending volume increases in the under-served neighborhood, if the prices also went up after adjusting for loan default risk, that would imply higher profit margins on loans to under-served regions, violating the model assumption that complying with the CRA is costly for banks. Instead, we find that the risk-adjusted mortgage rates are lower in census tracts with MFI just below the 80% threshold compared to those just above. The results are consistent with the model premise that the CRA regulation lowers the profit margins on loans to under-served neighborhoods.

We next empirically examine the extent to which CRA compliance costs lead to negative effects. Our model shows that in a prosperous region, CRA regulation facilitates lending to underserved neighborhoods, thereby reducing lending disparities. In this scenario, a bank with a higher shadow cost of CRA violation lends more than others. However, when CRA compliance costs increase, banks opt to close branches to avoid these expenses. In such circumstances, a bank with a higher shadow cost of CRA violation opens fewer branches and lends less compared to others. Empirically, exploiting cross-sectional variation by comparing the branching and lending decisions of banks with different shadow costs of CRA violation may lead to biases caused by correlation with other bank characteristics. To overcome this challenge, we exploit the transformative shift in the banking sector—the rise of shadow banks—which presumably results in time series variation in the CRA regulatory compliance cost. As our model illustrates, for any given level of banks' shadow cost of CRA violation, a decline in the demand for bank credit leads to a higher compliance cost. As the regulatory compliance cost increases sufficiently, banks with higher shadow costs of CRA violation are first in line to close branches.

We leverage the rise of shadow banks in the residential mortgage market, which serves as a negative shock to mortgage demand from traditional banks, increasing their CRA compliance costs. We compare the changes in branching and lending decisions of banks with different levels of shadow cost of CRA violation as the local residential mortgage markets experience an increase in the market share of shadow banks. To control for any time-varying observable and unobservable at the local level, such as demand-side fluctuations and economic fundamental variations, we include county-by-year fixed effects. Our findings indicate that, relative to banks with low shadow cost of CRA violation, those with higher cost of CRA violation close 4% more branches in response to a 10% increase in the local market share of shadow banks.[3] Moreover, we find that the impact of CRA regulation is predominantly concentrated in poor regions or regions with more minority populations, corroborating the model predictions.

We next examine the effect on small business lending to shed light on the potential real impact. Given the prevalence of relationship lending in small business lending, where branches play a crucial role, the closure of branches by banks facing high CRA violation costs could adversely affect small business lending. Conversely, a bank substitution hypothesis posits an increase in lending under similar conditions. In detail, banks confronting higher CRA violation costs might expand lending to small businesses to meet the CRA requirement. Our findings show that for banks with high CRA violation costs, a 10% rise in shadow bank market share leads to a 5% greater reduction in lending volume compared to banks with low CRA violation costs.

Having shown the impact of the CRA on individual banks, we finally evaluate the overall effect of the CRA on the regional aggregate supply of financial services that account for the possible market-level adjustments and study the implications for the real economy. For instance, could new entrants with a lesser inclination towards CRA compliance possibly pick up the slack in lending as incumbent banks close branches to bypass the CRA regulation?

As our model suggests, the regional variation in the CRA treatment intensity comes from two sources: the distribution of banks with different levels of shadow costs of CRA violation and the differences in local economic fundamentals. To measure the CRA treatment intensity across assessment areas, we implement a similar RD design at the MSA level. The estimation suggests 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 the estimated values in the top quartile. Consistent with the model prediction, CRA binding areas tend to have weaker economic fundamentals than non-CRA binding areas.

[3] The reduction in the number of branches in an assessment area can help banks reduce the likelihood of being subject to a full scope evaluation in that assessment area, as explained in Section 1.

We find that CRA binding areas tend to experience more pronounced decreases in the number of bank branches and small business lending as shadow banks expand in the local mortgage market, which led to more deteriorating local economic conditions measured by the number of business establishments and employment. Specifically, a 10% increase in shadow bank growth results in a 2% reduction in small business loans in CRA binding areas compared to non-binding areas. This effect is stronger in LMI census tracts than in non-LMI census tracts and is more pronounced for loans to firms with less than $1 million in revenue. Consequently, the number of business establishments and employment decline more in CRA binding areas as shadow bank market share in local mortgage origination increases. The negative real impact concentrates in LMI census tracts. This finding underscores that the departure of banks goes beyond the mortgage market and extends to wider economic ramifications.

Taken together, the market-level results suggest that the rise of shadow banks makes it costlier for banks to comply with the CRA. This shift leads some areas that previously benefited from the CRA to suffer, as banks close branches to bypass regulation. Market forces do not make up for the reduction in subsidized bank credit, resulting in real consequences. Importantly, the above regime shifts are more likely to happen in CRA binding areas, the economically disadvantaged areas that the CRA aims to assist.

Related Literature Our paper contributes to the literature that studies the consequences of transformative 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 between services provided by banks and 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.

Our paper also contributes to the debate about the effect of the CRA. 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.[4] Regarding the unintended consequences of the CRA, Cespedes et al. (2023) document that some banks near the new $250M asset threshold strategically reduced their asset growth to avoid increased regulatory burdens, negatively impacting mortgages, small business shares, and independent innovation. We contribute to this debate by underscoring that a significant paradox of the CRA. Moreover, to the best of our knowledge, this paper is the first to show that the rise of shadow banks increases the CRA compliance cost for banks, making some areas transition from benefiting to suffering under the CRA as banks close branches to avoid regulation.

Finally, we contribute to the literature on the significance of geographic proximity, distance, and the role of branches in shaping credit allocation. The traditional banking business is local, in which branches play a crucial role in promoting financial inclusion and local economic development.[5] As financial technology advances, banking has been undergoing a digital transformation, which provides alternative ways to access banking services. Yet, a 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).

[4]Although not closely related to the focus of our paper, the literature also examines the effect of the CRA 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) and Avery and Brevoort (2015) find no evidence of increased risk taking due to the CRA.

[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); Allen et al. (2021).

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 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 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 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).

[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.

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 areas 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.

1.2 CRA Exam and the Relevance for Banks

To comply with the CRA, banks undergo a comprehensive examination involving lending, investment, and service tests. The lending test, which plays a major component in the CRA evaluation, primarily focuses on evaluating loans, mainly mortgages and small business loans, reported in HMDA and CRA disclosure statements.[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 may encounter restrictions on branch expansion, participating 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.

[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 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 benefit and the cost of the CRA regulation. This model also serves as motivation for the empirical design.

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 fundamental, where a smaller β typically reflects 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:

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

[8] This setup is isomorphic to a monopolistic competition, in which banks offer differentiated products. 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.

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, operating 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 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, we consider a counterfactual scenario without the CRA regulation, i.e., setting $\delta = 0$ in the baseline model. The optimal lending and branching

[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.

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 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 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 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 on bank lending thus depends on whether the regulatory cost is sufficiently high to

[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, $\Delta\pi' - \Delta\pi = \delta(\bar{L} - \frac{\alpha+\alpha_1+\gamma+\frac{1}{2}\delta}{2\beta}) > 0$.

lead to branch closure, as characterized below:

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

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 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 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 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) (c) hold the same 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, as suggested by the positive difference between L_1^* and $L_1^{*'}$. In other words, in areas with strong economic fundamental, the CRA increases lending to the underserved neighborhood, 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 under the CRA. This result underscores a 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, 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 leads to 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 area.

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 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 and employment 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 coinciding with the rise of shadow banks focuses on the period from 2011 to 2017. Table 1 provides summary statistics for key variables. Some important statistics to highlight are that our sample exhibits a right-skewed bank size distribution, with a mean asset value of $7 billion and a median value of $510 million; and the average bank in our sample maintains 4.72 branches per county.

[14] Purchase mortgages also contribute to CRA ratings.

[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.

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 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 receive lower risk-adjusted returns in the under-served neighborhood to satisfy the CRA requirement, which implies that complying with CRA is costly for banks.[18]

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 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 promise 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 the CRA 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., $\alpha_1 =$

[18]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.

α_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:

$$\log(\text{Loans})_{b,i,t} = \hat{\delta}_b \mathbb{1}(\text{LMI}_{i,t}) + \beta_{b,1}(\text{MFI}_{i,t} - 80\%) + \beta_{b,2}\mathbb{1}(\text{LMI}_{i,t}) \times (\text{MFI}_{i,t} - 80\%) + \gamma_{m,t} + \epsilon_{b,i,t}, \tag{10}$$

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 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.[19] $\gamma_{m,t}$ 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 2005 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 $\frac{PCI_m}{PCI_{US}}$.[20] 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, or the shadow cost of CRA violation for bank b.

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

[20] The following example helps illustrate our approach. Assume that a bank has branches in two assessment areas, X and Y, and these two areas have different β. We can estimate $\frac{\delta_b}{2\beta_X}$ and $\frac{\delta_b}{2\beta_Y}$ based on observed lending in these two areas. To account for variations in β_j, we average $\frac{\delta_b}{2\beta_X}$ and $\frac{\delta_b}{2\beta_Y}$ with a weight $\frac{\beta_j}{\beta_{US}}$, where β_{US} is the average β across the US (average PCI across the US in our case). This approach gives us $\frac{\delta}{2\beta_{US}}$ as the measurement for the shadow cost of CRA violation for bank b. Since δ_b is scaled by the same β_{US}, the estimates are comparable across banks.

Identifying Assumption, Design Validity, and Placebo The key identifying assumption of the RD design is that tracts with MFI around 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 80% cutoff for various demographic variables.[21] 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 of population, demographics, and 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 CRA regulations.

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. This adjustment is 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 (±13%, ±15%, and ±17%) in our local polynomial regression estimates. The estimates suggest that banks' mortgage supply increases by 1.7%-1.9% 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

[21]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.

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. We classify banks in the top quartile of $\hat{\delta}_b$ 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 $\hat{\delta}$.

Table 4 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. The findings suggest that smaller and growing banks have higher costs of CRA violation. Specifically, column 1 shows a strong negative correlation between CRA violation cost and bank size. Our estimate primarily reflects the extent to which banks depend on mortgage loans to comply with CRA regulations. Consequently, larger banks may exhibit smaller effects for several reasons. Firstly, big banks often provide a wider array of financial services beyond just mortgages, allowing them to comply with the CRA regulation using other types of community investments. Secondly, smaller banks face a greater change in regulatory burden upon failing the CRA test. Typically, institutions with total assets exceeding 250 million are subjected to examinations every 1-2 years, irrespective of their rating. In contrast, smaller banks usually undergo these examinations every 4-5 years. However, if they receive a rating of 'needs to improve' or lower, the frequency of examinations increases to an annual basis.

Columns 2-8 examine other factors while controlling for bank size. Column 2 shows a significant positive correlation between receiving a satisfactory or outstanding CRA rating and high $\hat{\delta}$. Columns 3 and 4 present positive correlations between our measure of CRA violation cost and an indicator for whether a bank engaged in any mergers and acquisitions (M&A) as well as 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. Last, ROA, loan portfolio performance, and bank profitability are not correlated with our measure of CRA violation cost (columns 5-8).

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. Having shown that the lending volume increases in LMI neighborhoods, if loan rates also went up after adjusting for loan default risk, this would imply higher profit margins on loans to LMI regions, violating the model assumption that complying with the CRA is costly for banks.

We exploit the same CRA discontinuity and estimate the following loan-level specification using the CoreLogic LLMA data from 2005 to 2008:[22]

$$r_i = \beta_0 \mathbb{1}(\text{LMI}_i) + \beta_1(\text{MFI}_i - 80\%) + \beta_2 \mathbb{1}(\text{LMI}_i) \times (\text{MFI}_i - 80\%) + X_{i,t}\Gamma + \epsilon_i. \tag{11}$$

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 that miss 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 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).[23]

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

[22] 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.

[23] 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.

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 difference in driving mortgage rates, our above analysis uses risk-adjusted mortgage rates. The findings suggest banks lowering the rate for a given risk level to expand lending for the CRA. Another possible practice is to expand credit provision by lowering the lending standard. While this alternative practice would generate the same set of predictions,[24] 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.[25]

5 The Impact of the CRA on Banks' Branching and Lending Decisions

As shown in Section 2, in a strong economy with high loan demand, CRA regulation facilitates lending to underserved neighborhoods. In this case, a bank with a higher shadow cost of CRA violation lends more than others. Conversely, when compliance costs escalate—such as when the rise of shadow banks crowds out bank lending—banks opt to close branches to avoid these expenses, resulting in a disproportionate cut in lending to underserved neighborhoods. In such circumstances, a bank with a higher shadow cost of CRA violation opens fewer branches and lends less than other banks.

We empirically examine the extent to which CRA compliance costs in the current economy lead to negative effects. This section focuses on the impact on individual banks' deci-

[24]There are various reasons for why banks might not lend to riskier borrowers in the absence of the CRA, such as adverse selection, regulatory constraint, 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.

[25]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, credit score of the borrower, and 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.

sions, while the subsequent section will explore market-level effects that account for entry and substitution, or the lack of it, among heterogeneous banks.

5.1 Empirical Design

Lemma 1 states that the economic burden imposed by the CRA regulation is more likely to lead to a branch closure of banks facing a higher cost of CRA violation (i.e., a higher δ). Empirically, exploiting cross-sectional variation by comparing the branching and lending decisions of banks with different δ may lead to biases caused by correlation between δ and other bank characteristics. To overcome this challenge, we exploit the transformative shift in the banking sector—the rise of shadow banks—which presumably results in time series variation in the CRA regulatory compliance cost.[26]

As depicted in Equation (6), a decrease in the fundamental demand for bank credit, indicated by a lower α, results in higher compliance costs for any given level of a bank's shadow cost of CRA violation. We interpret the emergence of shadow banks as a negative shock to the demand for bank mortgage loans, thus amplifying the regulatory cost. As the regulatory compliance cost increases sufficiently, banks with higher δ are first in line to closure branches because they face higher shadow costs of CRA violation.[27]

We compare the changes in branching and lending decisions of banks with different estimated costs of CRA violation as the local areas experience the rise of shadow banks:

$$Y_{b,c,t} = \beta \text{SBank Share}_{m,t} \times \text{High } \hat{\delta}_b + \mu_b + \nu_{c,t} + \epsilon_{b,m,t}, \tag{12}$$

The testing sample spans from 2011 to 2017, the period of time witnessing rapid shadow bank growth (Buchak et al., 2018b). $Y_{b,c,t}$ represents the outcome variable at the bank-county-year level.[28] High $\hat{\delta}_b$ is an indicator for whether the estimated $\hat{\delta}_b$ falls within the top

[26]The expansion of shadow banks stands out as the most significant transformation in the mortgage market landscape in recent decades. 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]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.

[28]We measure outcome variables at the county level because the geographic scope of a county remains consistent

quartile among all banks. $\hat{\delta}_b$ is estimated using data from 2005-2008, so that the estimates are not contaminated by contemporaneous bank actions. We show in Figure A2 that $\hat{\delta}_b$ remains a valid predictor for the shadow cost of CRA violation during the analysis period. SBank Share$_{m,t}$ denotes the market share of shadow banks in the mortgage origination market in assessment area m in year t, which is calculated as the fraction of home purchase loans in assessment area m originated by independent non-depository financial institutions in year t. The specification incorporates bank fixed effects, μ_b, and assessment area by year fixed effects, $\nu_{c,t}$. We cluster standard errors at the assessment area level.

In this specification, any observable and unobservable time-varying variations at the assessment area level (e.g., demand-side fluctuations, economic fundamental variations) are all absorbed by the $\nu_{c,t}$ fixed effects. Thus, the specification mainly compares outcome variations across banks with different levels of $\hat{\delta}_b$ under fluctuating regulatory costs, enabling an empirical test of Lemma 1.

5.2 Impact on Banks' Branching Decisions

We begin by examining the impact of the CRA on banks' branching decisions as shadow banks grow in the residential mortgage market. Panel A in Table 5 presents the results. Column 1 corresponds to Specification (12). The estimated coefficient suggests that relative to banks with low CRA violation costs, banks with high CRA violation costs close 4.2% more branches in response to a 10% increase in the local shadow banks' market share.[29]

Since the shadow cost of CRA violation is negatively correlated with bank size as discussed in Section 4.2, one may be concerned about the above result being driven by differential responses to the rise of shadow banks across bank sizes. We show in columns 2-4 that the result in column 1 is robust to comparing banks with similar sizes. In column 2, we add the interaction between the pre-treatment asset size of a bank and local shadow bank share as a control. In columns 3 and 4, we further divide the full sample based on whether

throughout the sample period, whereas the geographic scope of assessment areas change over time, especially the assessment areas defined based on MSAs. This is because the geographic scope of an MSA changes over time. For example, some census tracts could belong to one MSA in earlier years of our sample period while belong to another 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.

[29] The magnitude of the impact is calculated using the formula $(\exp(-0.538) - 1) \times 100\% = 0.42$, which corresponds to the impact of a 100% increase in shadow bank share. In this calculation, -0.538 is the estimated coefficient in column 2 of Table 5. We apply the same formula in interpreting the coefficients in all future specifications with dependent variables in a logarithmic scale.

the average asset size of a bank during our sample period is below or above $1 billion. We achieve the same qualitative conclusion. In addition, the subsample analysis suggests that conditional on size, smaller banks with high shadow cost of CRA violation are more likely to close branches in response to the rise of shadow banks, compared to those larger counterparts. The finding is consistent with the finding in Table 4 that smaller banks rely more on mortgage lending to satisfy the CRA requirement, while larger banks could also meet the CRA requirement by other types of community investments.

Next, we 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 minority tend to be associated with weaker economic fundamentals, which allows us to test Lemma 2. Second, the initial motivation of creating the CRA was to address the issue about redlining which tended to target the poorest communities and communities of color.[30] Analyzing the effect heterogeneity along these two dimensions sheds light on whether the regulation distorts the allocation of financial services in a manner aligned with the intended objectives.

We categorize counties into sub-groups based on average income per capita and share of minority population. Panel B in Table 5 presents the findings. The results suggest that the effect of CRA regulation on bank branches is predominantly observed in economically disadvantaged areas and those with a higher proportion of minority populations. Specifically, in poorer counties, defined as those with an average income per capita from 2011 to 2017 not in the top quartile among all counties, banks with high CRA violation costs close about 2.2% more branches, compared to those with low CRA violation costs when the shadow bank market share increases by 10% (column 2). In contrast, in wealthier counties, the difference in branch closures between these two types of banks is not statistically significant (column 1). Similarly, in counties with a larger minority population, the branch closure rate in response to a 10% rise in shadow bank market share is about 2.3% higher for banks with high CRA violation costs compared to those with low costs, whereas this difference is not statistically significant in predominantly white counties.

Overall, the findings presented in this section corroborate the model predictions, implying that banks face a trade-off between the costs associated with CRA regulation and the benefits

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

of maintaining 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 from the local market by closing branches.

5.3 Spillover Impact on Small Business Lending

We next examine the effect on small business lending to shed light on the potential real impact of the mechanism we identified in the previous section. Conceptually, the effect on small business lending could be either positive or negative. On 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 (referred to as the *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 business to meet the CRA requirement. This *bank substitution channel* predicts a potential positive effect on small business lending.

To empirically examine this question, we estimate specification (12) for small business lending volume in dollars and the number of small business loans originated by banks, with Table 6 presenting these results. The estimate of -0.668 in column 1 shows that for banks with high CRA violation costs, a 10% rise in shadow bank market share leads to a 5% greater reduction in lending volume compared to banks with low CRA violation costs. A comparable effect is seen in loans to firms with revenues under $1 million (column 2), and this pattern is consistent in the analysis of loan numbers, as indicated in columns 3 and 4.

Taken together, the results in this section suggest that under the CRA regulation, there is a reduction in bank small business lending as shadow banks expand, indicating that the *branch closure channel* dominates the *bank substitution channel*.

6 Regional Effects and Real Implications

Having demonstrated the impact of the CRA on individual banks, we now evaluate its broader effect on regional aggregate supply of financial services, which accounts for the potential market-level adjustments, and study the implications for the real economy. For instance, could new entrants that are less committed to adhering to the CRA pick up the slack in lending as incumbent banks close branches to bypass the CRA regulation?

6.1 Measuring Areas' CRA Binding Degree

As our model suggests, the regional variation in the intensity of CRA treatment comes from two sources: firstly, the distribution of banks with varying levels of shadow costs of CRA violation and secondly, difference in local economic fundamental. To quantify the treatment intensity of the CRA regulation, 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 model using all newly originated home purchase loans by banks in a region:

$$\begin{aligned} \log(\text{Loans})_{i,m,t} = \hat{\eta}_m \mathbb{1}(\text{LMI}_{i,m,t}) + \beta_{b1}(\text{MFI}_{i,m,t} - 80\%) \\ + \beta_{b2} \mathbb{1}(\text{LMI}_{i,m,t}) \times (\text{MFI}_{i,m,t} - 80\%) + \nu_t + \epsilon_{i,m,t}, \end{aligned} \tag{13}$$

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 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 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 $\hat{\eta}_m$ in the top quartile. Panel A of Figure 5 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, smaller population sizes, reduced lending activity, and lower income per capita.

6.2 Impact on Branches and Small Business Lending

With the estimated treatment intensity of the CRA, we proceed to estimate the effects of the CRA on the supply of financial services, in which we focus on the total number of branches and the aggregate small business lending at county-level:[31]

$$Y_{c,t} = \beta_1 \text{SBank Share}_{m,t} \times \text{CRA Binding Area}_m + \beta_2 \text{SBank Share}_{m,t} + X_{m,t}\Gamma + \mu_c + \nu_t + \epsilon_{c,t}, \tag{14}$$

where CRA Binding Area_m equals 1 if the estimated effect of CRA regulation on bank lending in market m ($\hat{\eta}_m$) falls within the top quartile among all markets.

Table 7 shows that CRA binding areas see more bank branch closures as shadow banks expand in local mortgage markets. In column 1, we observe that relative to non-CRA binding areas, CRA binding areas experience a 1% more branch closures as shadow bank market share increases by 10%. This net estimate remains consistent when we include local covariates such as population, GDP, and income per capita in column 2. We obtain consistent results when examining the number of branches per capita in columns 3 and 4.

In the wake of branch closures, there is a noticeable contraction in small business lending, as shown in Table 8, in which we estimate Specification 14 with the outcome variable being small business lending in a county. Following the literature, we define small business lending as business loans with loan amount less than $1 million (columns 1-3) or loans to businesses with annual revenues below $1 million (columns 4-6). In column 1 (column 4), we find that a 10% rise in the shadow bank market share in local mortgage origination is associated with an additional 2% (4%) decrease in small business loans within CRA binding areas, relative to non-binding areas.

The findings align with Lemma 3, suggesting 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. Moreover, our model

[31] 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.

predicts that in areas undergoing such regime shifts, both underserved and non-underserved neighborhoods experience increased lending reductions from branch closures, with previously subsidized underserved areas most impacted. The subsample analysis in columns 2 and 3 (columns 5 and 6) corroborates this prediction. Specifically, we conduct separate estimations for LMI neighborhoods and non-LMI neighborhoods.[32] As shadow banks expand, lending to both LMI and non-LMI neighborhoods declines more substantially in CRA binding areas that in non-binding areas, with a more marked decrease in LMI neighborhoods.

6.3 Real Implications

Finally, we study the implications for real economy. As lending is geographically segmented (Becker, 2007; Petersen and Rajan, 2002), a decrease in local credit supply could hinder local business growth. We obtain county-level real outcomes from the Business Dynamics Statistics provided by the U.S. Census Bureau and estimate specification (14) for the number of business establishments and the number of employees.

Table 9 presents the results. A 10% increase in the shadow bank market share in mortgage origination is associated with a 0.6% decrease in the number of establishments in a CRA binding area relative to a non-CRA binding area (column 1). The reduction in the number of business establishments is accompanied by the reduction in employment. As shadow bank market share increases by 10% in local mortgage origination, the number of employees decreases by 1.0% in CRA binding areas, relative to non-CRA binding areas.

Notably, this effect is concentrated and significant only in LMI neighborhoods, as shown in the subsample analysis results in columns 2 and 3 as well as in columns 5 and 6.[33] The results are consistent with the narrative that the market forces enable non-underserved neighborhoods to preserve their existing economic condition through alternative credit sources. However, the expansion of shadow banks does not appear to pick up the slack in *subsidized* bank credit in the underserved neighborhoods.

Taken together, the results in this section suggest that the rise of shadow banks makes it costlier for banks to comply with the CRA, leading to a regime shift in some areas. These

[32] The estimation remains at the county-level, but we group all LMI (non-LMI) census tracts within a county. Thus, in columns 2 and 5 (3 and 6), the outcome variables are the total lending to the LMI (non-LMI) census tracts of a county.

[33] Since we do not observe census tract level real outcomes, we define LMI neighborhoods of an assessment area as counties with the share of population in LMI census tracts exceeding the sample median.

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 which 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 CRA binding areas, the economically disadvantaged regions that the CRA aims to support.

7 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 and lower employment. These findings underscore a paradox inherent in the CRA, which is further intensified by the growth of shadow banks: while the CRA promotes equal credit access in economically robust areas, it adversely affects economically disadvantaged regions where banks shut down branches to bypass the CRA. 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.

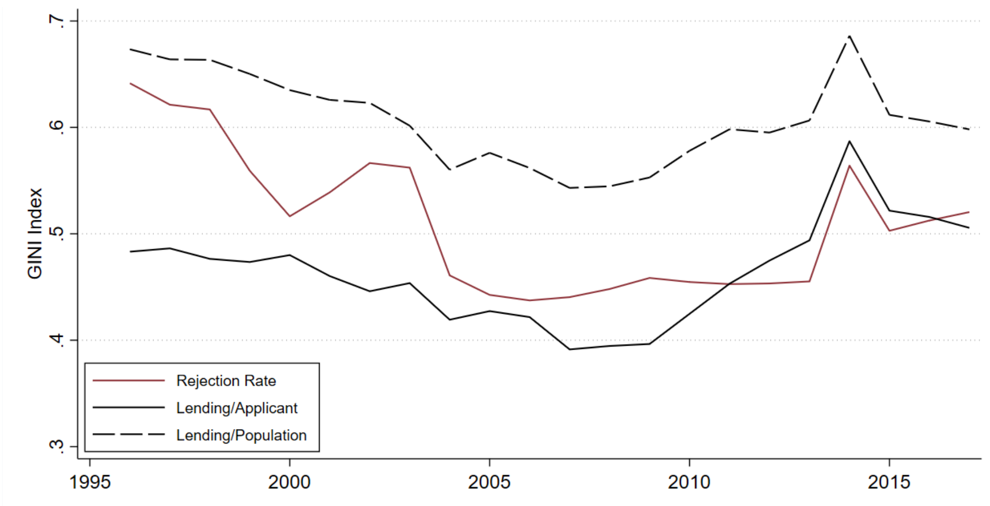
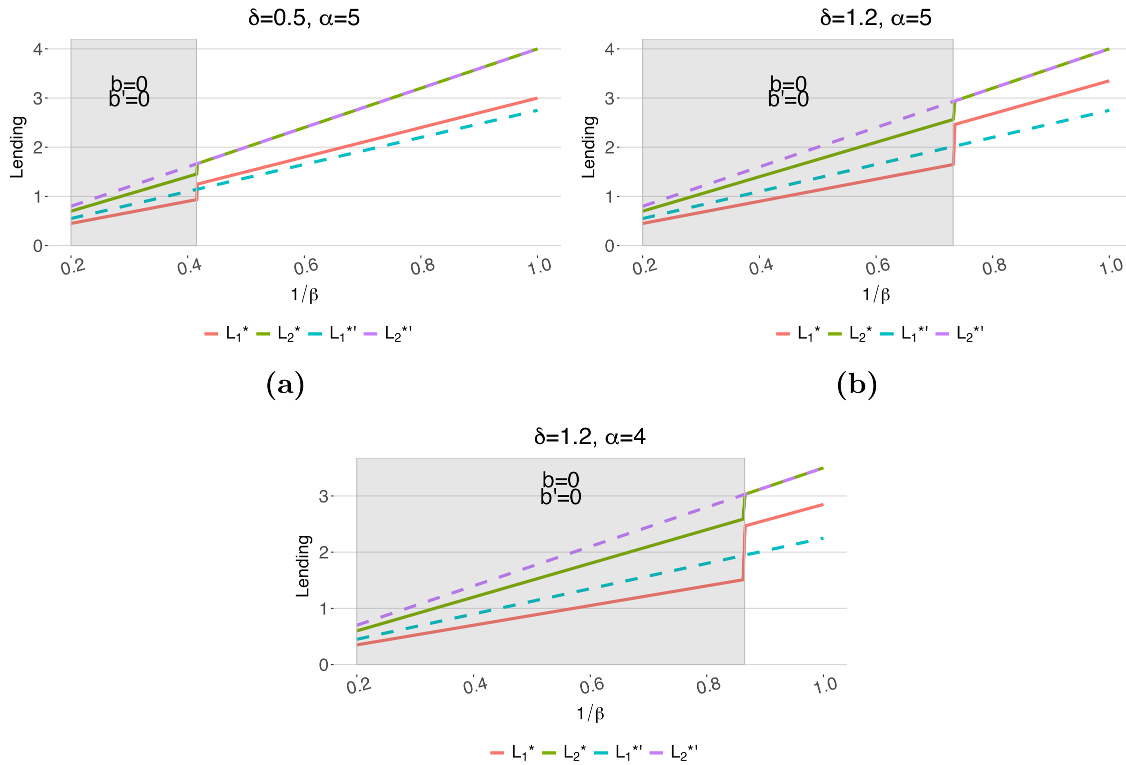


Figure 2. Model Illustration

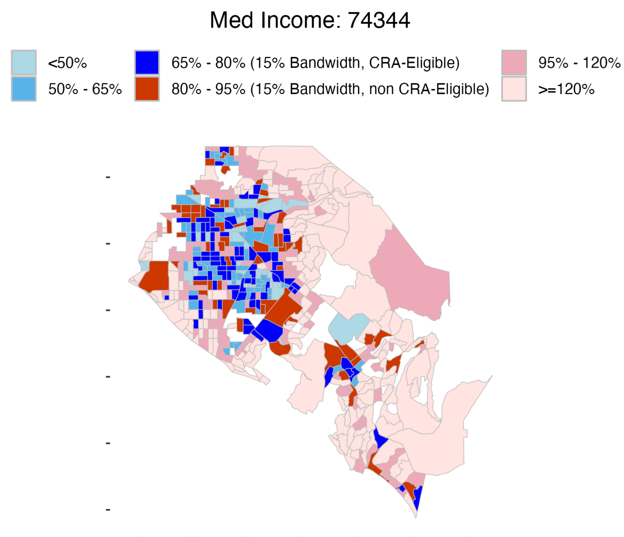
This figure graphically illustrates the model predictions by plotting lending (y-axis) against economic fundamental ($\frac{1}{\beta}$, x-axis). Panels (a) and (b) hold the same all other parameter values except for the level of shadow cost of CRA violation (δ). Panels (b) (c) hold the same all other 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 $\bar{L} = 6.5$.



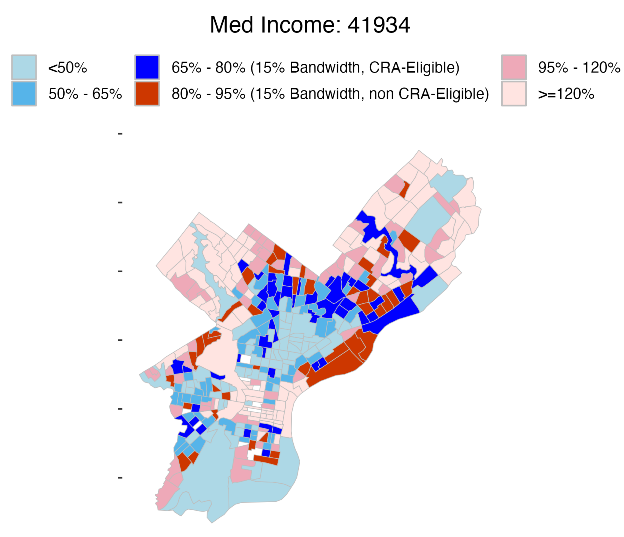
(a) (b) (c)

Figure 3. Examples of Tract Income and CRA Elibigiltiy 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.



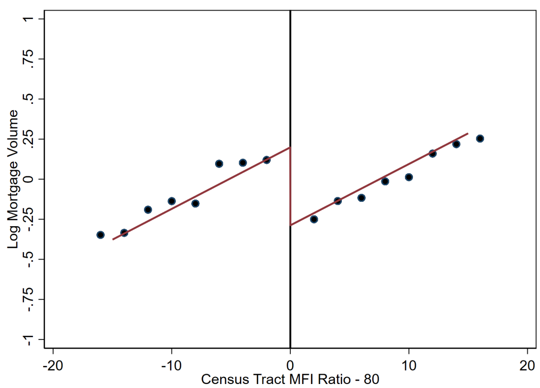
(a) Orange County



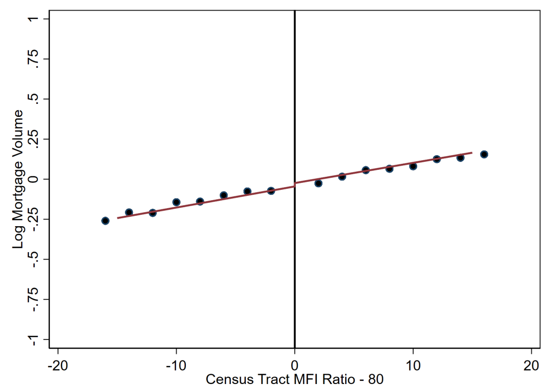
(b) Philadelphia County

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

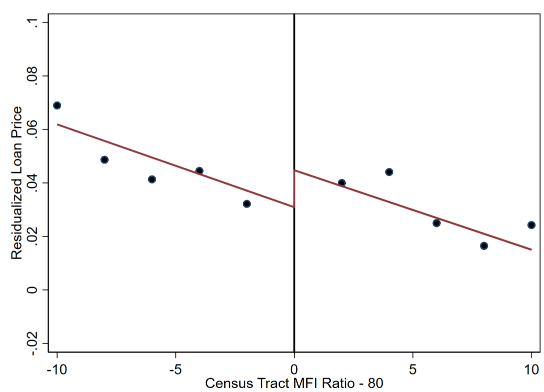
This figure depicts the discontinuity of lending volume and loan prices around the 80% median family income (MFI) threshold. The y-axis in panels (a) and (b) correspond to the logarithm of total lending, which includes both originated and purchased home-purchase loans. The y-axis in panel (c) corresponds 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 $\hat{\delta}$ in the top quartile, and Panel (b) uses the subsample of banks with $\hat{\delta}$ not in the top quartile. 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 $\hat{\delta}$



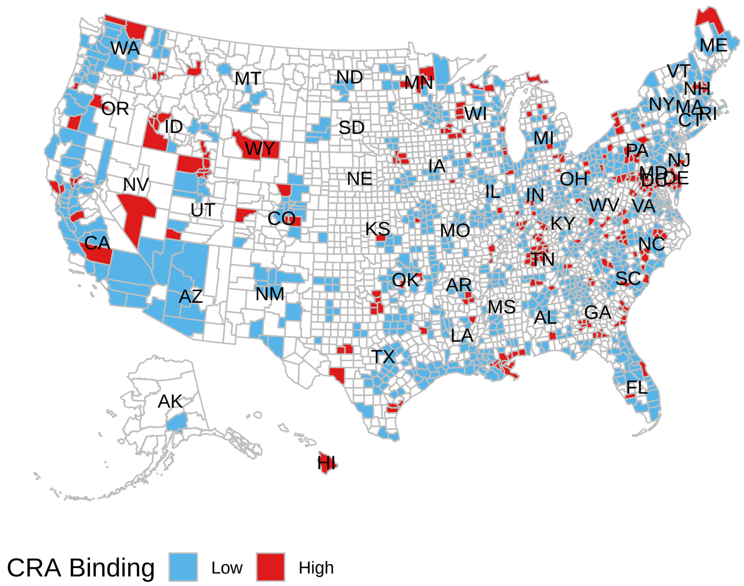
(b) Total Lending for non-High $\hat{\delta}$



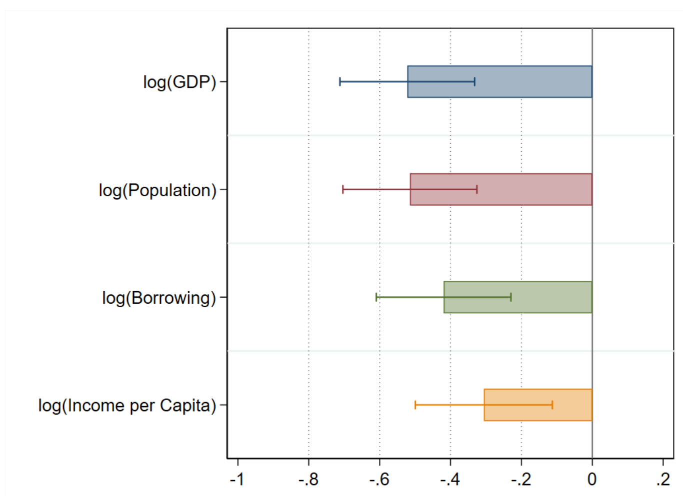
(c) Loan Pricing for Full Sample

Figure 5. 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 7. An MSA region is classified as a CRA binding area ("high" in the map) if the estimated η_m is in the top quartile 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 CRA binding dummy. 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, is a bank-county-year in Panel B, is a loan in Panel C, is a county-year in Panel D, and is 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 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 RD design's running variable 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:

$$\log(\text{Loans})_{b,i,t} = \hat{\delta}\mathbb{1}(\text{LMI}_{i,t}) + \beta_1(\text{MFI}_{i,t} - 80\%) + \beta_2\mathbb{1}(\text{LMI}_{i,t}) \times (\text{MFI}_{i,t} - 80\%) + \mu_b + \nu_{m,t} + \epsilon_{b,i,t}$$

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. Standard errors are clustered at the level of the assessment area-year. Numbers in parentheses represent standard errors.*, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	[-17,+17]		[-15,+15]		[-13,+13]	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(LMI)	0.017**	0.017**	0.018**	0.018**	0.019*	0.019*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
MFI-80	0.016***	0.017***	0.016***	0.016***	0.017***	0.017***
	(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	0.379	0.383	0.378	0.382	0.378	0.381
Observations	361095	360369	312609	311873	266107	265362

Table 3 CRA Effect on Loan Pricing

This table presents the results of regression discontinuity (RD) analysis on banks' loan pricing. As the loan pricing data records only zip code information, we aggregate census tract median family income (MFI) to zipcode 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:

$$Y_i = \beta_0 \mathbb{1}(\text{LMI}_i) + \beta_1(\text{MFI}_i - 80\%) + \beta_2 \mathbb{1}(\text{LMI}_i) \times (\text{MFI}_i - 80\%) + X_i \Gamma + \mu_{c,t} + \epsilon_i$$

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 zipcodes 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 zipcodes 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 that miss 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 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. 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 the level of the assessment area-year. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at 10%, 5% and 1% level, 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 The Shadow Cost of CRA Violation and Bank Characteristics

This table presents results about the relation between the shadow cost of CRA regulation and bank characteristics. Each estimate corresponds to a separate regression of the following form:

$$\text{High}\,\hat{\delta}_b = \beta_1 \text{Bank Characteristic}_b + \beta_2 \text{Assets}_{b,2004} + \epsilon_b,$$

where $High\,\hat{\delta}$ is an indicator variable for whether the bank has a $\hat{\delta}_b$ in the top quartile. Assets correspond to the mean total assets measured between 2005 and 2008. CRA passing rating corresponds to the average of an indicator variable for whether the bank obtained at least a "Satisfactory" CRA rate 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. 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. Variables are standardized to have unit variance and winsorized at the 1% level. Hetroskedasticity-robust standard errors are reported in parentheses. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	High $\hat{\delta}_b$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Assets	-0.047***							
	(0.01)							
CRA passing rating		0.020**						
		(0.01)						
Merger			0.059*					
			(0.04)					
Branch Growth				0.034**				
				(0.02)				
Roa					0.024			
					(0.02)			
Charge off ratio						-0.017		
						(0.02)		
Non performing ratio							-0.017	
							(0.02)	
Profitability								-0.003
								(0.02)
$\text{Assets}_{b,2004}$		-0.044***	-0.055***	-0.048***	-0.048***	-0.045***	-0.048***	-0.048***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Adjusted R^2	0.010	0.011	0.013	0.016	0.012	0.011	0.011	0.009
Observations	753	628	753	753	753	753	753	753

Table 5 Rise of Shadow Banks, Shadow Cost of CRA Violation, 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:

$$\log(\text{Branch})_{b,c,t} = \beta_1 \text{SBank Share}_{m,t} \times \text{High } \hat{\delta}_b + \beta_2 \text{SBank Share}_{m,t} \times \text{Assets}_{b,2010} + \mu_b + \nu_{c,t} + \epsilon_{b,m,t}$$

$\text{Branch}_{b,c,t}$ is the number of branches bank b has in county c in year t. $\text{SBank Share}_{m,t}$ is the market share of shadow banks in the mortgage origination market in assessment area m in year t. $\text{Assets}_{b,2010}$ is the total asset size in 2010, standardized to have unit variance. High $\hat{\delta}_b$ is an indicator for whether the estimated shadow cost of the CRA regulation for bank b ($\hat{\delta}_b$) is in the top quartile 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. Panel A presents results for the full sample in the first three columns and sub-samples based on average asset size during our sample period in the last two columns. Panel B presents results for sub-samples based on assessment area characteristics. Column 1 is restricted to a subsample of rich counties, defined as those with an average income per capita above the top quartile during 2011-2017, whereas column 2 concentrates on the remaining counties. Column 3 focuses on a subsample of non-minority counties, characterized by an average minority population share below the bottom quartile during 2011-2017, while column 4 examines the remaining counties with a higher proportion of minority residents. Standard errors are clustered at the level of the assessment area-year. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

Panel A: Full Sample Analysis

	log(Branch)			
	Full Sample	Full Sample	Asset <1 Billion	Asset ≥1 Billion
	(1)	(2)	(3)	(4)
SBank Share× High $\hat{\delta}_b$	-0.538***	-0.232***	-0.560**	-0.283***
	(0.07)	(0.07)	(0.24)	(0.08)
SBank Share× $\text{Assets}_{b,2010}$		0.084***	0.254**	0.123***
		(0.01)	(0.12)	(0.01)
Bank FE	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓
Adjusted R^2	0.466	0.470	0.517	0.485
Observations	85577	85577	6993	73200

Panel B: Sub-samples Split Based On Assessment Area Characteristics

	log(Branch)			
	Rich	Poor	Non-Minority	Minority
	(1)	(2)	(3)	(4)
SBank Share× High $\hat{\delta}_b$	-0.101	-0.247*	-0.194	-0.261***
	(0.21)	(0.13)	(0.21)	(0.08)
SBank Share× $\text{Assets}_{b,2010}$	0.008	0.117***	0.044***	0.091***
	(0.01)	(0.01)	(0.01)	(0.01)
Bank FE	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓
Adjusted R^2	0.540	0.455	0.545	0.479
Observations	18921	37667	7659	77912

Table 6 Shadow Cost of the CRA and Small Business Lending

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

$$Y_{b,c,t} = \beta_1 \text{SBank Share}_{m,t} \times \text{High } \hat{\delta}_b + \beta_2 \text{SBank Share}_{m,t} \times \text{Assets}_{b,2010} + \mu_b + \nu_{c,t} + \epsilon_{b,c,t},$$

$Y_{b,c,t}$ is bank-county-year level small business lending. SBank Share$_{m,t}$ is the market share of shadow banks in the mortgage origination market in the MSA that county c belongs to. Assets$_{b,2010}$ is the total asset size in 2010, standardized to have unit variance. High $\hat{\delta}_b$ is an indicator for whether the estimated shadow cost of CRA regulation for bank b is in the top quartile among all banks. Panel A uses the full sample. The outcome variable in column 1 (3) of Panel A is the log total dollar volume (loan count) lent by bank b in assessment area m in year t. The outcome variable in column 2 (4) of Panel A is the log dollar volume (loan count) lent by bank b to firms with annual revenue below 1 million dollars in assessment area m in year t. Standard errors are clustered at the level of the assessment area-year. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	log(Dollar Volume)		log(Loan Count)	
	Total Lending	Revenue <1 Million	Total Lending	Revenue <1 Million
	(1)	(2)	(3)	(4)
SBank Share× High $\hat{\delta}_b$	-0.681***	-0.634***	-0.322***	-0.484***
	(0.10)	(0.12)	(0.08)	(0.10)
SBank Share× Assets$_{b,2010}$	0.266***	0.292***	0.294***	0.344***
	(0.01)	(0.01)	(0.01)	(0.01)
County× FE	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Adjusted R^2	0.301	0.309	0.337	0.356
Observations	185155	130325	185207	130341

Table 7 Regional Analysis — Branch Closure

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

$$Y_{c,t} = \beta_1 \text{SBank Share}_{m,t} \times \text{CRA Binding Area}_m + \beta_2 \text{SBank Share}_{m,t} + \gamma X_{m,t-1} + \mu_c + \nu_t + \epsilon_{c,t},$$

$Y_{c,t}$ is county-year level outcome variable. SBank Share$_{m,t}$ is the market share of shadow banks in the mortgage origination market in assessment area m that county c belongs to in year t. CRA Binding Area$_m$ is equal to 1 if the estimated CRA treatment intensity in assessment area m is in the top quartile among all assessment areas. The estimation procedure is described in Section 6.1. In estimating the CRA treatment intensity, we employ a 15% bandwidth to estimate local polynomials. The outcome variable in columns 1 and 2 is the logarithm of total number of branches in county c in year t. The outcome variable in columns 3 and 4 is the number of branches per thousand population in county c in year t. In columns 2 and 4, we include lagged county controls: log income per capita, log population, and log GDP in the previous year. Observations are weighted by county population size. Standard errors are clustered at the assessment area level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	log(Branch)		Branch per Thousand Population	
	(1)	(2)	(3)	(4)
SBank Share×CRA Binding Area	-0.14***	-0.13**	-0.03*	-0.03**
	(0.05)	(0.05)	(0.01)	(0.01)
SBank Share	-0.10**	-0.11**	-0.04***	-0.04***
	(0.05)	(0.04)	(0.01)	(0.01)
Controls		✓		✓
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Adjusted R^2	1.00	1.00	0.98	0.99
Observations	8604	8374	8604	8374

Table 8 Regional Analysis — Small Business Lending

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

$$SBL_{c,t} = \beta_1 \text{SBank Share}_{m,t} \times \text{CRA Binding Area}_m + \beta_2 \text{SBank Share}_{m,t} + \gamma X_{m,t-1} + \mu_c + \nu_t + \epsilon_{c,t},$$

$SBL_{c,t}$ is county-year level small business lending. SBank Share$_{m,t}$ is the market share of shadow banks in the mortgage origination market in assessment area m that county c belongs to in year t. CRA Binding Area$_m$ is equal to 1 if the estimated CRA treatment intensity in assessment area m is in the top quartile among all assessment areas. The estimation procedure is described in Section 6.1. In estimating the CRA treatment intensity, we employ a 15% bandwidth to estimate local polynomials. Columns 1-3 focus on all small business lending reported in the CRA dataset, i.e., all loans with less than 1 million origination amount. Columns 4-6 focus on loans to businesses with less than $1 million annual revenue. The outcome variable in columns 1 and 4 is the logarithm of county total dollar volume (of the corresponding loans describe above). In columns 2-3 and 5-6, the analysis remains at the county-level, but we group all LMI (non-LMI) census tracts within a county. Thus, in columns 2 and 5 (3 and 6), the outcome variables are the total lending to the LMI (non-LMI) census tracts of county c in year t. In all specifications, we include lagged county controls: log income per capita, log population, and log GDP in the previous year. Observations are weighted by county population size. Standard errors are clustered at the assessment area level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	log(Dollar Volume)					
	Loans<1 Million			Revenue<1 Million		
	Full Sample (1)	LMI (2)	Non-LMI (3)	Full Sample (4)	LMI (5)	Non-LMI (6)
SBank Share× CRA Binding MSA	-0.255*	-0.625***	-0.418***	-0.488**	-1.027***	-0.857***
	(0.14)	(0.22)	(0.15)	(0.20)	(0.29)	(0.23)
SBank Share	0.081	0.300*	0.011	0.069	0.224	0.083
	(0.11)	(0.17)	(0.13)	(0.18)	(0.21)	(0.18)
Controls	✓	✓	✓	✓		
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.994	0.972	0.990	0.988	0.962	0.984
Observations	8410	7327	8242	8409	7322	8240

Table 9 Regional Analysis — Real Outcomes

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

$$Y_{c,t} = \beta_1 \text{SBank Share}_{m,t} \times \text{CRA Binding Area}_m + \beta_2 \text{SBank Share}_{m,t} + \gamma X_{m,t-1} + \mu_c + \nu_t + \epsilon_{c,t},$$

$Y_{c,t}$ is county-year level real outcomes. SBank $\text{Share}_{m,t}$ is the market share of shadow banks in the mortgage origination market in assessment area m that county c belongs to in year t. CRA Binding Area_m is equal to 1 if the estimated CRA treatment intensity in assessment area m is in the top quartile among all assessment areas. The estimation procedure is described in Section 6.1. In estimating the CRA treatment intensity, we employ a 15% bandwidth to estimate local polynomials. The outcome variable in columns 1-3 is the logarithm of the number of establishments in county c in year t. The outcome variable in columns 4-6 is the logarithm of the number of employees. Columns 1 and 4 use the full sample of counties. In columns 2 and 3 (5 and 6), we divide the sample into two groups: counties with population share in LMI census tracts above or below the sample median ("LMI County" and "non-LMI County", respectively). In all regulations, we include lagged county controls: log income per capita, log population, and log GDP in the previous year. Observations are weighted by the county population size. Standard errors are clustered at the assessment area level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at 10%, 5% and 1% level, respectively.

	log(#Establishments)			log(#Employees)		
	Full Sample (1)	LMI County (2)	Non-LMI County (3)	Full Sample (4)	LMI County (5)	Non-LMI County (6)
SBank Share× CRA Binding MSA	-0.065**	-0.068**	-0.019	-0.108**	-0.111*	-0.011
	(0.03)	(0.03)	(0.05)	(0.06)	(0.06)	(0.12)
SBank Share	0.026	0.026	-0.002	0.087	0.086	0.063
	(0.03)	(0.03)	(0.03)	(0.06)	(0.06)	(0.05)
Controls	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Adjusted R^2	1.000	1.000	1.000	1.000	1.000	0.999
Observations	8410	6200	2005	8410	6200	2005

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.

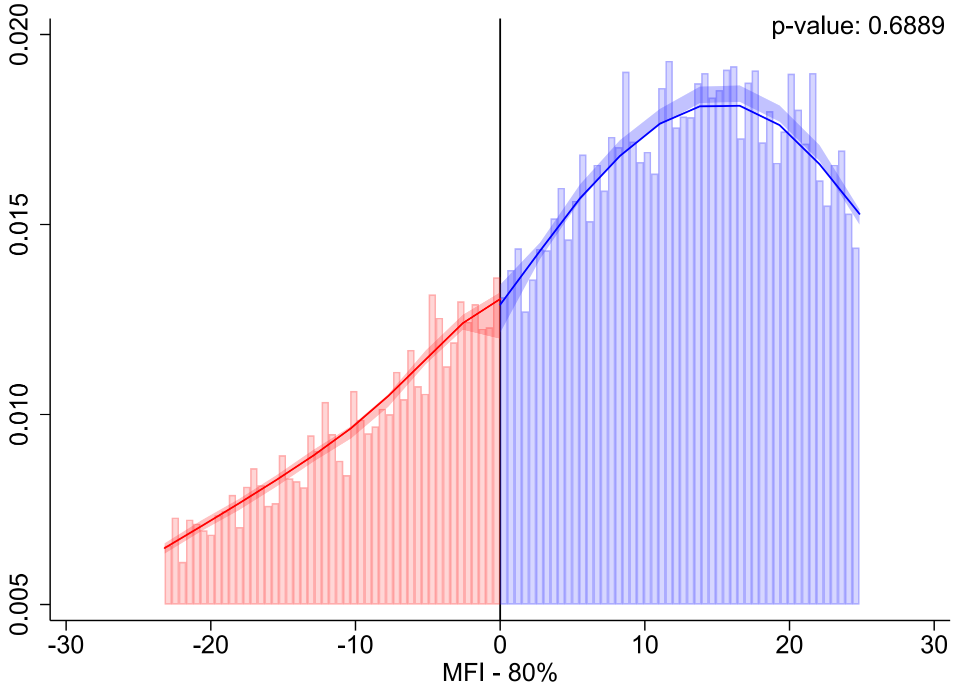


Figure A2. Shadow Cost of CRA Violation Estimation Persistence

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., quartile 1, 2, 3, or 4), and the smaller numbers next to rankings indicate the number of banks in each categories. 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.

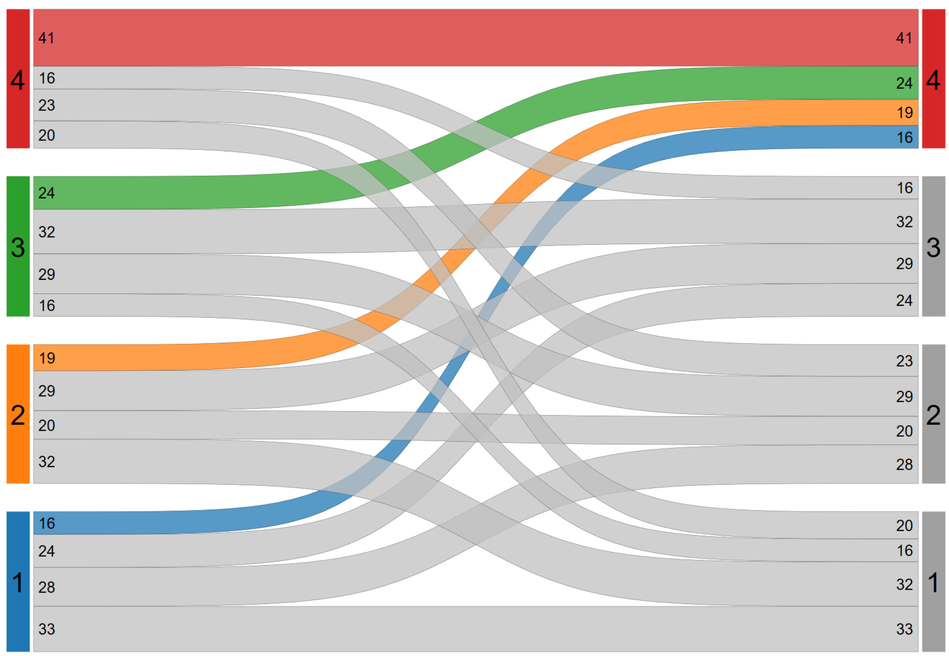


Table A1 Test of Discontinuities in Covariates before the Threshold Implementation

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 β_0 for different dependent variables for the following RD design using:

$$Y_i = \beta_0 \mathbb{1}(\text{LMI}_i) + \beta_1(\text{MFI}_i - 80\%) + \beta_2 \mathbb{1}(\text{LMI}_i) \times (\text{MFI}_i - 80\%) + \nu_c + \epsilon_i$$

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 10%, 5% and 1% level, 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 β_0 for different dependent variables for the following RD design using:

$$Y_i = \beta_0 \mathbb{1}(\text{LMI}_i) + \beta_1(\text{MFI}_i - 80\%) + \beta_2 \mathbb{1}(\text{LMI}_i) \times (\text{MFI}_i - 80\%) + \nu_c + \epsilon_i$$

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 10%, 5% and 1% level, 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 assessment area-year level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at 10%, 5% and 1% level, 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)	0.009	0.009	0.012	0.012	0.020	0.020
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
MFI-120	0.011***	0.011***	0.010***	0.010***	0.011***	0.011***
	(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***	0.006***	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	0.401	0.406	0.404	0.409	0.406	0.410
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)	0.001	-0.000	0.004	0.003	0.004	0.003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
MFI-60	0.015***	0.015***	0.015***	0.015***	0.016***	0.016***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\mathbb{1}$(MFI<60)×(MFI-60)	-0.007***	-0.007***	-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	0.389	0.394	0.390	0.395	0.392	0.396
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 atCBSA-year level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at 10%, 5% and 1% level, 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 for 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:

$$Y_i = \hat{\delta}\mathbb{1}(\text{LMI}_i) + \beta_1(\text{MFI}_i - 80\%) + \beta_2\mathbb{1}(\text{LMI}_i) \times (\text{MFI}_i - 80\%) + \nu_{c,t} + \epsilon_i$$

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 10%, 5% and 1% level, 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