Branching Out Inequality:
The Impact of Credit Equality Policies in the Non-Bank Era

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

Abstract

We show that the Community Reinvestment Act (CRA), a major policy aimed at reducing geographic inequality in credit access, can paradoxically widen disparities across regions while enhancing credit equality within certain regions. Banks strategically withdraw branches from lower-income areas to avoid CRA requirements—a response amplified by the expansion of non-bank lenders. We identify banks with higher CRA violation costs using a regression discontinuity design around the CRA eligibility threshold and show these banks retract more branches following non-bank expansion. These branch closures reduce small business lending, financial inclusion, and local economic activity in low-income areas, worsening regional economic disparities.

*Cespedes is from University of Minnesota, Carlson School of Management. cespe013@umn.edu. Jiang is from University of Southern California, Marshall School of Business. erica.jiang@marshall.usc.edu. Parra is from Pontificia Universidad Católica de Chile. parra.c.carlos.r@gmail.com. Zhang is from the UCLA Anderson School of Management. jinyuan.zhang@anderson.ucla.edu. We thank Kenneth Ahern, Tony Cookson, Sergey Chernenko (Discussant), Agustin Hurtado (Discussant), Gerard Hoberg, Emma Kalish (Discussant), Paolina Medina (Discussant), Christopher Palmer, Chris Parson, Vincenzo Pezone (Discussant), Giorgia Piacentino, Matthew Plosser (Discussant), Daniel Ringo (Discussant), Vahid Saadi (Discussant), Antoinette Schoar, Huan Tang (Discussant), Richard Thakor, Selale Tuzel, Rodrigo Wagner (Discussant), Derek Wenning (Discussant), Andrew Winton, Anthony Zhang, and the seminar participants at BYU, MIT Sloan, UC Berkeley Hass, BI Oslo, Fudan University, Federal Reserve Board, USC Marshall, Federal Reserve Bank of Kansas City, Federal Reserve Bank of Minneapolis, Federal Reserve Bank of Boston, Federal Reserve Bank of Dallas, Federal Reserve Bank of Richmond CORE week, OCC, University of Minnesota, Virtual Household Finance Seminar, and the conference participants at NBER Corporate Finance spring meeting, HEC-McGill Winter Finance Conference, Holden Conference in Finance and Real Estate, Mortgage Market Research Conference, New York Fed/NYU Stern Conference on Financial Intermediation, Minnesota Junior Finance Conference, CFPB Research Conference, BoE/Imperial/LSE Conference on non-banks, CEPR Paris Symposium, JHU Carey Finance Conference, UNC Conference on Market-Based Solutions For Reducing Wealth Inequality, Tilburg Finance Summit, Community Banking Research Conference, and Finance UC Conference. *First version: September 2023.*

Promoting equal credit access is fundamental to reducing regional economic disparities and fostering inclusive growth.[1] Governments have pursued this goal through various interventions, with one prominent approach being a regulation that governs how private sector financial institutions lend in underserved areas. The Community Reinvestment Act (CRA) in the United States exemplifies this strategy.[2] It mandates banks to serve low-to-moderate income neighborhoods within their operational territories. While these policies aim to align institutional behavior with broader socioeconomic objectives, their effectiveness depends on private sector institutions' *incentives* and *capacity* to comply while maintaining their profit-maximizing goals under market discipline. This balance has become increasingly complex as the landscape of financial intermediation rapidly evolves after the global financial crisis. This evolution has triggered ongoing debates about adapting these regulations to changes in the banking sector.[3]

To shed light on the ongoing debate, we study the economic consequences of the CRA by examining banks' geographic footprints as non-bank expansion challenges their capacity to comply with the CRA. Our findings reveal that the CRA may widen regional economic disparities as non-banks grow. While the regulation successfully expands credit supply to underserved neighborhoods in prosperous regions, it has adverse effects in economically disadvantaged areas where banks avoid establishing branches to circumvent CRA requirements. Non-bank growth amplifies this divergence. As non-banks expand, banks facing higher CRA violation costs are more likely to close branches, withdrawing from lower-income regions. These branch closures lead to subsequent declines in small business lending, financial inclusion, and local economic activity, particularly affecting less economically developed regions.

We begin by developing a parsimonious model of bank lending under the CRA regulation. The policy requires banks to provide adequate lending to underserved neighborhoods in areas where they operate branches. Banks face a key tradeoff when deciding whether to establish branches: they must weigh the costs of extending credit beyond optimal levels in underserved neighborhoods against the benefits of maintaining branches to serve the entire area. When

[1] See, for example, Jayaratne and Strahan (1996), Black and Strahan (2002), Chodorow-Reich (2014), Beck et al. (2010), and Chen et al. (2017).

[2] Examples include India's Priority Sector Lending program and Brazil's National Partnership for Financial Inclusion program. In the US, interventions are also implemented through the mortgage market only; for instance, Hurst et al. (2016) discusses how GSEs' national borrowing rate policy results in cross-regional transfers via implicit government subsidies.

[3] For example, the CRA reform to adapt the regulation to address digital banking and non-bank lending was initially planned for April 2024 but postponed to January 2026 for additional public comments due to disagreements.

benefits exceed costs, banks increase lending to underserved neighborhoods above what they would provide without the CRA. However, when costs outweigh benefits, banks strategically withdraw from an area by closing branches to avoid CRA requirements altogether. Since this strategic withdrawal is more prevalent in economically weaker areas, the CRA may widen regional disparities, hurting the very regions the policy aims to help.

The key premise that the theoretical predictions rest on is the material cost of CRA violation, providing banks with an incentive to foster lending to underserved neighborhoods. Indeed, failing to comply with CRA regulations hinders banks from opening new branches and participating in mergers and acquisitions, but the cost of CRA violation may not be material if banks are not constrained by such enforcement.

We test the premise using a regression discontinuity (RD) design centered on the CRA eligibility threshold. The CRA designates census tracts as underserved (or low- and median-income, LMI) neighborhoods if their Median Family Income (MFI) falls below 80% of the surrounding area's MFI. This sharp threshold allows us to identify banks' shadow costs of CRA violation by comparing lending behavior in neighborhoods around the income cutoff.

Comparing census tracts around the 80% MFI threshold, we find a 2% increase in mortgage lending to LMI census tracts relative to non-LMI tracts by banks *with branches*. This effect is robust to different RD bandwidth choices and remains quantitatively stable over time. The persistent lending differential suggests that the CRA's incentive to serve LMI neighborhoods remains constant for banks maintaining branches in a given assessment area. The effect is unique to the 80% policy threshold — placebo tests at alternative MFI thresholds show no significant differences in lending behavior. Moreover, using the same RD design, we find lower risk-adjusted mortgage rates in census tracts just below the 80% threshold compared to those just above, consistent with our model's premise that CRA regulation compresses profit margins on loans to underserved neighborhoods.

Next, we empirically examine how CRA compliance costs contribute to branch closures and affect credit accessibility. Our model highlights that the economic burden of CRA regulation depends on two key components: banks' costs of CRA violations and their difficulty achieving compliance, which varies with local demand for bank credit. Our empirical strategy exploits variation in both components.

First, we exploit cross-sectional variation in banks' compliance incentives. Using bank-specific RD estimates, we measure individual banks' shadow costs of CRA violation. These costs vary significantly across banks and correlate positively with bank expansion activities, including mergers and branch openings. This suggests that banks with strategic growth objectives face higher costs of CRA violations, increasing their incentives to comply.

However, relying solely on cross-sectional variation may introduce biases from unobserved bank characteristics. We address this challenge by exploiting the rise of non-bank lenders over the past decade. As non-banks capture a growing market share, they reduce demand for bank loans, thereby increasing the economic burden of CRA compliance. This shift provides a framework to test whether banks with higher CRA violation costs experience more branch closures in response to non-bank growth.

Our identification thus relies on two key sources of variation: cross-sectional differences in banks' compliance incentives and time-varying regulatory pressure from non-bank growth. We include county-by-year fixed effects to control for time-varying local factors and instrument non-bank growth using a Bartik-style measure. The IV is constructed with local non-bank market shares from 2005-2008, which captures local exposure to national non-bank expansion after the global financial crisis.

Our results suggest that banks with above-median CRA violation costs, compared to those with below-median costs, close 1.8 more branches per million population and are 3.0% more likely to fully withdraw from local markets, as non-banks' market share in mortgage lending grows by 30 percentage-points. This reduction in branch presence is associated with a significant decline in the supply of both mortgages and small business loans. Banks with high CRA violation costs reduce mortgage loans by 21.5% and small business loans by 19.6% more than their low-cost counterparts when non-bank market share increases by 30 percentage points. Moreover, CRA-induced branch closures are concentrated in assessment areas with below-median per capita income, suggesting that economically weaker areas shift from benefiting from the CRA to suffering from it as non-banks expand.

The empirical analysis reveals a dual impact of the CRA on credit accessibility. The regulation successfully expands credit access in underserved neighborhoods within affluent areas where banks maintain physical branches. However, it simultaneously curtails credit supply in economically disadvantaged regions where banks avoid establishing branches to bypass CRA obligations. This spatial dichotomy raises a crucial question about whether the credit expansion in served areas outweighs the contraction in avoided ones.

We estimate our model to quantify the net effect of the CRA amid the rise of non-bank lenders. Our estimation suggests that the bottom 22% of counties ranked by per-capita income experience CRA-induced branch closures, reducing total lending by up to 2.3%. In contrast, the more prosperous 78% counties see lending increases of up to 8.3%. Aggregating these opposing effects, we estimate that the CRA's net impact on overall lending ranges from -0.5% to 7.6%. Through a counterfactual analysis, we demonstrate that continued non-bank expansion could transform the CRA's impact. A mere 4% decrease in bank credit demand could trigger CRA-induced branch closures in up to 80% of counties, substantially reducing aggregate lending relative to a non-CRA benchmark.

Our analysis thus far has focused on individual bank decisions, leaving open the question of market-level adjustments. These adjustments could potentially offset the economic impact of branch closures if new market entrants effectively compensate for exiting banks. To investigate this possibility, we analyze datasets that capture local lending activity from both banks and non-banks. We find that when the CRA regulatory burden causes branch closures in a region, total lending contracts significantly despite concurrent expansion in non-bank lending. Specifically, counties initially dominated by banks with higher CRA violation costs experience significant declines in both bank branches and lending activity following non-bank expansion. The reduction in small business lending notably exceeds the decline in mortgage lending, suggesting that non-bank lenders are less able to substitute for traditional banks in market segments that depend more heavily on local branches.

A more concerning finding emerges in the CRA's unintended consequence of exacerbating disparities in credit access. To examine this issue, we quantify CRA treatment intensity across areas using an assessment area-level RD design, defining areas with above-median estimated values as CRA-binding areas. This measure incorporates both the distribution of banks with varying shadow costs of CRA violation and differences in local economic fundamentals. We show that CRA-binding areas are associated with weaker economic fundamentals and are more adversely impacted during periods of non-bank expansion compared to non-binding areas. These areas experience higher rates of bank branch closures, more zip codes becoming branch deserts, declining financial inclusion, contracting small business lending, and reduced local firm presence. These findings suggest that CRA regulations may unintentionally distort the allocation of financial services in ways that contradict their intended objectives.

A substantial body of economic research shows that firms rarely respond passively to regulatory mandates, instead engaging in strategic adaptations that can undermine or even reverse intended policy effects (Stigler, 1971; Peltzman, 1975; Jordan, 1972). Such regulatory avoidance is particularly consequential in the financial sector, where institutions' strategic responses can have profound implications for macroeconomic stability, social welfare, and financial resilience. Since Kane (1981), researchers have recognized that changing economic conditions and technological developments progressively erode traditional banking regulations' effectiveness, as banks' dynamic responses—such as organizational restructuring—often diminish regulation's intended disciplinary effects (Kroszner and Strahan, 2011). This pattern is well-documented in banking literature examining responses to financial stability regulations, such as capital requirements and liquidation regulation.[4]

Unlike these financial stability regulations, the CRA functions more as an industrial policy tool, rewarding institutions for meeting political goals. To our knowledge, we provide the first systematic analysis of how such financial policies can distort the geographic allocation of financial resources through private institutions' strategic responses. Our study contributes to a growing literature on spatial banking that examines the regional distribution of financial resources and institutions' role in this allocation (Kroszner and Strahan, 1999; Hurst et al., 2016; Aguirregabiria et al., 2024; Oberfield et al., 2024). Similar issues have been explored in the insurance industry, where strategic reallocations can yield unintended spillovers across regions (Oh et al., 2022; Wenning, 2024).

The CRA literature has evolved in response to reflect the evolving challenges within the financial sector. Early post-crisis research examined whether the CRA contributed to risky lending practices (Agarwal et al., 2012; Avery and Brevoort, 2015; Saadi, 2020; Ringo, 2023; Ghent et al., 2015). As the financial system stabilized, research focus shifted to the CRA's effectiveness in promoting financial inclusion amid the changing landscape of financial intermediation (Conway et al., 2023; Ding and Nakamura, 2021). These studies analyze the CRA's impact *within* assessment areas by comparing lending between underserved and non-underserved neighborhoods.[5] Ding and Reid (2020) find that banks close fewer branches in census tracts just below the 80% CRA income threshold compared to those just above it. However, like other studies, their analysis focuses on CRA effects within assessment areas

[4]See, for example, Dell'Ariccia et al. (2012); Begenau and Landvoigt (2022); Sundaresan and Xiao (2018, 2024).

[5]Other papers in this category include Berry and Lee (2008); Bhutta (2011); Lee and Bostic (2020); Ding et al. (2018); Chakraborty et al. (2020); Dahl et al. (2000); Brevoort (2022).

rather than across regions. Cespedes et al. (2023) takes a different approach, examining banks' strategic responses to the 1995 CRA reform. They find that banks deliberately limit their growth to avoid crossing the asset size threshold for stricter CRA compliance, leading to reduced LMI mortgage lending and small business activity in affected markets.

We contribute to this debate by revealing a fundamental paradox: while the CRA successfully promotes credit access in prosperous areas, it harms disadvantaged regions through banks' strategic branch withdrawals. Our findings uncover a new dimension of the CRA's unintended consequences, demonstrating how it may exacerbate cross-regional inequality in credit access and, ultimately, economic inequality.

The rise of non-bank lenders, which operate outside CRA regulations, compounds these challenges. Recent research documents non-banks' increasing dominance in markets that banks find unprofitable under compliance burdens (Buchak et al., 2018; Gopal and Schnabl, 2022; Irani et al., 2021; Hamdi et al., 2023; Begley and Srinivasan, 2022). This shift not only reduces the CRA's effectiveness but widens credit availability disparities across regions. Our analysis further shows that non-bank growth cannot fully substitute for traditional banking functions, particularly those dependent on local branches and relationship lending. This finding aligns with existing literature highlighting the persistent importance of geographic proximity, physical distance, and bank branches in credit allocation, even in the digital era.[6]

1 The CRA Rules: A Quantity Regulation

This section introduces key institutional features of the CRA relevant to our study, with detailed historical background and legal references provided in Appendix A.

The Community Reinvestment Act (CRA), enacted in 1977, applies to all FDIC-insured depository institutions but excludes credit unions and non-depository institutions (non-banks). Banks undergo periodic comprehensive examinations for CRA compliance, which include lending, investment, and service tests. The lending test forms a major component of CRA evaluation, focusing primarily on mortgage and small business lending. Rather than evaluating interest rates, this test assesses loan *quantities* — specifically examining the ge-

[6]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); Rice and Strahan (2010); Huang (2008); Allen et al. (2021); Bruhn and Love (2014); Sakong and Zentefis (2022); Nguyen (2019); Fonseca and Matray (2022), and Jiang et al. (2022).

ographic distribution of loans and lending volume to underserved neighborhoods within a bank's assessment areas.

A bank's assessment areas are defined by the geographic regions where it operates branches and deposit-taking ATMs, typically delimited by metropolitan statistical areas (MSAs) or counties outside MSAs. The Federal Reserve Board publishes the list of assessment areas for each bank in the CRA Analytics Data Tables. According to this data, 90% of banks' assessment areas overlap with where they have branches.[7] Thus, while a regulatory reform in 1995 revised the definition of a bank's CRA assessment areas to include regions without branches but with significant lending activity, branch operations continue to serve as the primary determinant for delineating assessment areas.

Within each assessment area, underserved neighborhoods are identified using census tract median family income (MFI). Census tracts are classified as underserved, or LMI (low-to-moderate-income), if their MFI falls below *80%* of their surrounding area's MFI—typically an MSA or, for non-MSA regions, a non-metro area within the state. Figure 2 illustrates these LMI designations using two examples.

Each bank receives a public CRA rating following its comprehensive examination. Non-compliance can result in restrictions on branch expansion and merger activities, more frequent assessments, and heightened public scrutiny.[8]

2 Model

Given the institutional background, we set up a stylized model of bank lending under the CRA regulation. We simplify the model to include only the key components necessary for studying the costs and benefits of the CRA. This model also serves as motivation for the empirical design.

[7] Appendix A provides detailed calculation.

[8] For example, Chen et al. (2023) finds that banks experience a decline in deposit growth following negative CRA ratings.

2.1 Setup

We consider a representative bank supplying credit in one assessment area while facing downward-sloping credit demand.[9] The assessment area comprises two neighborhoods, denoted by i: the underserved ($i = l$) and the non-underserved ($i = h$). The two neighborhoods have different credit demands, characterized by

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

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 baseline loan demand in the assessment area, while α_i captures neighborhood-specific variations in this demand. β determines the slope of the demand curve: a higher β indicates a steeper curve, meaning that to increase lending by one unit, the bank must offer a larger price reduction compared to markets with lower β. $\gamma > 0$ captures borrowers' preference for local branches, making them willing to pay a premium for the convenience offered by the branch.

Facing the demand, the bank decides (1) whether to have branches ($b \in \{1, 0\}$) in the assessment area and (2) its lending volume in each of the two neighborhoods (L_i), to maximize its total profit defined below. Note that we focus solely on banks' extensive-margin decisions to maintain any branches in a county, rather than their intensive-margin choices of specific branch locations within an assessment area—which would be analogous to the decision about lending volume across neighborhoods.

$$\begin{aligned}
\max_{L_l, L_h, b} \quad \pi(L_l, L_h, b) &= \underbrace{r_1(L_l, b)L_l + r_2(L_h, b)L_h}_{\text{Lending Profit}} \\
&\quad - \underbrace{\max\left\{0, \delta[\eta_1(\bar{L} - L_l) + \eta_2(L_h - L_l)]\right\} \times \mathbb{1}(b > 0)}_{\text{Cost of Failing to Meet CRA Requirements}} \qquad (2) \\
\text{s.t. } \; r_i(L_i, b) &= \alpha + \alpha_i - \beta L_i + \gamma b, \;\; i \in \{l, h\}
\end{aligned}$$

The first term captures lending profits, while the second term represents penalties for failing to meet CRA requirements. As discussed in Section 1, CRA oversight in an assessment area is

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

primarily triggered by the presence of bank branches. When a bank operates branches in an assessment area, regulators evaluate two key dimensions: (i) the volume of lending to CRA-designated underserved neighborhoods and (ii) the geographic distribution of loans across neighborhoods within the assessment area.[10] We model CRA requirements through two components: an implicit lending target $\bar{L}$ for underserved neighborhoods, and a constraint on lending disparities between underserved and non-underserved areas. A bank incurs a per-unit cost of $\eta_1\delta$ when lending falls below the target ($L_l < \bar{L}$), and a per-unit cost of $\eta_2\delta$ when lending disparities are high ($L_h > L_l$). The weights $\eta_i \in (0, 1)$ sum to unity ($\eta_1 + \eta_2 = 1$), and δ represents the shadow cost of CRA violations. This shadow cost is higher for banks that are more likely to pursue mergers and acquisitions, plan branch expansion, or value their community reputation—activities that require favorable CRA ratings.

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

$$L_l^* = \begin{cases} \frac{\alpha+\alpha_l+\gamma+\delta}{2\beta} & \text{if } b = 1 \\ \frac{\alpha+\alpha_l}{2\beta} & \text{if } b = 0, \end{cases} \qquad L_h^* = \begin{cases} \frac{\alpha+\alpha_h+\gamma-\delta\eta_2}{2\beta} & \text{if } b = 1 \\ \frac{\alpha+\alpha_h}{2\beta} & \text{if } b = 0 \end{cases} \tag{3}$$

Defining $\Delta\pi \equiv \pi(L_l^*, L_h^*, 1) - \pi(L_l^*, L_h^*, 0)$ as the difference between the profit with a branch and the profit without a branch in the assessment area, we obtain the optimal branching strategy as follows:

$$b^* = \begin{cases} 1 & \text{if } \Delta\pi > 0 \\ 0 & \text{if } \Delta\pi \leq 0, \end{cases} \tag{4}$$

where

$$\Delta\pi = \underbrace{\frac{\gamma(2\alpha + \alpha_l + \alpha_h + \gamma)}{2\beta}}_{\text{Benefit}} - \underbrace{\left(\delta\eta_1 \times (\bar{L} - L_l^*|_{b=1}) + \delta\eta_2(L_h^*|_{b=1} - L_l^*|_{b=1})\right.}_{\text{Cost of not Fully Complying CRA}} + \underbrace{\left.\delta^2 \frac{1+\eta_2^2}{4\beta}\right)}_{\text{Cost of Deviating from the Optimal}} . \tag{5}$$

[10] See Appendix A for additional details. Other CRA evaluation metrics include the total lending volume within assessment areas and the ratio of lending within versus outside these areas. These metrics highlight the importance of sufficient lending within designated areas, reinforcing our focus on lending within assessment areas.

Intuitively, the bank faces a trade-off in its branching decision. On the one hand, since consumers value branches, establishing branches enables the bank to charge higher markups, increasing lending profits, which is the benefit of having a local branch. On the other hand, the CRA requires the bank to lend beyond its profit-maximizing level (in the absence of the CRA), reducing the bank's profit; and in addition, there is a direct, shadow cost associated with not fully complying with the two CRA requirements as defined in Eqn. (2). When the cost exceeds the benefit, the bank optimally chooses not to operate a branch in the assessment area; and vice versa.

2.2 The Effects of the CRA Regulation

We now examine the effects of CRA regulation by comparing the equilibrium outcomes with and without the regulation. The analysis will demonstrate how the CRA promotes equal credit access within assessment areas while potentially exacerbating credit access disparities across regions.

In our simplified model, we exclude any non-CRA-related costs associated with branch operations. Consequently, in the non-CRA benchmark scenario ($\delta = 0$), it is always optimal for banks to retain their branches due to the presence of a convenience premium for maintaining a local branch ($\gamma > 0$). The optimal lending levels are given by:

$$L_l^{\#} = \frac{\alpha + \alpha_l + \gamma}{2\beta}, \qquad L_h^{\#} = \frac{\alpha + \alpha_h + \gamma}{2\beta}. \tag{6}$$

Compared to the non-CRA benchmark, branch closures as described in Eqn. (4) are solely driven by regulatory costs associated with the CRA. Since branch closures directly impact banks' lending, the CRA's effect on lending is a piecewise function that depends on whether the cost of maintaining a branch under the CRA exceeds its benefits:

$$L_l^* - L_l^{\#} = \begin{cases} \frac{\delta}{2\beta} & \text{if } \Delta\pi > 0 \\ \frac{-\gamma}{2\beta} & \text{if } \Delta\pi \leq 0, \end{cases} \qquad L_h^* - L_h^{\#} = \begin{cases} -\frac{\delta\eta_2}{2\beta} & \text{if } \Delta\pi > 0 \\ \frac{-\gamma}{2\beta} & \text{if } \Delta\pi \leq 0. \end{cases} \tag{7}$$

As it illustrates, when the CRA cost associated with having a branch is so low that the bank decides to keep the local branch ($\Delta\pi > 0$), the CRA (1) increases lending in the underserved neighborhood, (2) lowers the lending dispersion between the underserved and the non-underserved neighborhood, and (3) increases total lending in the assessment area. This underscores the benefits of the CRA in *promoting equal access to credit* within assessment areas.

However, when the CRA cost associated with having a branch is so high that the bank decides to close the local branch ($\Delta\pi < 0$), lending in both neighborhoods declines. Such CRA-induced branch closures are more likely when: 1) the bank's CRA compliance incentive is high (high δ), 2) the local demand curve is steep (low $\frac{1}{\beta}$), or 3) overall demand for bank loans is low (low α).[11]

Low-income areas are particularly vulnerable to CRA-induced branch closures due to, e.g., their characteristically steeper demand curves (low $\frac{1}{\beta}$).[12] Their borrowers exhibit less flexible loan demand because they face: limited alternative financing options, minimum threshold needs (like starter home costs), barriers to rate shopping from thin credit histories, lower financial sophistication, and higher opportunity costs of search time relative to income. The potential prevalence of CRA-induced branch closures in low-income areas thus suggests that the CRA may paradoxically *widen credit access disparities*.

To illustrate the effect of the CRA in promoting within-region credit access equality while exacerbating cross-region credit access disparity, we plot lending against $\frac{1}{\beta}$ in Figure 1. We vary the values of other primitives to make different panels in this figure. In each panel, we plot the equilibrium lending under the CRA, L_l^* and L_h^*, and the equilibrium lending in the non-CRA benchmark, $L_h^\#$ and $L_h^\#$. The gray-shaded areas highlight regions where the bank closes its local branch to avoid CRA compliance.

In all panels, when $\frac{1}{\beta}$ is relatively high, the bank chooses to establish a branch and lend more to underserved neighborhoods under the CRA regulation. Thus, the CRA reduces lending disparities between neighborhoods in areas with strong economic fundamentals. However, as $\frac{1}{\beta}$ decreases, the regulatory costs associated with maintaining branches increase, as discussed above. Once $\frac{1}{\beta}$ falls below a critical threshold, $(\frac{1}{\beta})^*$, the bank closes its branch, leading to lending reduction in *both* neighborhoods. The shaded area highlights the set of areas, characterized by $\frac{1}{\beta}$, in which the CRA adversely impacts bank lending. This

[11]See Appendix B.1 for proofs and additional discussion of comparative statics related to within-assessment area demand dispersion (i.e., α_1 relative to α_2).

[12]Lower-income areas may also be more vulnerable to CRA-induced branch closures because of lower overall demand for bank loans (i.e., low α).

finding underscores that the CRA may limit bank lending to low-income areas, widening the cross-region disparities.

From Panel A to B, we increase δ. As δ increases, CRA's positive effect in areas with relatively high $\frac{1}{\beta}$ becomes stronger, but the minimal value of $(\frac{1}{\beta})^*$ needed for upholding a positive effect of CRA is also higher ($\frac{\partial(1/\beta)^*}{\partial\delta} > 0$).[13] This comparative static indicates that a high-δ bank — who has a higher incentive to comply — indeed lends more to the underserved neighborhood, but its incentive to bypass the regulation by closing branches is also higher.

From Panel A to C, we decrease α. A decrease in α compresses the range of $\frac{1}{\beta}$ values under which the CRA regulation leads to a positive effect ($\frac{\partial(1/\beta)^*}{\partial\alpha} < 0$).[14] Thus, shocks to the demand for bank loans, such as the rise of non-banks, could intensify the adverse consequences of the CRA, further compromising banking access in underprivileged areas.

In conclusion, our stylized model illustrates an important but previously overlooked outcome of the CRA: although it promotes credit equality in wealthier areas, this comes at the expense of poorer regions experiencing diminished banking access.

Discussion The key trade-off in our model is that while branches enable banks to charge a markup, they also require banks to forgo some profits by subsidizing underserved neighborhoods to comply with CRA requirements. This trade-off remains robust even when we extend the model to incorporate additional realistic assumptions. For example, we could include the operational costs of maintaining branches or introduce penalties for closing branches, particularly if lending without a branch incurs higher compliance costs under the CRA. Furthermore, we interpret the rise of non-banks as reducing demand for bank loans, thereby lowering bank profitability. This mechanism can also be modeled by introducing competition between banks and non-banks, where the growth of non-banks intensifies competition, leading to further reductions in bank profitability. Our framework is robust to these extensions.

[13] See Appendix B.2 for proof.

[14] See Appendix B.2 for proof.

3 Data

We combine multiple datasets covering mortgage lending, small business lending, bank branches, and local economic conditions. We obtain the list of assessment areas for each bank in the CRA Analytics Data Tables published by the Federal Reserve Board, which indicates whether a county falls into a bank's assessment areas. To identify LMI census tracts within these areas, we use demographic data from the Federal Financial Institutions Examination Council (FFIEC). The FFIEC data also provides relevant control variables and reports the median family income metrics that regulators use to define LMI census tracts.

For mortgage lending analysis, we use Home Mortgage Disclosure Act (HMDA) data, which captures nearly all U.S. mortgage applications with detailed information including loan amounts, borrower locations, and originating institutions. The data covers both originated and purchased loans—both considered in CRA lending tests—at the census tract level. We utilize this comprehensive dataset to construct non-bank market shares, estimate banks' shadow costs of CRA violations, and analyze how the CRA's effects on mortgage lending evolve with non-bank growth.

For mortgage pricing analysis, we use CoreLogic Loan-Level Market Analytics (LLMA) data, which provides details on mortgages and borrower characteristics, including interest rates, credit scores, loan-to-value ratios, debt-to-income ratios, documentation types, and product types.

We obtain bank branch data from the Summary of Deposits (SOD) and financial information from banks' regulatory filings ("call reports"). For small business lending analysis, we utilize three complementary datasets. The CRA data, which covers banks with assets above \$1.503 billion (as of 2023), is the most widely used source and accounts for approximately 75% of small business loans outstanding at banks (FFIEC, 2021). The second dataset, from Uniform Commercial Code (UCC) filings (Gopal and Schnabl, 2022), provides a broader perspective by including all secured lenders—both non-banks and small banks—though it only captures the number of secured loans rather than loan amounts. The third source, the Small Business Administration (SBA) 7(a) Loan Program data, specifically tracks government-guaranteed loans.

For local economic analysis, we use the Census Bureau's Business Dynamics Statistics (BDS) for business establishment data. We obtain local economic characteristics from the

2000 and 2010 Decennial Census, and measure financial inclusion using data from the FDIC Survey of Household Use of Banking and Financial Services.

4 Is CRA Compliance Costly for Banks?

The theoretical predictions rest on the key premise that there is a material cost associated with CRA violations (i.e., $\delta > 0$). In practice, non-compliance with CRA regulations hinders banks from opening new branches or participating in mergers and acquisitions. However, this cost may be negligible if banks are not constrained by these enforcement measures. To support this, we will show in this section that banks engage in excessive lending in underserved neighborhoods, which yields lower risk-adjusted returns, thereby imposing a significant cost on banks to comply with CRA requirements.

4.1 Empirical Design

According to Eqn. (7) in Section 2, the CRA effect on bank lending to the underserved neighborhoods is captured by the difference between a bank's equilibrium lending under the CRA regulation and its equilibrium lending in the absence of such regulation:

$$L_l^*|_{b=1} - L_l^{\#}|_{b=1} = \frac{\delta}{2\beta} \tag{8}$$

However, we do not simultaneously observe a bank's lending behavior with and without the regulation. To address this empirical challenge, we exploit the discontinuity in the CRA's designation of LMI neighborhoods at the 80% MFI threshold, comparing lending to census tracts near this income threshold. According to Eqn. (3),

$$L_l^*|_{b=1} - L_h^*|_{b=1} = \frac{\alpha_l - \alpha_h + \delta(1+\eta_2)}{2\beta}. \tag{9}$$

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

$$L_l^*|_{b=1} - L_h^*|_{b=1} = \frac{\delta(1+\eta_2)}{2\beta}. \tag{10}$$

This approach provides a measurement proportional to the intensive margin effect identified in Eqn. (8). However, we acknowledge that for any $\eta_2 > 0$, our estimate represents an upper bound of the CRA's intensive margin effect on bank lending.[15]

To this end, we employ the following Regression Discontinuity (RD) design.[16]

$$\log(\text{Loans}_{b,i,t}) = \tilde{\delta}\mathbb{1}(\text{lmi}_{i,t}) + \kappa_1(\text{MFI}_{i,t} - 80\%) + \kappa_2\mathbb{1}(\text{lmi}_{i,t}) \times (\text{MFI}_{i,t} - 80\%) + \mu_b + \gamma_{m,t} + \epsilon_{b,i,t}, \tag{11}$$

where b denotes a bank, i denotes a census tract, m denotes an assessment area, and t denotes a year. An assessment area is an MSA or a county if an area does not belong to any MSA, according to Regulation 12 CFR 25.41. $\log(\text{Loans}_{b,i,t})$ is the logarithm of total mortgage lending, including both originated and purchased loans, by bank b in census tract i during year t. We focus on mortgage loans because (1) mortgage lending is the most important category contributing to CRA's lending test (See reference here); (2) there is a lack of small business lending data with similar granularity about lender and borrower location information; and (3) the shocks that we will introduce later for identifying the extensive margin effects are from the mortgage market. $\mathbb{1}(\text{lmi}_{i,t})$ is an LMI census tract indicator. $(\text{MFI}_{i,t} - 80\%)$ is the distance between census tract i's MFI and the 80% MFI threshold. We adopt triangular weights in the estimation to prioritize local behavior, providing more accurate results (Imbens and Lemieux, 2008). We do not include higher-degree polynomials which tends to result in noisier estimates (Gelman and Imbens, 2019). Finally, μ_b and $\gamma_{m,t}$ are bank fixed effects and assessment area-by-year fixed effects, respectively.

To estimate Specification 11, we use a sample of bank–census tract–year observations, focusing on census tracts within bank b's CRA assessment areas. Following Calonico et al. (2017), we compute mean squared error (MSE)-optimal bandwidths. The resulting bandwidths range from 15% to 19% for each year during the period 2005 to 2017.[17] To ensure

[15] Intuitively, η_2 is the regulatory weight on within-area dispersion in lending relative to the weight on absolute lending level in the LMI neighborhoods, which directly distorts the distribution of bank lending within an assessment area in which a bank has branches and for banks that have incentives to comply with the CRA.

[16] Bhutta (2011) also use the HMDA data to estimate an RD design. Our estimation differs from theirs in terms of methodology and sample construction. First of all, we include both originated and purchased mortgage loans, as both qualify for CRA compliance, whereas they all focus only on originated loans. Methodologically, we adopt a more advanced estimation approach by employing triangle weighting in the RD design. Additionally, we incorporate non-MSA assessment areas into our analysis and examine a sample period spanning 2005—2017. Our findings largely align with those of Bhutta (2011), though we find a smaller effect: 2% in our case compared to 3.4% for all MSAs during 1994—2002. Berry and Lee (2008) test originated loans in adjacent tract pairs around the 80% threshold but fail to detect a treatment effect. However, the relative sparsity of adjacent tract pairs may yield imprecise results.

[17] Due to the computation limitations in efficiently handling large fixed effects, we estimate the optimal bandwidth for each year individually, where we select the optimal bandwidth based on the median of one-common and two different MSE-optimal bandwidths. The estimated bandwidths are stable across years, ranging from 15% to 19%.

robustness, we report results using three distinct bandwidths in our local polynomial regression estimates: $\pm 15\%$, $\pm 20\%$, and the MSE-optimal bandwidth.

The key identifying assumption of the RD design is that tracts with MFI around the 80% threshold share similar underlying characteristics. We provide two sets of empirical support for this assumption. First, if the treatment variation near the cutoff is approximately random, all baseline characteristics determined *prior* to the realization of the assignment variable should exhibit similar distributions just above and below the cutoff. As Table E1 shows, there is no evidence of discontinuities at the 80% cutoff for various demographic variables, using the 1990 Census (i.e., the census conducted before the introduction of the threshold in 1995). Second, we find no evidence for population flowing to the census tracts with MFI right below the 80% cutoff over time. Figure E1 shows no sorting of census tracts around the 80% MFI threshold (Cattaneo et al., 2020). Table E2 shows no statistically significant jumps in population, demographics, or loan demand around the threshold using 2010 data.

4.2 Lending Quantity Distortion

Table 2 presents estimation results of Specification (11) using the entire time series from 2005 to 2017. The estimates indicate that banks' mortgage supply increases by about 2% in LMI census tracts compared to those just above. The estimates are consistent under different choices of RD bandwidth around the 80% MFI threshold. Figure 3 illustrates the result non-parametrically. The figure presents a sharp increase in the lending amount from the right-side to the left-side of the 80% threshold.

Figure 4 plots the dynamic RD estimates using four-year rolling samples. The estimates are quantitatively similar over time, suggesting that the incentives to foster lending to LMI neighborhoods under the CRA remains constant over time for banks maintaining branches in a given assessment area. However, in the next section, we will show that the extensive margin impact of the CRA on branch closures changes over time, in response to shocks to the competitive landscape, such as the rise of non-bank lenders in the mortgage market.

Notably, this pronounced discontinuity is unique to the 80% policy cutoff threshold. Placebo tests in Table E3, using alternative MFI thresholds of 50% and 110%, reveal no significant differences in lending behavior at these thresholds. These results underscore that

We then average these annual bandwidths for the full sample estimation.

the discontinuity effect observed at the 80% threshold is directly attributable to the CRA regulation.

4.3 Risk-Adjusted Prices

While we have shown similar economic conditions in census tracts near the 80% MFI cutoff, the observed increase in lending to census tracts right below the cutoff could still be driven by excessive loan demand caused by unobserved factors. To rule out this explanation, we analyze loan pricing around the cutoff. If loan rates are lower in LMI neighborhoods, the demand-driven explanation is unlikely to be the main driver of our results. Importantly, examining loan pricing can also shed light on whether excess lending to underserved neighborhoods lowers banks' profit margins. If banks have to accept investments with lower risk-adjusted returns to expand lending, complying with the CRA is indeed costly.

We apply a similar RD design around the 80% policy cutoff using the CoreLogic LLMA data. Unlike the HMDA data, CoreLogic LLMA does not include lender identities, preventing us from distinguishing between banks and non-banks. As a result, we cannot isolate a sample consisting solely of banks subject to CRA regulation. This limitation could dilute the effectiveness of our RD design, as the estimated effect would represent an average across both banks and non-banks, potentially biasing the results downward. To mitigate this issue, we restrict our analysis to the period from 2005 to 2008, before the significant rise of non-bank lenders. Moreover, since the most detailed geographic information available is at the zip code level, we aggregate MFI data from the census tract level to the zip code level. More details are provided in Appendix D.

Table E4 reports the estimates under various bandwidth choices consistently show that risk-adjusted mortgage rates are about 2-2.5bps lower in census tracts with MFI just below the 80% threshold compared to those just above, supporting the model's premise that CRA regulation reduces profit margins on loans to underserved neighborhoods. This pronounced discontinuity effect is closely tied to the 80% policy cutoff as before. Placebo tests in Table E5, using alternative MFI thresholds of 60% and 100%, reveal no significant differences in loan rates at these thresholds.[18]

[18] The placebo cutoff points are selected to ensure that the estimation window does not overlap with the 80% cutoff and that a sufficient number of observations are available around each chosen cutoff. Unlike the placebo cutoffs in Table E3, we select different thresholds here to account for the fact that the unit of observation is at the zip code level, leaving too few observations to estimate reliably at the 50% cutoff.

Riskiness of Bank Loan Portfolio. Our model abstracts away from more complicated aspects of bank lending to focus on the basic economic concepts of price and quantity. In practice, banks also decide on the risk level of the investment, which affects their returns beyond quantity and price. To account for risk differences in driving mortgage rates, our above analysis uses risk-adjusted mortgage rates. The findings suggest banks lower the rate for a given risk level to expand lending to comply with the CRA regulation. Another possible practice is to expand credit provision by lowering the lending standard. There are various reasons why banks might not lend to riskier borrowers in the absence of the CRA, such as adverse selection, regulatory constraints, and securitization restrictions. In all these cases, if a bank lowered the lending standard in response to the CRA, the return on investment would decline, e.g., because of higher loan default rates or increased difficulty in securitization, which in turn might induce branch closures. While this alternative practice would generate the same set of predictions, it would have additional implications for financial stability (see, for example, Agarwal et al. (2012)). However, in Table E6, we do not find supporting evidence for banks lowering the lending standard because of the CRA regulation, where 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, and the credit score of the borrower and the loan-to-value ratio of the loan conditional on the loan having full documentation.

5 The Extensive Margin Effects of the CRA

Next, we empirically investigate the extent to which CRA compliance costs in the current economy contribute to branch closures and the subsequent impact on credit accessibility.

5.1 Empirical Design

As our model illustrates, the economic burden imposed by the CRA regulation is influenced by two key components: the per-unit cost of CRA violations for banks (δ) and the difficulty of compliance with the CRA. The latter is determined by local demand for bank credit (α, α_l relative to α_h, and β) and regulatory requirements ($\bar{L}$, η_1, η_2). Our empirical approach leverages variation in both components. In what follows, we introduce the research design and describe the measurement construction.

The incentive to comply with the CRA may vary across banks: some banks may be more constrained by CRA enforcement measures than others. As our model predicts, banks with more incentives to comply (i.e., banks with a higher δ_b) should lend more in underserved neighborhoods when they have local branches but are also more subject to CRA-induced branch closures. Motivated by this prediction, we measure cross-sectional variation in banks' compliance incentives, δ_b, by estimating Specification (11) for individual banks, with key adjustments that we will describe in detail later.

Relying solely on cross-sectional variation in δ_b may introduce biases due to potential correlations with unobserved bank characteristics. To address this challenge, we leverage a transformative shift in the mortgage market over the past decade: the rise of non-banks, which is shown to be driven by technological advancements and regulatory arbitrage (Buchak et al., 2018; Fuster et al., 2019). As non-banks capture a growing share of the market, they amplify the economic burden of CRA compliance by reducing demand for bank loans. Within the context of our model, the rise of non-banks can be interpreted as a negative shock to α. This shift provides a natural difference-in-differences framework to examine whether high-δ banks are disproportionately impacted, experiencing more CRA-induced branch closures in response to the growth of non-banks.

Specifically, we estimate the following specification to study CRA-induced branch closures and the resulting consequences on branch-dependent lending:

$$\Delta Y_{b,c,m,t} = \kappa_1 \text{NBank Shock}_{m,t} \times \text{High-}\delta_b + \mu_b + \nu_{c,m,t} + \epsilon_{b,c,m,t}. \tag{12}$$

The underlying sample is constructed at the bank-county-year level and comprises a balanced panel of bank-county pairs with branch presence in at least one year from 2011 to 2017, a period of significant non-bank growth. To minimize potential distortions from M&As, we exclude bank-year observations in which a bank has no branches across all counties during the year. $\Delta Y_{b,c,m,t}$ represents the change in bank b's branching or lending activity in county c, within assessment area m, in year t, relative to its level in 2010. We measure outcome variables at the county level because the geographic scope of a county remains consistent throughout the sample period, whereas the geographic scope of assessment areas—

usually at the MSA level—changes over time.[19] NBank Shock$_{m,t}$ represents the exposure of assessment area m to the national growth of non-banks from 2010 to year t. High-δ_b is a binary indicator identifying whether bank b's incentive to comply with the CRA exceeds the median value among all banks. Both measures will be formally defined shortly. We include county-year fixed effects, $\nu_{c,m,t}$, to control for regional economic variations, and bank fixed effects, μ_b, to account for time-invariant characteristics of banks. Consequently, our identification primarily relies on the variation in banks' incentives to comply and the time-varying regulatory pressures arising from the growth of non-banks.

We next describe the construction of key measurements: NBank Shock$_{m,t}$ and High-δ_b.

Estimation of δ_b. To capture the cross-sectional variation in δ_b, we estimate Specification (11) for each bank using HMDA data from 2005 to 2008. The estimation uses historical data to avoid confounding effects from contemporaneous bank actions during the rise of non-banks. Furthermore, we make critical adjustments to Specification (11) to account for differences in banks' geographic presence that potentially lead to discrepancies between the ranking of the estimated $\tilde{\delta}_b$ from Specification (11) and the true ranking of δ across banks.

Specifically, according to Eqn. (10), the RD estimate yields $\frac{\delta(1+\eta_2)}{2\beta}$. Thus, banks primarily located in areas with lower β, for example, may mechanically exhibit higher estimated $\tilde{\delta}_b$, even if their true δ is relatively small. To correct this bias, we make adjustments to the baseline estimation by weighting each observation by the assessment area's β and multiplying the estimated coefficient $\tilde{\delta}_b$ by the average β across bank b's assessment areas, $\bar{\beta}_b$. Appendix C provides the econometric proofs and the procedural details. These adjustments purge the variation in β across banks, yielding an estimate of $\tilde{\delta}_b\bar{\beta}_b \propto \delta_b(1+\eta_2)$, where η_2 is the regulatory weight on within-area lending dispersion in CRA's assessments. Since η_2 is largely constant across banks, the ranking of the adjusted estimates captures the ranking of banks' incentives to lend beyond the optimal level under pure market forces in order to comply with the CRA regulation.[20] To simplify the notation, we use $\bar{\delta}_b$ to denote $\tilde{\delta}_b\bar{\beta}_b$ hereinafter.

The estimated $\bar{\delta}_b$ exhibits considerable variation across banks. The difference between

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

[20] A caveat is that the three regulators—FDIC, FRB, and OCC—may apply slightly different weights, potentially causing variation in η_2 across banks regulated by different entities. However, our main results remain robust even when accounting for the possibility that η_2 varies across regulatory settings.

the 75th and the 25th percentiles of $\bar{\delta}_b$ is 8%, suggesting that the difference in the intensive margin effect of the CRA on their mortgage lending is as large as 8%. In contrast, the ranking of $\bar{\delta}_b$ remains largely persistent over time. In Figure 5, we repeat the estimation using four-year rolling samples from 2005 to 2017, and plot the transition probabilities. In particular, we dynamically classify banks into a high-δ sample or a low-δ sample based on their estimates as compared to the median value in each estimation period, and calculate the transition probabilities over years. The transition probabilities for both the high-δ sample and the low-δ sample reach about 80% throughout the sample period.

To validate the economic meaning of our estimates, we examine the relationship between the ranking of a bank's estimate and its CRA rating, and its involvement in structural changes. Since failing to satisfy the CRA increases regulatory hurdles to conducting mergers and acquisitions (M&As) or branch openings or closures, banks with growth plans should be subject to higher costs of CRA violation and thus are more inclined to comply with the CRA regulation. Consistently, Figure 6 shows that high-δ banks are significantly more likely to receive a satisfactory or outstanding CRA rating, to engage in M&As, and to open new branches from 2005 to 2008. In contrast, ROA, loan portfolio performance, and bank profitability are not correlated with our estimates. Moreover, high-δ banks do not appear to serve different market segments compared to high-δ banks. We also compute the share of FHA mortgages, the share of non-white borrowers, the share of female borrowers, and the average income of borrowers for each bank using HMDA. None of these variables strongly correlates with the high-δ indicator.

Non-bank Shocks. To establish causality, we aim to construct shocks to bank loan demand arising from exogenous local expansion of non-banks. However, a key empirical challenge emerges from potential reverse causality in our specification (12) — local non-bank growth may partly result from banks' exit decisions in response to post-Financial Crisis regulatory tightening (Buchak et al., 2018). To address this identification challenge, we construct a Bartik-style instrument that exploits differential local exposure to national non-bank growth based on variation in the historical presence of non-banks across markets. This approach builds on the rationale that expansion is less costly in regions where an institution has historically maintained a strong presence.

Specifically, we calculate the non-bank mortgage market share in assessment area m

during 2005-2008 ($s_{m,0508}$) and multiply it by the cumulative national non-bank growth rate from 2010 to year t ($\frac{S_{t,-m}}{S_{10,-m}}$):

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

where $s_{m,0508} = \frac{1}{4}\sum_{2005}^{2008} \frac{\text{non-bank Origination}_{m,t}}{\text{Total Origination}_{m,t}}$, and $\frac{S_{t,-m}}{S_{10,-m}}$ is the leave-one-out national non-bank market share growth rate from 2010 to year t. $S_{t,-m} = \frac{\sum_{m' \neq m} \text{non-bank Origination}_{m',t}}{\sum_{m' \neq m} \text{Total Origination}_{m',t}}$ is constructed by excluding the focal assessment area to mitigate finite sample bias associated with using own-observation data.

The IV exhibits a strong correlation with the actual growth in local non-bank market share from 2011 to 2017. Figure 7 provides non-parametric evidence of a nearly linear relationship between the shift-share component of the IV, $s_{m,0508}$, and non-bank market share growth over this period. Table E7 formally tests the IV relevance condition, demonstrating robust results across specifications with varying fixed effects.

The validity of our Bartik IV relies on the assumption that banks do not withdraw branches from regions with historically high non-bank shares, except through the channel of changes in CRA regulatory costs. Although this exclusion restriction cannot be directly tested, we provide suggestive evidence supporting this assumption, following Goldsmith-Pinkham et al. (2020). First, as shown in column 1 of Table E8, we find that assessment areas with high non-bank shares from 2005 to 2008 are associated with lower per capita income, more population, higher unemployment rates, and higher FHA shares during that period. This indicates that non-banks tend to concentrate in economically disadvantaged areas. While such areas might have fewer branches in absolute terms, columns 2 and 3 show no significant association between non-bank shares and *changes* in the number of branches before the national growth of non-banks. This finding suggests that historical non-bank shares do not directly influence banks' decisions to adjust their branch operations, consistent with our exclusion restriction assumption.

5.2 The Effect on Branch Closures

We begin by examining the impact of the CRA on banks' branching decisions as non-banks grow in the residential mortgage market. Panel A of Table 3 reports the results, suggesting that high-δ banks are the first to close branches as non-banks expand. In columns 1 and 2, the outcome variable is the change in the number of branches, scaled by local population in 2010. From 2011 to 2017, the market share of non-banks grew by about 30 percentage-points.The results indicate that, in response to a 30-percentage-point increase in the instrumented local non-bank market share, high-δ banks close 1.8 more branches per million population compared to low-δ banks (column 1). To control for bank size as a potential confounding factor in driving the result, in column 2, we include the interaction between bank size in 2010 and non-bank shocks. The result is quantitatively similar.

Columns 3-4 and 5-6 separately examine the intensive and extensive margins of adjustment that drive the total branch response in columns 1-2. The analysis reveals that adjustments primarily occur at the extensive margin. When local non-bank market share increases by 30 percentage points, high-δ banks are 3.0% more likely than low-δ banks to completely withdraw their branch network within the same assessment area. In contrast, we find minimal intensive margin effects, with little evidence that banks scale down their local branch networks conditional on maintaining presence. These patterns align with banks' incentives under CRA regulations, as complete branch withdrawal from an area effectively removes the region from CRA oversight.

As our model predicts, assessment areas with weaker economic fundamentals are more likely to be the marginal areas experiencing such branch closures. Panel B tests this hypothesis by interacting our variable of interest, NBank Shock$_{m,t}$ $\times$ High-δ_b, with local characteristics. We define poor areas as those with below-median per capita income in 2010, and minority-dominated regions as those with a non-white population share exceeding 50%. The results show that CRA-induced branch closures are more prevalent in both poor and minority-dominated areas. However, when both characteristics are included in the same regression, only the interaction with poor areas remains statistically significant. This suggests that income level plays a more critical role than racial composition in driving CRA-induced branch closures.

To validate that branch closures stem from increased CRA regulatory burdens amid non-bank expansion, we conduct a placebo test in Table E9 using data from 2005 to 2008, when national non-bank market share grew modestly from 15% to 20%. We find no significant differences in branching behavior between high- and low-δ banks during this period. These results support our interpretation that the observed branch closures primarily reflect responses to changing CRA regulatory burdens driven by non-bank growth.

In summary, our findings validate the model predictions that CRA imposes a regulatory cost on maintaining branch presence in a particular area. When faced with declining demand due to non-bank expansion, banks with higher costs of CRA violation are more likely to withdraw their local branches, particularly from lower-income assessment areas.

5.3 The Resulting Impact on Lending

Table 4 examines the lending implications of our identified mechanism, focusing on two key CRA-targeted categories: mortgage lending (Panel A) and small business lending (Panel B). The outcome variables measure cumulative changes in lending since 2010. Due to a low proportion of zeros in the balanced lending panels (6% for mortgages and 8% for small business lending) and large-scale lending volumes, we calculate these changes using the log(1+Y) transformation.[21]

Mortgage Lending. The extent to which the branch closure channel affects mortgage lending is an empirical question. As banks close branches to sidestep the increased compliance cost amid the expansion of non-banks, mortgage supply would decline if having a local branch could facilitate mortgage provision. Yet, as technology advances, branches may become less important for mortgage supply (Loutskina and Strahan, 2009).

Panel A shows that CRA-induced branch closures led to a reduction in the supply of mortgage credit. Column 1 analyzes changes in the logarithm of total mortgage volume, while column 2 examines changes in the logarithm of total mortgage count. With a 30-percentage-point increase in the local non-bank market share, high-δ banks reduce the total dollar volume of originated and purchased mortgage loans by 21.5% and the total number of loans by 14.4% more than low-δ banks.[22]

[21] By using log changes rather than levels as the dependent variable, our approach avoids the re-scaling issues associated with "log-like" transformations, as highlighted by Chen and Roth (2024). Applying $log(1+Y)$ to compute cumulative changes from 2010 to year t yields $log\left(\frac{1+Y_t}{1+Y_{2010}}\right) = log\left(1+\frac{Y_t-Y_{2010}}{1+Y_{2010}}\right)$. When $Y_{2010} \gg 1$, this approximates $log\left(1+\frac{Y_t-Y_{2010}}{Y_{2010}}\right)$, effectively capturing percentage changes and ensuring invariance to re-scaling.

[22] The magnitude of the dollar volume impact, for example, is calculated using the formula $(\exp(-0.805\times 0.3)-1) = -21.5\%$, which reflects the effect of a 30-percentage-point increase in the non-bank market share. We will use the same formula to interpret the coefficients that involve dependent variables measured on a logarithmic scale.

A possible confounding story that explains our findings is that non-banks more directly compete with high-δ banks, which forces them to close branches as their mortgage profits decline. For instance, if high-δ banks happen to originate more FHA mortgages or lend more to low-income borrowers like non-banks, they may lose more business to non-banks as non-banks expand. However, we do not find evidence consistent with this alternative story: as shown in Figure 6, there is no significant difference in the loan portfolios or customer demographics between high-δ and low δ banks. This evidence suggests that the growth of non-banks alone cannot fully account for our results, reinforcing the specific impact of the CRA on banks' operations.

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

Results in Panel B suggest that the CRA regulation leads to a reduction in bank small business lending as non-banks expand, indicating that the *branch closure channel* dominates the *substitution channel*. As the non-bank market share increases by 30 percentage points, high-δ banks reduce small business lending by 19.6% in terms of dollar volume and by 9.5% in terms of loan counts, compared to low-δ banks.

Collectively, the results suggest that as high-δ banks reduce their local branch presence to offset increased CRA compliance costs driven by the growth of non-bank lenders, their supply of mortgage and small business credit declines. In Section 7, we show that this adverse effect is not offset by low-δ banks or new market entrants, leading to an overall reduction in lending and negative impacts on the local economy.

6 The Net Effect of the CRA

Our empirical analysis thus far highlights the dual impact of the CRA on credit accessibility. On one hand, the CRA improves credit access in underserved neighborhoods within prosperous areas where banks maintain branches. On the other hand, it curtails credit supply in economically disadvantaged regions, where banks refrain from establishing branches to avoid CRA obligations. This dichotomy underscores the need for a comprehensive evaluation of the CRA's overall effect on bank lending. In particular, how significant are the adverse effects of the CRA compared to the magnitude of its positive impacts?

To quantify the net effect of the CRA, we estimate the model outlined in Section 2. Specifically, we identify the CRA-induced branch closure cutoff to classify counties as either positively or negatively affected by the CRA and subsequently calculate its overall impact on bank lending. This estimation procedure is closely aligned with our reduced-form analysis, providing a framework to interpret the magnitudes of our empirical findings in the context of the model. Additionally, we perform a counterfactual analysis to estimate the fraction of counties that transitioned from benefiting to suffering under the CRA as non-banks expanded following the financial crisis.

6.1 Estimation

Our estimation proceeds in two steps. First, we estimate the four pivotal demand and supply parameters by analyzing the relationship between lending and local economic conditions as illustrated in Equation (3). Next, we identify the marginal county where banks just break even in maintaining a branch under the CRA requirements after the rise of non-banks. Figure E3 facilitates the following discussion of parameter identification.

Equation (3) describes the relationship between lending and local economic fundamentals $\frac{1}{\beta}$ in LMI versus non-LMI neighborhoods, given banks' branching decisions. These relationships help estimate $\alpha + \alpha_l$, $\alpha + \alpha_h$, γ, and δ in our model. Specifically, when $b = 0$, lending in LMI neighborhoods is given by $L_l = \frac{\alpha+\alpha_l}{2\beta}$ and in non-LMI neighborhoods by $L_h = \frac{\alpha+\alpha_h}{2\beta}$. From this, we can derive the following equations, which identify the values of $\alpha + \alpha_l$ and

$\alpha + \alpha_h$:

$$L_l'(b=0) := \frac{\partial L_l(b=0)}{\partial \frac{1}{\beta}} = \frac{\alpha + \alpha_l}{2},$$
$$L_h'(b=0) := \frac{\partial L_h(b=0)}{\partial \frac{1}{\beta}} = \frac{\alpha + \alpha_h}{2}. \tag{14}$$

When banks have branches in the local market, the relationship between their lending to LMI or non-LMI neighborhoods and local economic fundamentals is expressed as follows:

$$L_l'(b=1) := \frac{\partial L_l(b=1)}{\partial \frac{1}{\beta}} = \frac{\alpha + \alpha_l + \gamma + \delta}{2}$$
$$L_h'(b=1) := \frac{\partial L_h(b=1)}{\partial \frac{1}{\beta}} = \frac{\alpha + \alpha_h + \gamma - \delta\eta_2}{2}. \tag{15}$$

Eqn. (15) does not precisely pin down γ and δ due to the presence of the additional parameter η_2. Given that $\eta_2 \in (0,1)$, we can nonetheless establish the ranges for δ and γ as follows:

$$(\Delta L_l' - \Delta L_h') < \delta < 2(\Delta L_l' - \Delta L_h')$$
$$\gamma = 2\Delta L_l' - \delta, \tag{16}$$

where $\Delta L_l' := L_l'(b=1) - L_l'(b=0)$ and $\Delta L_h' := L_h'(b=1) - L_h'(b=0)$.

To obtain these parameters, we estimate Eqn. (3) using bank-county level data from 2011 to 2017. We use average county-level per capita income (PCI) across years to proxy for the local economic fundamental ($\frac{1}{\beta}$) and estimate the following specification for LMI and non-LMI neighborhoods, separately:

$$\log(\text{Loan Amount})_{b,c,m,t} = \kappa_1 \Big(\log \text{PCI}_c \times \text{I(Branch} = 1)_{b,c,m,t} \Big) + \kappa_2 \log \text{PCI}_c$$
$$\tau \text{I(Branch=1)}_{b,c,m,t} + \mu_{b,s,t} + \epsilon_{b,c,m,t}. \tag{17}$$

Here, $\log(\text{Loan Amount})_{b,c,m,t}$ is the log of total dollar volume of mortgage loans or small business loans supplied by bank b in county c in year t. $\text{I(Branch=1)}_{b,c,m,t}$ is an indicator for whether bank b has at least one branch in county c in year t. $\log \text{PCI}_c$ is the average log of per capita income during 2011-2017 in county c. We include bank-state-year fixed effects, $\mu_{b,s,t}$, to exploit variations in fundamentals across counties within the same state.

The estimated κ_2 for non-LMI neighborhoods, $\hat{\kappa}_2^h$, corresponds to $L_h'(b=0)$. The estimated $\hat{\kappa}_1^h$ corresponds to $\Delta L_h'$. Similarly, from the estimates using the LMI sample, we deduce the values of $L_l'(b=0)$ and $\Delta L_l'$. We then map $\{\hat{\kappa}_1^l, \hat{\kappa}_2^l, \hat{\kappa}_1^h, \hat{\kappa}_2^h\}$ to our model parameters, $\{\alpha+\alpha_l,\ \alpha+\alpha_h,\ \gamma,\ \delta\}$ according to Eqn. (14)-(16).

Next, we identify the marginal county where banks just break even in maintaining a branch under the CRA requirements following the rise of non-banks. This threshold is denoted as $(\frac{1}{\beta})^*$ and is illustrated in Figure E3, where banks are induced to withdraw from a county due to CRA obligations. From Eqn. (3), we know that a bank's branch closure leads to a reduction in lending by $\frac{\gamma+\delta}{2\beta^*}$ in LMI neighborhoods and by $\frac{\gamma-\delta\eta_2}{2\beta^*}$ in non-LMI neighborhoods. Therefore, if we can determine (1) $\gamma+\delta$ and $\gamma-\delta\eta_2$ and (2) the lending reductions caused by CRA-induced branch closures, we can identify $(\frac{1}{\beta})^*$.

First, based on Eqn. (14) and Eqn. (15), the regression (17) yields the precise estimates for $(\gamma+\delta)$ and $(\gamma-\delta\eta_2)$:

$$\frac{\widehat{\gamma+\delta}}{2} = \hat{\kappa}_1^l, \quad \frac{\widehat{\gamma-\delta\eta_2}}{2} = \hat{\kappa}_1^h. \tag{18}$$

Next, we estimate the following specification to obtain the changes in lending triggered by the CRA-induced changes in branch presence:

$$\Delta \log(\text{Loan Amount})_{b,c,t} = \kappa_3 \Delta \mathrm{I}(\widehat{\text{Branch}}{=}1)_{b,c,t} + \nu_b + \mu_{s,t} + \epsilon_{b,c,t}, \tag{19}$$

where $\Delta \mathrm{I}(\widehat{\text{Branch}}{=}1)_{b,c,t}$ represents the predicted change in branch presence induced by CRA regulation, constructed using the interaction of Nbank Shock and High-δ_b, as specified in Eqn. (12). Unlike column (3) of Table 3, this estimation utilizes a pooled sample that includes both mortgage and small business loans.

Finally, we obtain the critical value $(\frac{1}{\beta})^*$ using the estimated $\hat{\kappa}_1^l$, $\hat{\kappa}_1^h$ and $\hat{\kappa}_3$:

$$\left(\frac{1}{\beta}\right)^* = \frac{2\hat{\kappa}_3}{(\gamma+\delta)+(\gamma-\delta\eta_2)} = \frac{\hat{\kappa}_3}{\kappa_1^l + \kappa_1^h}. \tag{20}$$

6.2 Quantification Results

Panel A of Table 5 presents the estimates of Eqn. (17) in columns 1 and 2 and the estimates of (19) in column 3. The estimated $\hat{\kappa}_2^l$ and $\hat{\kappa}_2^h$ reveal a strong positive correlation between bank lending and local economic fundamentals. This relationship is amplified in

LMI neighborhoods when local bank branches are present, suggesting a positive value for $\frac{\gamma+\delta}{2}$. Conversely, the effect of branches in non-LMI neighborhoods is not statistically significant, implying that $\frac{\gamma-\delta\eta_2}{2}$ is approximately zero. Additionally, the positive estimate of $\hat{\kappa}_3$, the coefficient on $\Delta\widehat{\text{I(Branch=1)}}_{b,c,t}$, supports the model's prediction that banks are more likely to increase lending in counties where they maintain branch operations.

Panel B of Table 5 reports the estimated model parameters based on the results in Panel A. The estimated $\alpha + \alpha_h$ exceeds $\alpha + \alpha_l$, indicating stronger overall lending demand in non-LMI neighborhoods. Importantly, the identified marginal county, where banks are indifferent to maintaining branch operations, has a log PCI of 10.39. As Panel A of Figure 8 illustrates, this implies that about 22% of counties with log PCI below this cutoff experienced CRA-induced branch closures as non-banks expanded after the financial crisis, while the remaining 78% of counties were not adversely affected in this regard. The estimated δ ranges from 0.85 to 1.7, reflecting a substantial regulatory cost imposed by the CRA.

Net Effect. To quantify the net effect of the CRA, we first use the estimated parameters to calculate CRA's impact on lending for each county based on Eqn. (7), where log PCI serves as our proxy for $\frac{1}{\beta}$. We then aggregate the effect across all counties as follows:

$$NetL_{tot} = \underbrace{\sum_{c\in\mathbb{C}^+} \frac{\delta(1-\eta_2)}{2\beta}}_{NetL_+} + \underbrace{\sum_{c\in\mathbb{C}^-} \frac{-\gamma}{2\beta}}_{NetL_-}. \tag{21}$$

The two terms in the above expression decompose the net effect into contributions from counties with log PCI above the CRA-related branch closure cutoff, $NetL_+$, and from counties with log PCI below the CRA-related branch closure cutoff, $NetL_-$. Finally, we express the net effects of the CRA as percentage changes of the aggregate lending in the non-CRA benchmark by computing the following ratios

$$\%NetL_x = 100 \times \frac{NetL_x}{\sum_{\forall c}\left(L^{\#}_{hmi,c} + L^{\#}_{lmi,c}\right)},\ x \in \{tot, +, -\}. \tag{22}$$

Following the notations in Eqn. (7), $L^{\#}_{lmi,c}$ and $L^{\#}_{hmi,c}$ represent the equilibrium lending in the absence of the CRA.

Panel C of Table 5 presents the net effect of the CRA from 2011 to 2017 under different η_2 scenarios. As previously discussed, the precise γ estimate, which influences our calculation of $L^{\#}$, depends on the regulatory weight on within-area lending dispersion η_2. The quantification indicates that, for η_2 between 0.25 and 0.75, CRA-induced branch closure results in a 0.7%-2.3% reduction in total lending in the bottom 22% of counties ranked by per-capita income. In contrast, in the more prosperous regions above the critical value for maintaining bank branches, the CRA is associated with a 1.8%-8.3% increase in lending. Overall, the net effect of the CRA across regions ranges from -0.5% to 7.6%, depending on the regulatory weight on within-area dispersion.

Counterfactual: Rise of Non-banks To illustrate the effect of non-bank growth on bank lending under the CRA, we simulate a counterfactual scenario, where the demand for bank credit declines. In particular, we reduce α by 4% of $\alpha + \alpha_l$ while keeping the dispersion, $\alpha_h - \alpha_l$, unchanged. This adjustment effectively lowers credit demand from both LMI and non-LMI neighborhoods.

A critical step in constructing the counterfactual is to determine the counterfactual CRA-induced branch closure cutoff, $\frac{1}{\beta^{*\prime}}$. At the cutoff, banks are indifferent about maintaining local branches or not. Therefore, the cutoff must solve the following break-even condition:

$$\Delta\pi(\frac{1}{\beta^{*\prime}}|\Delta\alpha) = 0 \tag{23}$$

where $\Delta\pi(\cdot)$, analogous to Eqn. (5), represents the difference between banks' profits with and without local branches, and $\Delta\alpha$ represents the change in $\alpha + \alpha_l$. Note that Eqn. (23) precisely determines the counterfactual cutoff based on our estimates in Table 5, and its value remains invariant with respect to η_2. Appendix B.3 provides a detailed derivation of $\frac{1}{\beta^{*\prime}}$ and the proof.

Panel B of Figure 8 highlights the regions experiencing CRA-induced branch closures in the counterfactual scenario. When demand for bank credit decreases by 4%, a larger set of counties—up to 80% of total counties—experience CRA-induced branch closures.

Next, we map the above change to the change in aggregate lending relative to the non-CRA benchmark in this counterfactual scenario, following the same procedures previously described. Columns 5-8 in Panel C of Table 5 report the results. As non-banks continue to expand and demand for bank credit declines, we observe a substantial drop in the aggregate lending under the CRA compared to the non-CRA benchmark, especially if the current regulatory weight on within-area lending dispersion (η_2) is high.

This decline in the effect of CRA on aggregate lending arises from the withdrawal of bank branches reported in Figure 8; however, the contributing factors vary depending on the value of η_2. This is because the value of η_2 is closely associated with the values of γ and δ shown in Eqn. (15), while γ and δ differently influence the CRA's effect on lending in high- and low-income areas. Intuitively, the CRA's effect on higher-income areas mainly works through requiring banks to subsidize LMI neighborhoods, which is governed by δ; whereas the CRA's effect on lower-income areas mainly works through branch closures, whose impact on lending is governed by γ.

Therefore, when η_2 is low, implying a larger δ, the reduction in aggregate lending is primarily driven by reduced subsidized lending in higher-income areas. As shown in the comparison between columns 2 and 6, the positive lending increase in regions above the $(1/\beta)^*$ threshold decreases from 8.3% to 1.5%, while the effect in regions below the threshold changes only marginally, from -1.7% to -2.7%. In contrast, when η_2 is high, implying a larger γ and thus a more critical role of bank branches for credit access, the reduction in aggregate lending is driven more substantially by lower-income areas. This is illustrated in the comparison between columns 4 and 8.

These findings highlight the need for a thorough re-examination and potential adjustment of the CRA's design to address the challenges posed by the evolving lending landscape.

7 Market Level Adjustment and Widened Geographic Disparities

The preceding bank-county level analysis focuses on the decisions of individual banks and overlooks market-level adjustments. The observed effects on lending by individual banks might not translate to significant impacts on the regional economy if low-δ banks or new market entrants, like non-bank lenders who are not subject to CRA regulations, pick up the slack in lending as high-δ banks close branches. Furthermore, a more concerning adverse impact of the CRA lies in its unintended consequences in widening disparity in credit access.

In this section, we evaluate the effect on the regional aggregate supply of credit and the geographic disparities that stem from the CRA.

7.1 The Effect on Regional Lending

To evaluate the impact on regional aggregate lending, we utilize datasets that capture local lending activity from both banks and non-banks. This includes private sector lending data, such as mortgage origination information from the HMDA and UCC filings for secured and non-real estate business loans. Additionally, we consider lending data from government-supported programs, such as the SBA 7(a) program.

For the variable of interest, we calculate the aggregate share of high-δ banks in a county, weighted by their number of branches in the county: $\sum_b w_b$ High-δ_b. Higher values of this measure indicate that a larger proportion of local banks are concerned about CRA violations, thereby increasing the likelihood of CRA-induced branch closures. Using this measure, we conduct a similar DiD analysis to examine CRA's effect on local aggregate lending amid the rise of non-banks from 2011 to 2017:

$$\begin{aligned}\Delta Y_{c,m,t} = \kappa_1\big(\text{NBank Shock}_{m,t} \times \sum_b w_b \text{ High-}\delta_b\big) + \kappa_2\big(\text{NBank Shock}_{m,t} \times X_c^{2010}\big) \\ + \kappa_3 \text{NBank Shock}_{m,t} + \kappa_4 \Delta X_{c,t-1} + \mu_{c,m} + \nu_t + \epsilon_{c,m,t},\end{aligned} \tag{24}$$

$\Delta Y_{c,t}$ is the cumulative change in county total number of branches or one of the lending-related outcomes since 2010.[23] NBank Shock$_{m,t}$ has been previously defined in Section 5.1. We include county fixed effects ($\mu_{c,m}$) and year fixed effects (ν_t) to account for time-invariant local characteristics and macroeconomic conditions. We include interactions between non-bank shocks and local economic fundamentals in 2010, NBank Shock$_{m,t} \times X_c^{2010}$, to control for differential responses to the rise of non-banks associated with varying economic fundamentals across regions. X_c^{2010} includes county population, GDP, housing prices, per capita income, and branch-weighted bank size in 2010. Additionally, we include a set of dynamic controls, $\Delta X_{c,t-1}$, which capture lagged cumulative changes in these variables from 2010 to year $t-1$. These controls account for varying local economic fundamentals over time.

Table 6 presents the results for various county-level outcomes. Panel A examines branch

[23] Given the rarity of zeros in the county-level panels, we calculate cumulative changes using log transformations without the need for $log(1+Y)$ adjustments for zero observations.

and private lending activities by both banks and non-banks. Specifically, columns 1 and 2 analyze the total number of bank branches, while columns 3 and 4 focus on aggregate mortgage lending amounts reported to HMDA. Columns 5 and 6 provide insights into the count of collateralized small business loans from both bank and non-bank lenders, constructed by Gopal and Schnabl (2022). The data reveals a pronounced negative impact of rising CRA regulatory costs. Counties with a higher concentration of high-δ banks experience notable declines in both the number of bank branches and lending activity following the rise of non-bank lenders. Specifically, these counties see a 5.0% reduction in the total number of bank branches, a 11.9% decrease in mortgage origination, and a substantial 30.9% decline in small business lending, coinciding with a 30-percentage-point increase in the market share of non-bank lenders. The disproportionate impact on small business lending, which is substantially greater than that observed in mortgage lending, underscores the importance of relationship lending and local branches in facilitating small business loans, suggesting that individual lenders are less substitutable for one another.

Panel B focuses on the government subsidized lending, the SBA 7(a) Program loans. The 7(a) Program supports small business lending in the U.S. by providing guarantees on loans made by participating lenders, reducing their risk and expanding access to capital for small businesses.[24] Results across the columns consistently indicate that counties with a higher concentration of high-δ banks also experience a significant reduction in government-sponsored loans: revolving lines of credit drop by 55.1%, term loans decrease by 44.4%, and jobs supported by these small business loans shrink by 33.6%, as non-bank lenders increase their local market share by 30 percentage points.

The above results together suggest that non-banks cannot fully substitute for the role of banks, particularly in supporting small businesses. Consequently, as the increased CRA regulatory burden drives branches out of a region, that region experiences a significant reduction in lending, even though non-bank lending grows simultaneously.

[24] While traditionally dominated by regulated banking institutions, non-bank lenders can participate through the Small Business Lending Company (SBLC) program. SBLCs are non-depository lending institutions specifically licensed by the SBA to make 7(a) loans nationwide. Additionally, Community Advantage Small Business Lending Companies (CA SBLCs), a subset of SBLCs, consist of mission-oriented and primarily non-profit financial intermediaries focusing on underserved markets and communities (Title 13 CFR Part 120). To participate in the 7(a) program, lending institutions must demonstrate financial soundness, maintain professional management, and meet SBA's requirements. However, unlike banks which are already federally regulated, non-bank lenders face the additional requirement of obtaining SBLC approval before they can participate in the program.

7.2 Cross-Region Disparities

The results above suggest that market adjustment does not fully compensate for the reduction in lending associated with CRA-induced branch closures. Hence, the increased CRA compliance costs due to the rise of non-banks may shift some areas from benefiting to suffering from the CRA, as banks close branches to avoid the regulation. Since lower-income areas are likely the marginal areas encountering such a shift, the CRA may inadvertently exacerbate geographic disparities in credit access as non-banks expand.

To empirically study whether the CRA widens cross-region disparities, we begin by quantifying the treatment intensity of the CRA, or the degree of CRA bindingness, across different areas. As our model suggests, CRA compliance is more challenging in regions with weaker economic fundamentals. However, regulators may adjust lending requirements based on local economic conditions. Therefore, it remains an empirical question whether CRA requirements are more binding in economically disadvantaged areas. To this end, we characterize the areas with higher CRA bindingness before examining whether these areas become worse off relative to those with lower bindingness as non-banks expand.

7.2.1 Measure and Characterize CRA-Binding Areas

We employ a similar RD design to the one introduced in Section 4.1 to quantify the treatment intensity of the CRA. For each assessment area, we estimate the following specification using census tract-year level observations:

$$\begin{aligned}\log(\text{Loans}_{i,m,t}) = {} & \tilde{\eta}_m \mathbb{1}(\text{lmi}_{i,m,t}) + \kappa_1(\text{MFI}_{i,m,t} - 80\%) \\ & + \kappa_2 \mathbb{1}(\text{lmi}_{i,m,t}) \times (\text{MFI}_{i,m,t} - 80\%) + \epsilon_{i,m,t}.\end{aligned} \tag{25}$$

$\log(\text{Loans}_{i,m,t})$ is the aggregate amount of mortgages loans in census tract i originated by banks that are subject to the CRA in assessment area m in year t. $\tilde{\eta}_m$ captures the extent to which lending under the CRA regulation exceeds the equilibrium lending volume that would exist in the absence of the CRA. This estimation accounts for both the shadow costs of CRA violation among banks operating in the area, as well as the local economic fundamentals.

As shown in Panel D of Table 1, the standard deviation of $\tilde{\eta}_m$ is 3.99, indicating substantial variation in CRA treatment intensity across assessment areas. We define areas where

CRA requirements significantly influence the lending by banks subject to the CRA as *CRA binding areas*, which correspond to markets with $\tilde{\eta}_m$ values above the sample median. Panel A of Figure 9 depicts CRA binding areas across the United States. In Panel B, we characterize these CRA binding areas. Consistent with our model predictions, CRA binding areas tend to exhibit weaker economic fundamentals, characterized by lower GDP, lower income per capita, and greater income dispersion compared to non-binding areas. This finding highlights the role of the CRA in promoting credit access equality within these regions, thereby narrowing the lending gap between LMI and non-LMI neighborhoods. However, this benefit is accompanied by widened *cross-regional* disparities. Indeed, the same binding areas showed worse per capita income, a declining population, and widening income dispersion during 2014-2017 after non-bank lending expanded.

Next, we will provide additional evidence of the widened cross-region disparities driven by CRA regulations amid the growth of non-bank lenders.

7.2.2 Cross-Region Disparities in Real Outcomes

With the estimated CRA bindingness, we now turn to assessing the real implications of the increased CRA regulatory burden as non-bank lenders grow:

$$\begin{aligned}\Delta Y_{c,m,t} = {} & \kappa_1(\text{NBank Shock}_{m,t} \times \text{CRA Binding Area}_m) \\ & + \kappa_3 \text{NBank Shock}_{m,t} + \kappa_4 \text{CRA Binding Area}_m + \kappa_6 \Delta X_{c,t-1} + \mu_c + \nu_t + \epsilon_{c,m,t},\end{aligned} \tag{26}$$

where CRA Binding Area$_m$ is equal to 1 if the estimated effect of CRA regulation on bank lending in market m, $\tilde{\eta}_m$, is above the median of markets during the period from 2005 to 2008. Additional variables are defined in Section 7.1. The specification incorporates lagged time-varying county controls as well as county and year fixed effects to eliminate many potential confounding factors. Table 7 presents the results for a set of county-level real variables, which are described below.

Branch Desert. Column 1 shows that CRA binding areas experience a higher rate of bank branch closures, resulting in an increase in the number of zip codes classified as branch deserts—defined as those without any bank branches—as non-banks expand their presence in local mortgage markets. Specifically, CRA binding areas witness a 2 percentage-point rise in the share of branch deserts compared to non-CRA binding areas due to this expansion.

Financial Inclusion. In the wake of branch closures, there is a noticeable decline in financial inclusion. The underbanked rate among low-income individuals with annual incomes below $30,000—the marginal users of banking services—rises significantly in CRA binding areas compared to non-CRA binding areas, as non-banks expand their presence in the local market. As shown in column 2, the underbanked rate among the low-income population in CRA binding areas increases by 8.28 percentage points relative to non-CRA binding areas when the non-bank market share grows by 30 percentage points.

SBA 7(a) Program. At the same time, there is a significant contraction in government-subsidized loans to small businesses, leading to a corresponding decline in job support. Specifically, the loan amount provided through the Small Business Administration's (SBA) 7(a) Loan Program decreases by 10.4% in CRA binding areas, while job support drops by 12.8% compared to non-CRA binding areas as the non-bank market share grows by 30 percentage points.

Local Firms. As lending is geographically segmented (Petersen and Rajan, 2002; Becker, 2007), a decrease in local credit supply could hinder local business growth. In the last three columns, we present results regarding the number of business firms, drawn from the Business Dynamics Statistics provided by the U.S. Census Bureau. Our analysis shows that a 30-percentage-point increase in the non-bank market share in mortgage origination corresponds to a 1.6% decrease in the number of firms in CRA binding areas compared to non-CRA binding areas. This decline is even more pronounced among young firms (those less than five years old) and small firms with fewer than 500 employees. The results are consistent with the narrative that the regulatory expenses imposed by the CRA increase cross-region disparities in economic development in the aftermath of the emergence of non-banks.

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

8 Conclusion and Discussion

Our findings highlight a fundamental tension in policies like the CRA: using private institutions to achieve social objectives can produce unintended consequences through strategic firm behavior, consistent with Kroszner and Strahan (2011)'s observation that regulatory frameworks must evolve to address financial innovation and inter-institutional linkages.

We document a previously overlooked aspect of the CRA's effectiveness in promoting credit access: while the regulation successfully enhances credit equality within prosperous areas, it can paradoxically exacerbate regional disparities. As non-banks expand, banks facing higher CRA violation costs tend to close branches to avoid regulatory oversight, particularly in economically disadvantaged regions. This withdrawal of traditional banks has substantial consequences, including significant declines in small business lending and subsequent business activity. These patterns reveal a fundamental tension in CRA regulation that non-bank growth intensifies.

The implications extend beyond bank-level responses to broader market outcomes. The impact is particularly pronounced in small business lending, where non-banks have not effectively replaced traditional banks. Unlike the mortgage market where non-bank lenders have partially filled the void, small business credit remains heavily dependent on relationship lending through traditional banking channels. Thus, when CRA regulatory burden drives branches from a region, the resulting decline in credit access can have persistent effects on local economic activity, especially in already struggling areas.

The October 2023 CRA modernization introduces significant changes, including expanded assessment areas through Retail Lending Assessment Areas (RLAAs) and updated asset thresholds. However, our findings suggest that fundamental challenges may persist under the new framework. The volume-based thresholds for RLAA designation could incentivize banks to strategically reduce lending in economically disadvantaged areas to avoid triggering these requirements. While the new rule makes important strides in modernizing the regulatory framework, achieving the CRA's core objectives may require additional policy innovations—such as explicit incentives for maintaining branches in economically disadvantaged areas or assessment frameworks that better account for local economic conditions. These considerations are crucial for ensuring that efforts to strengthen the regulation do not inadvertently reduce banking access in communities most in need of financial services.

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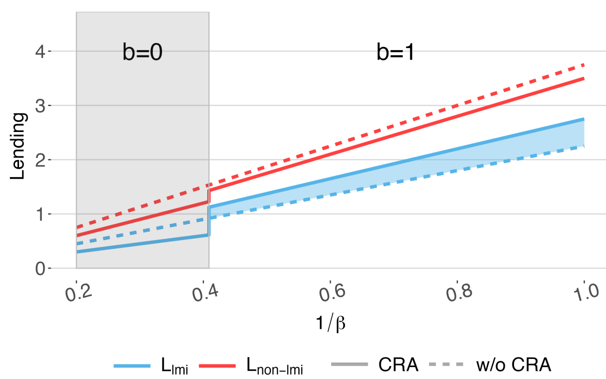
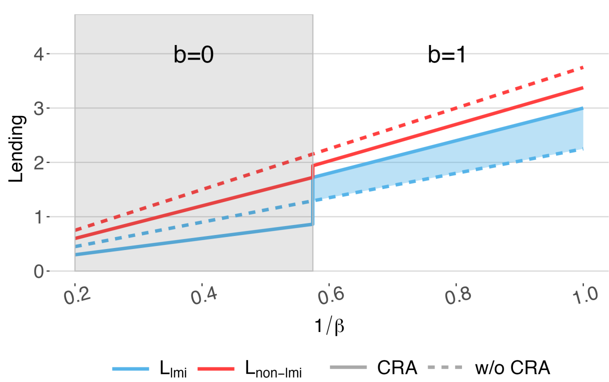
Figure 1. Model Illustration

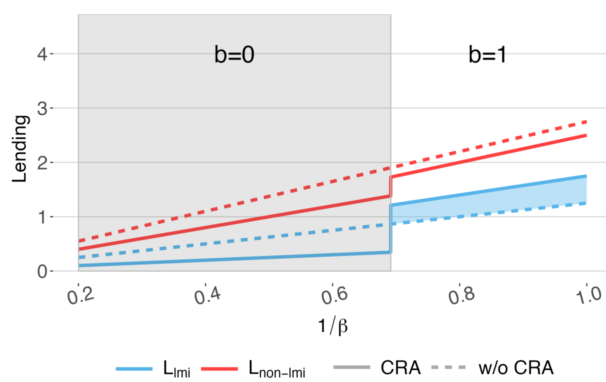
This figure graphically illustrates the model predictions by plotting lending (y-axis) against economic fundamentals 1β (x-axis). Panels (a) and (b) hold the same as all other parameter values except for the level of shadow cost of CRA violation (δ). Panels (a) (c) hold the same as all other parameter values except for the level of demand (α). In each panel, we plot the lending in the underserved neighborhood, with (L_1^*) and without ($L_1^\#$) the CRA, and the lending in the non-underserved neighborhood, with (L_2^*) and without ($L_2^\#$) the CRA. The shaded area indicates regions where the bank does not open a branch ($b = 0$). Parameters: $\alpha = 5$, $\alpha_l = -2$, $\alpha_h = 1$, $\delta = 1$, $\gamma = 1.5$, and $\bar{L} = 7$.



(a) Baseline



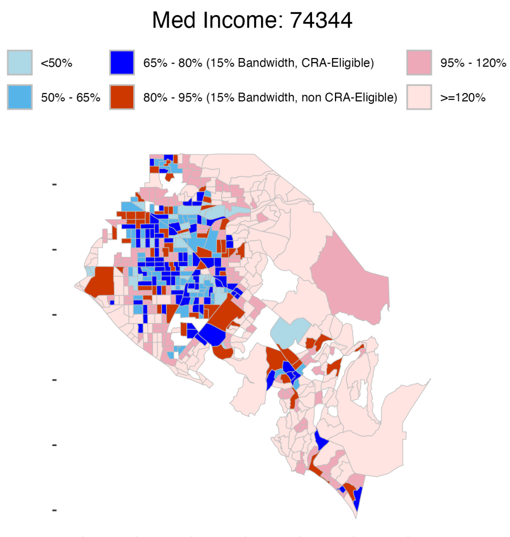
(b) δ increases 1.5



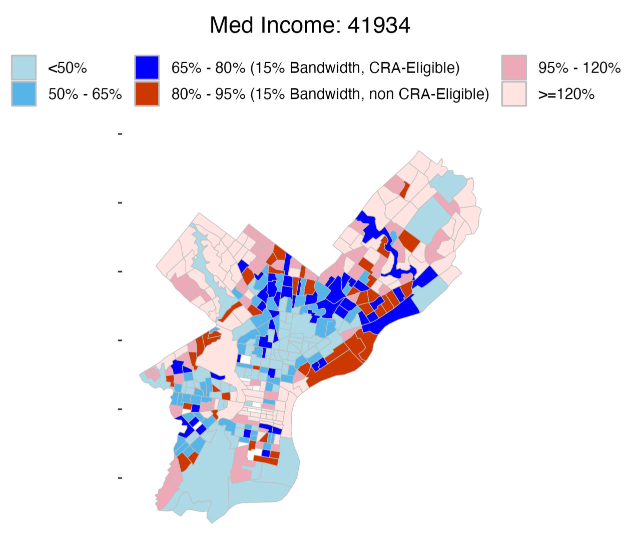
(c) α decreases to 4

Figure 2. Examples of Tract Income and CRA Eligibility Areas

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



(a) Orange County



(b) Philadelphia County

Figure 3. Discontinuity Around the CRA Eligibility Threshold: Loan Volume

This figure illustrates the discontinuity in lending volume around the 80% MFI threshold, utilizing a non-parametric regression discontinuity (RD) plot based on data from 2005-2017. The y-axis represents the residualized logarithm of total lending, encompassing both originated and purchased home-purchase and refinance loans, using the regression model:

$$\log(\text{Loans})_{b,i,t} = \alpha(\text{MFI}_{i,t} - 80\%) + \text{FEs} + \epsilon_{b,i,t}.$$

Here, $(\text{MFI}_{i,t} - 80\%)$ serves as the running variable, quantifying the deviation of the MFI ratio in census tract i from the 80% threshold. The fixed effects (FEs) include both bank and assessment area-year FEs. The plot features circles that represent average values within each of six bins, which contain equal numbers of observations. The solid lines denote fitted values employing triangular weights, with the shaded area reflecting the 90% confidence interval.

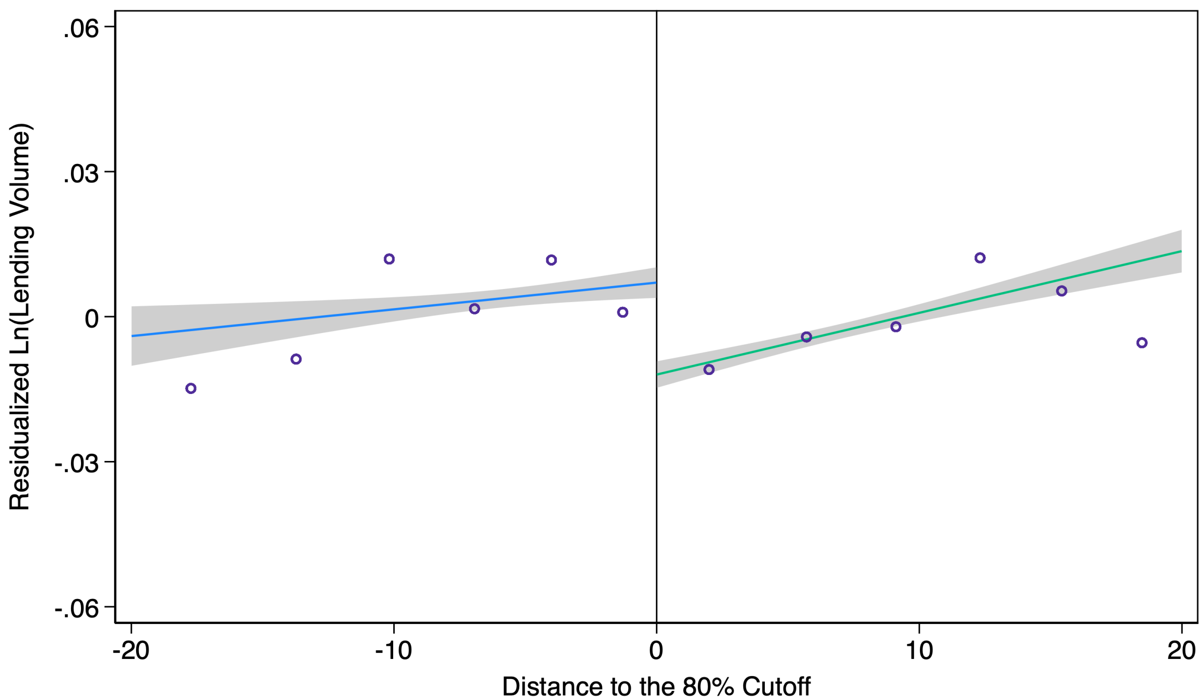
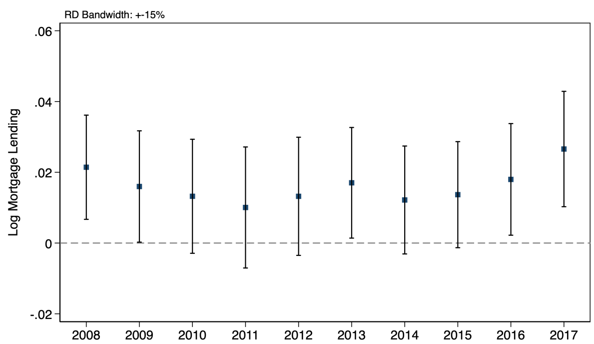


Figure 4. Rolling Sample RD Estimates: Loan Volume

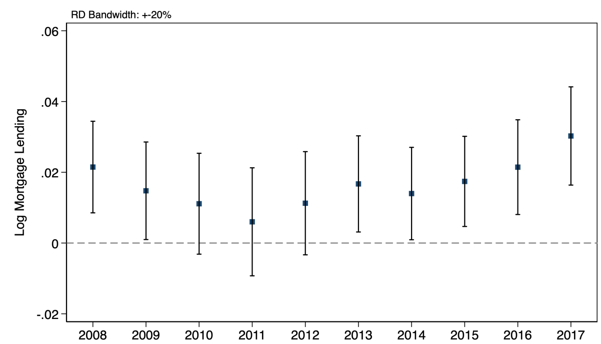
This figure presents the $\tilde{\delta}$ estimates derived from a regression discontinuity (RD) design using a four-year rolling sample from 2008 to 2017:

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

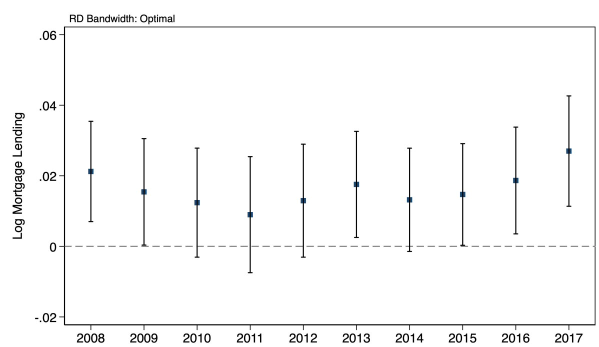
$\log(\text{Loans})_{b,i,t}$ represents the logarithm of total lending, both originated and purchased home-purchase and refinance loans, by bank b in census tract i during year t. $(\text{MFI}_{i,t} - 80\%)$ is the running variable measuring the deviation of a census tract's MFI ratio from the 80% threshold. $\mathbb{1}(\text{LMI}_{i,t})$ is an indicator for tracts where the $\text{MFI}_{i,t}$ falls below 80%, identifying them as low-to-moderate-income (LMI) tracts. To ensure robustness, three distinct bandwidths around 80% threshold are employed for the local polynomial regression: 20%, 15%, and the average optimal bandwidth that minimizes squared error loss, as suggested by Calonico et al. (2017). The plot displays the estimated $\tilde{\delta}$ values and their 90% confidence intervals.



(a) 15% Bandwidth Estimates



(b) 20% Bandwidth Estimates



(c) Optimal Bandwidth Estimates

Figure 5. Persistence of Bank-Level Estimates

This figure demonstrates the persistence of estimated bank-level CRA violation shadow costs using a four-year rolling window, as detailed in Section 5.1. Starting in 2005, we calculate bank-specific $\tilde{\delta}_b \bar{\beta}_b$ for overlapping periods, such as 2005-2008 and 2006-2009. Banks are then categorized into high-δ_b or low-δ_b groups based on the sample median of $\tilde{\delta}_b \bar{\beta}_b$ for each period. The figure displays transition probabilities for both groups, illustrating the likelihood of banks maintaining their classification in the subsequent period.

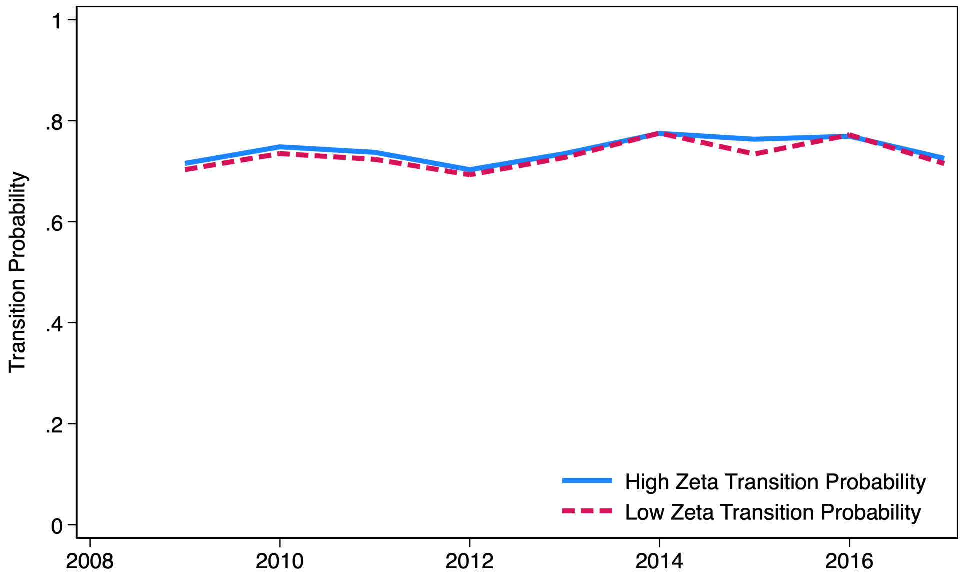


Figure 6. The Shadow Cost of CRA Violation and Bank Characteristics

This figure presents estimates about the relation between the shadow cost of CRA violation and bank characteristics. Each estimate corresponds to a regression of High-δ, an indicator variable for whether the estimated shadow cost of the CRA violation for bank b ($\tilde{\delta}_b$) is above median among all banks, on each covariate. CRA passing rating corresponds to the average of an indicator variable for whether the bank obtained at least a "Satisfactory" CRA rating. Merger is an indicator variable for whether the bank was involved in any merger or acquisition between 2005 and 2008. New branches correspond to the total number of branches opened between 2005 and 2008. Assets correspond to the mean total assets measured between 2005 and 2008, adjusted by CPI (based period 2005). ROA corresponds to the mean of the return on assets between 2005 and 2008. Charge-off ratio comprises the mean of total loans and leases charge-off divided by year-end loan values between 2005 and 2008. Non-performing ratio corresponds to the mean of the sum of non-accruing loans and leases, along with loans that are more than 90 days late, divided by year-end loan values between 2005 and 2008. Profitability is defined as the mean of the ratio of net interest income to year-end loan values between 2005 and 2008. Branch intensity is the mean of the ratio of number of branches to total deposits for each bank between 2005 and 2008. % FHA mortgages is the average share of FHA loans in the mortgage market between 2005 and 2008. % Non-white borrowers is the average of the non-white indicator in the mortgage market for each bank between 2005 and 2008. % Female borrowers is the average of the female indicator in the mortgage market for each bank between 2005 and 2008. ln(income) borrowers is the log of the average income of borrowers in the mortgage market for each bank between 2005 and 2008. Variables are standardized to have unit variance and winsorized at the 0.5% level.

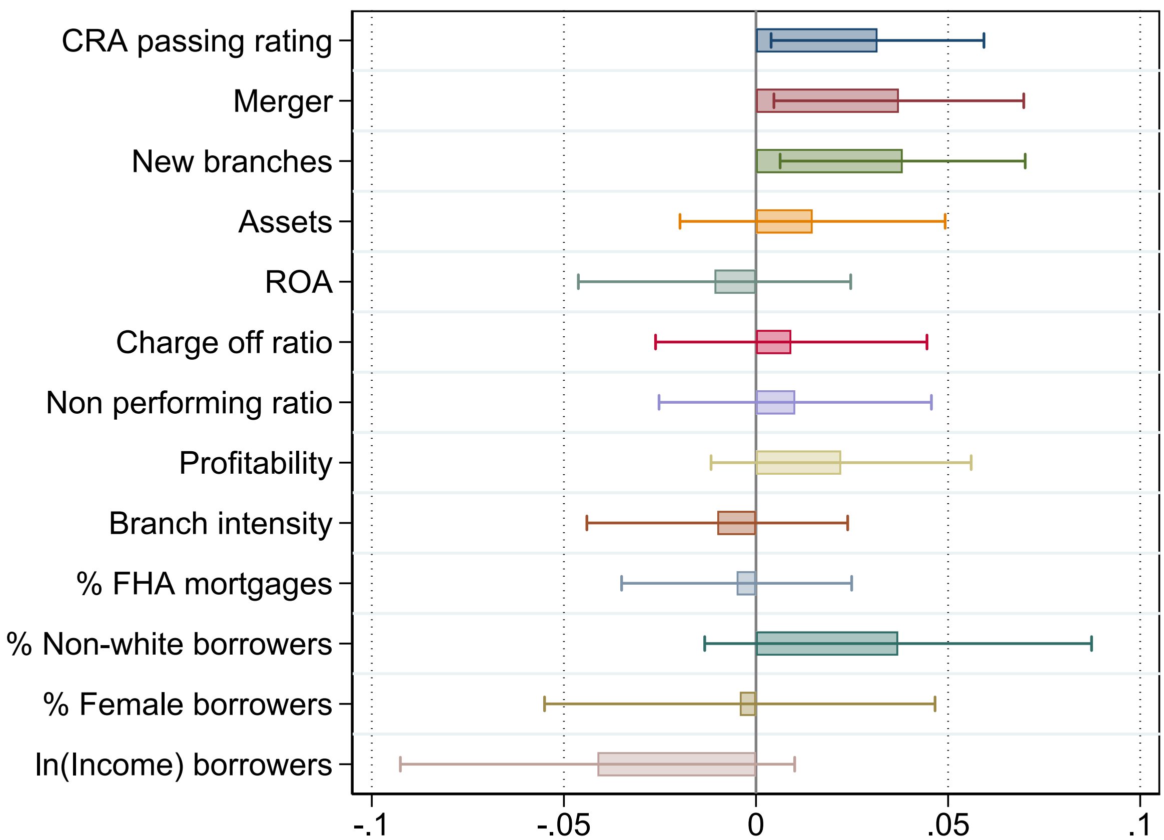


Figure 7. Relevant Condition of Bartik IV

This figure displays the relevant condition to our Bartik instrument variable. The x-axis represents the average share of originated home-purchase and refinance loans by non-banks in each assessment area during 2005-2008, while the y-axis shows the cumulative growth in non-bank market share from 2011 to 2017 within those areas. The plot features circles representing the average values within each of twenty equally populated bins. Solid lines denote the fitted values, accompanied by a shaded area that reflects the 90% confidence interval.

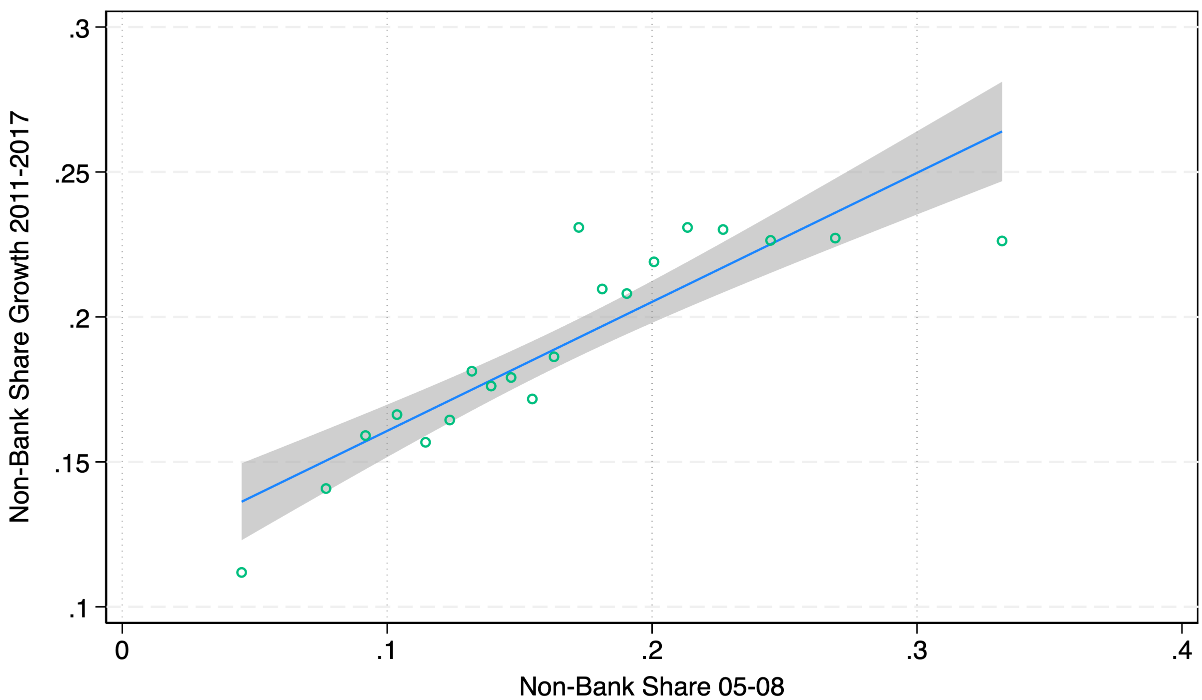
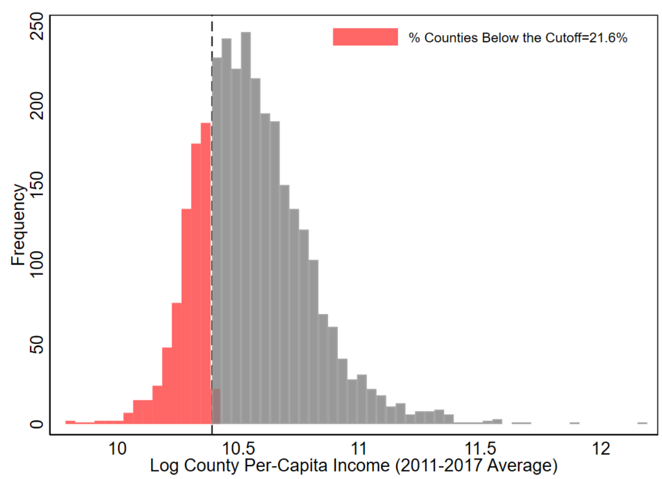
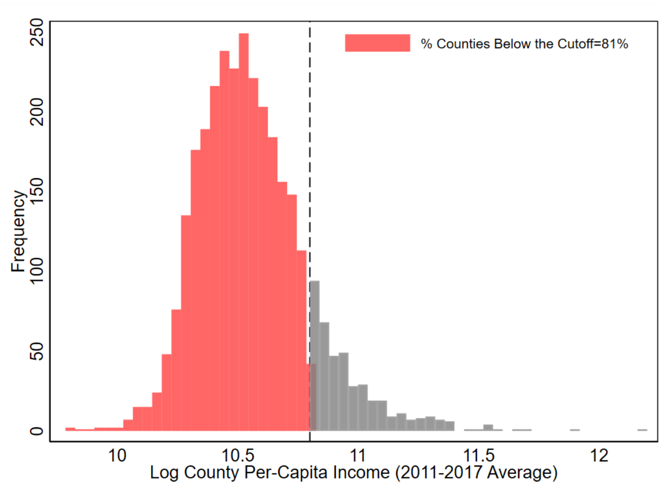


Figure 8. Marginal County—Quantification

The figure displays the density distribution of the average log(PCI) for U.S. counties between 2011 and 2017. The cutoff, $(\frac{1}{\beta})^*$, is estimated using Eqn. (20) based on the results in Table 5. The red area highlights counties that experienced CRA-induced branch closures as non-banks expanded, while the gray area represents counties that were not adversely affected. Panel (a) plots the cutoff estimated for the sample period of 2011–2017. Panels (b) displays the cutoff for the simulated counterfactual scenario: where demand for bank credit decreases by 4% (the "More Non-banks" case).



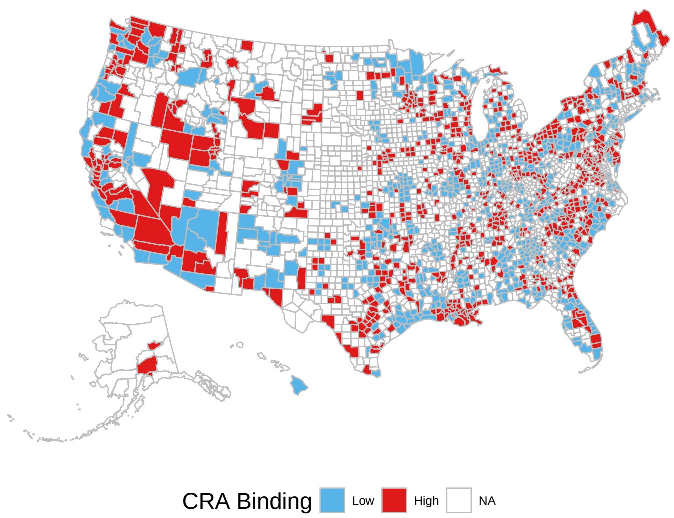
(a) During 2011-2017



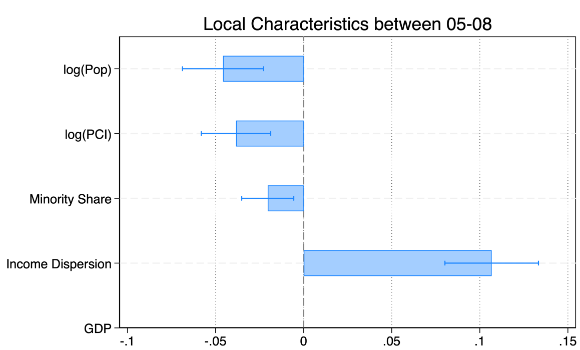
(b) Counterfactual: More Non-banks

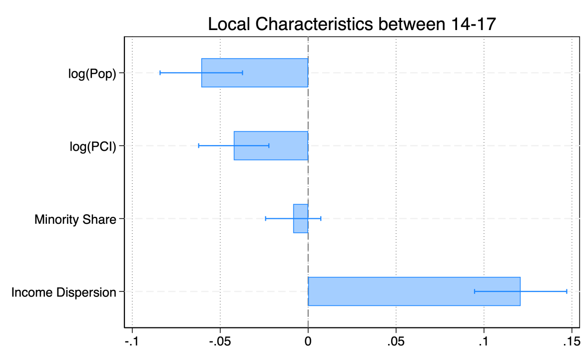
Figure 9. CRA Regulation Binding Areas

Panel A illustrates the map of CRA-binding areas. The CRA effect for each assessment area is estimated using census-tract-level mortgage loan data, including both originated and purchased home-purchase and refinance loans, during the 2005–2008 period. Details of the estimation procedure are provided in Section 7.2. Assessment areas are classified as CRA-binding ("high" on the map) if the estimated $\tilde{\eta}_m$ exceeds the median value among all assessment areas. Conversely, areas below the median are categorized as non-CRA-binding ("low" on the map). Blank regions represent areas with fewer than 20 census-tract lending observations, rendering estimation infeasible. Panel B compares the economic conditions of CRA-binding and non-CRA-binding areas by regressing a CRA-binding indicator on local characteristics, which are standardized to have unit variance. The left panel displays results for local characteristics observed during 2005–2008, while the right panel uses data from 2014–2017. In both cases, the CRA-binding indicator is derived from the 2005–2008 sample.



(a)





(b)

Table 1 Summary Statistics

This table presents the summary statistics for the final samples. Bank- and local-level outcomes are derived from the Home Mortgage Disclosure Act, Summary of Deposits, Community Reinvestment Act, SBA 7(a) Program, and Business Dynamics Statistics datasets covering the years 2011 to 2017. Bank characteristics are sourced from year-end Call Reports and represent averages over the period 2005 to 2008. The unit of observation varies by panel: bank-county-year level in Panel A, county-year level in Panel B, and bank-level in Panel C.

Panel A: Bank-County Panel

	N	Mean	SD	p25	Median	p75
Branches	96,896	4.18	9.19	1	2	4
Mortgage (Thousands)	82,618	51,865	309,269	1,170	5,430	23,324
Mortgage (count)	82,618	205.80	942.6	8	32	117
Small Business Loans (Thousands)	92,946	10,022	28,409	547	2,621	8,776
Small Business Loans (count)	92,946	128.50	655.5	7	26	84

Panel B: County (Assessment Area) Panel

	N	Mean	SD	p25	Median	p75
Branches	17,490	33.05	78.58	7	13	27
Mortgage (Thousands)	17,490	621,521	2,727,081	26,024	77,307	306,323
UCC Small Business Loans (count)	15,002	407.8	973.1	94	180	358
SBA 7(a) #Revolving Lines	9,201	12.12	33.11	1	3	9
SBA 7(a) Term Loans (Thousands)	13,177	9,248	35,094	550.1	2,020	6,552
SBA Total Loans (count)	9,387	34.87	96.32	3	9	30
SBA #Jobs Supported	13,781	278.73	953.74	12	46	185
Bank Desert	11,078	0.02	0.05	0	0	0.03
Underbank Rate	1017	0.39	0.19	0.27	0.39	0.50
Number of Firms	10,659	3205.79	8055.56	489	1020	2666
Non-bank Market Share (05-08)	11,131	0.18	0.06	0.14	0.18	0.22
NBank Shock	11,131	0.27	0.11	0.19	0.26	0.33

Panel C: High- vs Low-δ Bank Characteristics (2005-2008)

	High-δ Bank			Low-δ Bank		
	N	Mean	SD	N	Mean	SD
$\tilde{\delta}_b \times \bar{\beta}_b$	453	0.12	0.86	453	-0.10	0.23
Assets (Billions)	453	12.45	79.22	453	8.47	54.24
Mergers	453	0.38	0.49	453	0.31	0.46
New branches	453	41.00	193.00	453	22.00	108.00
CRA Passing Rating	449	1.00	0.05	360	0.99	0.11

Table 2 Costly CRA Compliance—Lending Quantity Distortion

This table presents the regression discontinuity (RD) estimates examining the effect of CRA on loan amounts around the policy cutoff. The dependent variable across all columns is the logarithm of total lending (both originated and purchased home-purchase and refinance loans) by bank b in census tract i during year t. The running variable of the RD design is the ratio of the 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%. We estimate the following RD design using bank-census tract-year level total lending volume from 2005 to 2017:

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

To demonstrate robustness, we use three distinct bandwidths for estimating local polynomial regression. Columns 1 and 2 focus on census tracts within a 20% bandwidth, where the ratio of a tract's MFI to the region's median MFI falls between 60% and 100%. Columns 3 and 4 analyze tracts within a narrower 15% bandwidth. Columns 5 and 6 employ the average of the optimal bandwidth across years, calculated to minimize squared error loss as suggested by Calonico et al. (2017). A triangular kernel is employed to construct the local estimator. Standard errors (in parentheses) are clustered at the assessment area-year level. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	[-20,+20]		[-15,+15]		Optimal Bandwidth	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(LMI)	0.018***	0.020***	0.019***	0.019***	0.019***	0.019***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
MFI-80	0.018***	0.019***	0.019***	0.019***	0.019***	0.019***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
$\mathbb{1}$(LMI)×(MFI-80)	-0.000	-0.001	-0.002**	-0.002***	-0.001*	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓	
Assessment Area FE	✓		✓		✓	
Assessment Area ×Year FE		✓		✓		✓
Adjusted R^2	0.417	0.430	0.419	0.432	0.419	0.432
Observations	1,924,611	1,922,328	1,458,005	1,455,460	1,259,182	1,256,623

Table 3 The Effect of the CRA on Branch Closures

This table examines how CRA regulation affects banks' branching decisions as non-banks expand in the residential mortgage market from 2011 to 2017. Panel A presents baseline effects specified in Equation (12). The outcome variable $\frac{\Delta\text{Branch}}{\text{Pop}_{2010}}$ measures the cumulative change in the number of branches from 2010 to year t, normalized by 2010 population in millions. Columns 3-4 examine the intensive margin by calculating branch changes conditional on having at least one branch in both years, year 2010 and year t. Columns 5-6 analyze the extensive margin, where $\Delta I(\text{Branch} = 1)$ capture changes in branch presence, i.e., whether a bank has any branches in the local market. The key independent variable NBank Shock$_{m,t}$ is our shift-share instrument, introduced in Section 5.1. High-δ_b indicates whether bank b's estimated CRA violation cost ($\bar{\delta}_b$) exceeds the sample median. We estimate $\bar{\delta}b$ following Section 5.1, using two MSE-optimal bandwidths in the local RD estimation. Assets$b$, 2010 is the total asset size in 2010. Panel B explores heterogeneous effects by interacting the main explanatory variable with assessment area characteristics. Poor denotes areas with below-median per capita income in 2010, while Minor indicates areas where non-white population share exceeds 50%. Standard errors (in parentheses) are clustered at the county level. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Baseline Effect

	$\frac{\Delta\#\text{Branch}}{\text{Pop}_{2010}}$ (Total Effect)		$\frac{\Delta\#\text{Branch}}{\text{Pop}_{2010}}\mid_{\#\text{Branch}\neq 0}$ (Intensive Margin)		Δ I(Branch=1) (Extensive Margin)	
	(1)	(2)	(3)	(4)	(5)	(6)
NBank Shock × High-δ_b	-5.892**	-5.759**	-1.576	-1.646	-0.102**	-0.093*
	(2.82)	(2.82)	(1.55)	(1.54)	(0.05)	(0.05)
NBank Shock × Assets$_{2010}$		-1.363**		-1.032***		-0.105***
		(0.61)		(0.28)		(0.01)
Bank FE	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.262	0.262	0.223	0.223	0.230	0.234
Observations	91,062	91,062	68,001	68,001	93,492	93,492

Panel B: Heterogeneous Effect

	$\frac{\Delta\text{Branch}}{\text{Pop}_{2010}}$		
	(1)	(2)	(3)
NBank Shock × High-δ_b × Poor	-19.363***		-18.526***
	(6.92)		(6.99)
NBank Shock × High-δ_b × Minor		-61.982*	-51.225
		(33.61)	(33.75)
NBank Shock × High-δ_b	0.626	-5.123*	0.738
	(2.95)	(2.83)	(2.96)
High-δ_b × Poor	7.219***		6.497***
	(2.11)		(2.13)
High-δ_b × Minor		36.016***	32.529***
		(8.34)	(8.32)
NBank Shock × Assets$_{2010}$	-1.372**	-1.369**	-1.369**
	(0.61)	(0.61)	(0.61)
Bank FE	✓	✓	✓
County × Year FE	✓	✓	✓
Adjusted R^2	0.263	0.264	0.264
Observations	91,062	91,062	91,062

Table 4 The Effect of the CRA on Bank Lending

This table examines how CRA regulation affects banks' mortgage and small business lending amid non-bank expansion in the residential mortgage market during 2011-2017. We estimate:

$$\Delta Y_{b,c,m,t} = \kappa_1 \text{NBank Shock}_{m,t} \times \text{High-}\delta_b + \kappa_2 \text{NBank Shock}_{m,t} \times \text{Assets}_{b,2010} + \mu_b + \nu_{c,m,t} + \epsilon_{b,c,m,t}.$$

$Y_{b,c,m,t}$ represents bank-county-year level outcomes, with $\Delta Y_{b,c,m,t}$ measuring cumulative changes from 2010 to year t. The key independent variable NBank Shock$_{m,t}$ is our shift-share instrument, introduced in Section 5.1. High-δ_b indicates whether bank b's estimated CRA violation cost ($\bar{\delta}_b$) exceeds the sample median. We estimate $\bar{\delta} b$ following Section 5.1, using two MSE-optimal bandwidths in the local RD estimation. Assets$b, 2010$ controls for bank size using 2010 total assets. Panel A examines mortgage lending using the logarithm of mortgage volume and count as outcomes. Panel B focuses on small business lending (SBL), using the logarithm of SBL volume and count. Standard errors (in parentheses) are clustered at the county level. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Mortgage Lending

	Δlog(1+\$Volume) (1)	Δlog(1+#Loan) (2)
NBank Shock $\times$ High-δ_b	-0.805**	-0.517***
	(0.32)	(0.13)
NBank Shock $\times$ Assets$_{2010}$	-0.885***	-0.571***
	(0.07)	(0.03)
Bank FE	✓	✓
County$\times$Year FE	✓	✓
Adjusted R^2	0.312	0.457
Observations	78,236	78,236

Panel B: Small Business Lending

	Δlog(1+\$Volume) (1)	Δlog(1+#Loan) (2)
NBank Shock $\times$ High-δ_b	-0.729*	-0.332*
	(0.44)	(0.20)
NBank Shock $\times$ Assets$_{2010}$	-0.573***	0.232***
	(0.07)	(0.03)
Bank FE	✓	✓
County$\times$ Year FE	✓	✓
Adjusted R^2	0.202	0.378
Observations	82,135	82,135

Table 5 Quantification

This table reports parameter estimates for $\alpha+\alpha_1$, $\alpha+\alpha_2$, $(\frac{1}{\beta})^*$, γ, and δ, based on a balanced sample of bank-county-year-level data on banks' mortgage and small business lending in assessment areas from 2011 to 2017. We begin by estimating Eqn. (17), which examines the relationship between bank lending and local average per capita income (PCI), separately for LMI and non-LMI neighborhoods across counties. We then use the instrumented changes in branch presence to assess the impact of CRA-induced branch exits on lending reduction. Panel B presents the back-out parameters derived from Eqns. (14), (16), and (20). Panel C presents the percentage lending change compared to the benchmark case without CRA regulation based on Eqn. (21) and (22). Standard errors are clustered at the county level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Estimation Results

	Log(1+$Volumn)		ΔLog(1+$Volumn)
	(1) LMI	(2) Non-LMI	(3) County
log(PCI)	0.985*** $[\hat{\kappa}_2^l]$	3.611*** $[\hat{\kappa}_2^h]$	
	(0.26)	(0.24)	
log(PCI) $\times$I(Branch=1)$_{b,c,t}$	0.752*** $[\hat{\kappa}_1^l]$	-0.095 $[\hat{\kappa}_1^h]$	
	(0.25)	(0.20)	
$\overline{\Delta \text{I(Branch=1)}}_{b,c,t}$			6.827*** $[\hat{\kappa}_3]$
			(0.57)
Adjusted R^2	0.274	0.570	-
Observations	183,327	183,327	181,028
Bank× State × Year FE	✓	✓	
State× Year FE			✓
Bank FE			✓

Panel B: Parameters

Parameter	Expression	Estimates
$\alpha+\alpha_l$	$2\hat{\kappa}_2^l$	1.97
$\alpha+\alpha_h$	$2\hat{\kappa}_2^h$	7.22
δ	$[\hat{\kappa}_1^l-\hat{\kappa}_1^h,\ 2(\hat{\kappa}_1^l-\hat{\kappa}_1^h)]$	[0.85, 1.70]
γ	$2\hat{\kappa}_1^l-\delta$	[-0.19, 0.66]
$(\frac{1}{\beta})^*$	$\frac{\kappa_3}{\hat{\kappa}_1^l+\hat{\kappa}_1^h}$	10.39

Panel C: Quantification

	Baseline				Counterfactual $NetL$ (4% More Non-banks)			
	(1) # Counties	(2) $NetL$ ($\eta2$=0.25)	(3) $NetL$ ($\eta2$=0.5)	(4) $NetL$ ($\eta2$=0.75)	(5) # Counties	(6) $NetL$ ($\eta2$=0.25)	(7) $NetL$ ($\eta2$=0.5)	(8) $NetL$ ($\eta2$=0.75)
Below $(\frac{1}{\beta})^*$	21.6%	-0.7%	-1.7%	-2.3%	81%	-2.7%	-6.5%	-9.0%
Above $(\frac{1}{\beta})^*$	78.4%	8.3%	4.4%	1.8%	19%	1.5%	0.8%	0.3%
Total	-	7.6%	2.7%	-0.5%	-	-1.2%	-5.7%	-8.6%

Table 6 The Effect on Regional Lending

his table presents the results of regional bank lending:

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

$\Delta Y_{c,m,t}$ measures the cumulative log change in county-level outcomes from 2010 to year t. Panel A examines branch counts (columns 1-2), bank and non-bank mortgage volume (columns 3-4), and collateralized small business loans from Gopal and Schnabl (2022) (columns 5-6). Panel B focuses on SBA 7(a) loan program outcomes. The key independent variable NBank Shock$_{m,t}$ captures assessment area m's exposure to national non-bank growth from 2010 to year t, as defined in Equation (13). $\sum_b w_b$ High-δ_b represents the branch-weighted share of high-δ banks in each county. We control for initial county characteristics ($X^{2010}c$) including population, GDP, housing prices, per capita income, and branch-weighted bank size. Dynamic controls ($\Delta Xc, t-1$) include lagged cumulative log changes in per capita income, population, and GDP since 2010. All regressions are weighted by 2010 population, with standard errors (in parentheses) clustered at the county level. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Branch and Private Lending (Including both from banks and non-banks)

	Δlog(#Branch)		Δlog($Mortgage)		Δlog(#SML)	
	(1)	(2)	(3)	(4)	(5)	(6)
NBank Shock × $\sum_b w_b$ High-δ_b	-0.212**	-0.164**	-0.781**	-0.422*	-1.513***	-1.231***
	(0.08)	(0.08)	(0.31)	(0.24)	(0.24)	(0.22)
NBank Shock	-4.743***	-3.616***	15.876***	23.925***	0.055	4.541**
	(1.14)	(0.99)	(3.50)	(3.36)	(2.46)	(2.27)
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Static Controls	✓	✓	✓	✓	✓	✓
Dynamic Controls		✓		✓		✓
Adjusted R^2	0.774	0.780	0.867	0.886	0.822	0.832
Observations	12,534	12,534	12,541	12,541	10,767	10,767

Panel B: SBA 7(a) Program Loans

	Δlog(#Revolving Lines)		Δlog($Term Loans)		Δlog(#Jobs Supported)	
	(1)	(2)	(3)	(4)	(5)	(6)
NBank Shock × $\sum_b w_b$ High-δ_b	-2.653***	-2.667***	-2.340***	-1.957***	-1.572**	-1.366**
	(0.82)	(0.82)	(0.66)	(0.65)	(0.68)	(0.68)
NBank Shock	-19.538**	-18.108**	6.677	10.896*	-5.730	-4.290
	(7.65)	(7.67)	(5.96)	(5.95)	(6.61)	(6.72)
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Static Controls	✓	✓	✓	✓	✓	✓
Dynamic Controls		✓		✓		✓
Adjusted R^2	0.718	0.719	0.662	0.664	0.408	0.409
Observations	5,980	5,980	9,602	9,602	14,962	14,962

Table 7 Widened Cross-Region Disparities

This table examines how CRA regulations affect cross-region disparities during non-bank expansion in the residential mortgage market (2011-2017). We estimate:

$$\begin{aligned}\Delta Y_{c,m,t} = &\kappa_1(\text{NBank Shock}_{m,t} \times \text{CRA Binding Area}_m)\\ &+ \kappa_3\text{NBank Shock}_{m,t} + \kappa_4\text{CRA Binding Area}_m + \kappa_6\Delta X_{c,t-1} + \mu_c + \nu_t + \epsilon_{c,m,t},\end{aligned}$$

$\Delta Y_{c,m,t}$ measures cumulative changes in county-level outcomes from 2010 to year t. The key independent variables are NBank Shock$_{m,t}$, which captures assessment area m's exposure to national non-bank growth as defined in Equation (13), and CRA Binding Area$m$, an indicator for above-median CRA treatment intensity in assessment area m. Dynamic controls ($\Delta Xc, t-1$) include lagged cumulative log changes in per capita income, population, and GDP since 2010. We examine several outcome variables: the change in branch desert prevalence (zip codes without bank branches) in Column 1; the change in underbanked population (those unbanked or using non-bank financial services) among individuals earning below \$30,000 annually from the FDIC Survey in Column 2; log changes in SBA 7(a) program outcomes (small business lending volume and supported jobs) in Columns 3-4; and log changes in business presence (total firms, firms under five years old, and firms with fewer than 500 employees) in Columns 5-7. All regressions are weighted by 2010 population, with standard errors (in parentheses) clustered at the county level. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	Branch Access		SBA 7(a) Program		Δlog(#Firms)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ΔBank Desert	ΔUnderbank Rate	Δlog (#Term Loans)	Δlog (#Jobs Supported)	All Firms	Young Firms	Small Firms
NBank Shock ×CRA Binding Area	0.024*	0.276**	-0.365**	-0.457**	-0.055**	-0.119**	-0.061**
	(0.01)	(0.13)	(0.16)	(0.21)	(0.02)	(0.05)	(0.03)
CRA Binding Area	0.012	-0.106*	0.094	0.150	0.014	0.036*	0.016
	(0.01)	(0.06)	(0.10)	(0.11)	(0.01)	(0.02)	(0.01)
NBank Shock	-0.028	-0.354*	1.973***	0.968**	0.114***	0.131*	0.145***
	(0.03)	(0.19)	(0.34)	(0.43)	(0.03)	(0.07)	(0.04)
County FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Dynamic Controls	✓	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.775	0.151	0.726	0.616	0.931	0.842	0.927
Observations	8,706	943	7,631	7,512	8,665	8,634	8,653

Appendix for Online Publication

A Supplementary Institutional Detail

A.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. Since 2022, the agencies overseeing the CRA have been jointly working on a new CRA reform that implements more quantitative metrics for compliance and adapt regulations to account for changes in the banking industry, such as the rise of internet and mobile banking.[25]

A.2 The CRA Rules: A Quantity Regulation

The following core content of the CRA regulation has remained unchanged since the revision in 1995. The primary categories of loans eligible under the CRA regulation include mortgages and small business loans, with both originated and purchased loans contributing to CRA

[25] For more details of the final rule, please refer to OCC. The original plan was for the rule to take effect on April 1, 2024. However, in March 2024, due to various oppositions, the applicability date was postponed to January 1, 2026, and additional public comments are requested during the interim period.

ratings. CRA evaluations are conducted by bank regulators.[26] The CRA regulation applies to all FDIC-insured depository institutions, such as commercial banks and thrifts, but does not require compliance from credit unions or non-depository institutions (i.e., non-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 delimited by metropolitan statistical areas (MSAs) or by counties if an area falls outside an MSA. The Federal Reserve Board publishes the list of assessment areas for each bank in the CRA Analytics Data Tables. According to this data, 90% of banks' assessment areas overlap with where they have branches.[27] Thus, while the 1995 CRA reform revised the definition of a bank's assessment areas to include regions without branches but with significant lending activity, branch operations continue to serve as the primary determinant for delineating assessment areas.

The CRA provides a clear definition of LMI census tracts: these are tracts where the median family income (MFI) is less than 80% of the MFI of the surrounding geographic area, typically defined as an MSA or, for non-MSA regions, a non-metro area within the state (Code of Federal Regulations Title 12, Section 25.12).

To comply with the CRA regulation, banks undergo a comprehensive examination involving lending, investment, and service tests. The lending test, which is a major component of the CRA evaluation, focuses primarily on evaluating loans reported in HMDA and CRA disclosure statements, mainly mortgages and small business loans.[28] 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

[26] 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.

[27] The CRA Analytics Data Tables provide bank-county-year level data, with `county_aa_flag` indicating whether a county is an assessment area for a bank. The dataset also includes merged information from the Summary of Deposits (SOD), where `sod_proxy_aa_flag` denotes whether the bank has a branch in the same county, and `cont_to_sod_proxy_aa_flag` indicates whether the bank has a branch in a nearby county, likely within the same MSA. Over the sample period (2005–2017), there are 238,983 bank-county-year observations with `county_aa_flag == 1`. Of these, 174,545 have branches in the same county, while 39,660 have branches in a nearby county. Thus, 90% of these observations ($\frac{174{,}545+39{,}660}{238{,}983} = 90\%$) correspond to banks' assessment areas overlapping with regions where they maintain branches.

[28] 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.

classified by geography (distinguishing between LMI and non-LMI areas).[29]

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

A.3 Supplementary Legal Excerpts

From the 12 CFR § 345.22 Lending test.

(a) **Scope of test.** *The lending test evaluates a bank's record of helping to meet the credit needs of its assessment area(s) through its lending activities by considering a bank's home mortgage, small business,* small farm, and community development lending.

(b) **Performance criteria.** The [regulator] evaluates a bank's lending performance pursuant to the following criteria:

  (1) **Lending activity.** The number and amount of the bank's home mortgage, small business, small farm, and consumer loans, if applicable, in the bank's assessment area(s);

  (2) **Geographic distribution.** *The geographic distribution of the bank's home mortgage, small business, small farm, and consumer loans, if applicable, based on the loan location, including:*

    (i) *The proportion of the bank's lending in the bank's assessment area(s);*

    (ii) The dispersion of lending in the bank's assessment area(s); and

    (iii) The number and amount of loans in low-, moderate-, middle-, and upper-income geographies in the bank's assessment area(s);

[29] More details are provided in Appendix A.

(3) **Borrower characteristics.** The distribution, particularly in the bank's assessment area(s), of the bank's home mortgage, small business, small farm, and consumer loans, if applicable, based on borrower characteristics, including the number and amount of:

  (i) Home mortgage loans to low-, moderate-, middle-, and upper-income individuals;

  (ii) Small business and small farm loans to businesses and farms with gross annual revenues of $1 million or less;

  (iii) Small business and small farm loans by loan amount at origination; and

  (iv) Consumer loans, if applicable, to low-, moderate-, middle-, and upper-income individuals;

(4) **Community development lending.** The bank's community development lending, including the number and amount of community development loans, and their complexity and innovativeness; and

(5) **Innovative or flexible lending practices.** The bank's use of innovative or flexible lending practices in a safe and sound manner to address the credit needs of low- or moderate-income individuals or geographies.

From the Large Institution CRA Examination Procedures OCC, FRB, and FDIC April 2014

1. Identify the institution's loans to be evaluated.

2. Test a sample of loan files to verify the accuracy of data collected and/or reported by the institution.

3. *Identify the volume, both in number and dollar amount, of each type of loan being evaluated that the institution has made or purchased within its assessment area. Evaluate the institution's lending volume considering the institution's resources and business strategy and other information from the performance context, such as population, income, housing, and business data.* Note whether the institution conducts certain lending activities in the institution and other activities in an affiliate in a way that could inappropriately influence an evaluation of borrower or geographic distribution.

4. Review any analyses prepared by or for and offered by the institution for insight into the reasonableness of the institution's geographic distribution of lending. Test the accuracy of the data and determine if the analyses are reasonable. If areas of low or no penetration were identified, review explanations and determine whether action was taken to address disparities, if appropriate.

5. Supplement with an independent analysis of geographic distribution as necessary. As applicable, determine the extent to which the institution is serving geographies in each income category and whether there are conspicuous gaps unexplained by the performance context. Conclusions should recognize that institutions are not required to lend in every geography. The analysis should consider:

    (a) (Excluding affiliate lending) the number, dollar amount, and percentage of the institution's loans located within any of its assessment areas, as well as the number, dollar amount, and percentage of the institution's loans located outside any of its assessment areas;

    (b) The number, dollar amount, and percentage of each type of loan in the institution's portfolio in each geography, and in each category of geography (low-, moderate-, middle-, and upper-income);

    (c) The number of geographies penetrated in each income category, as determined in step (b), and the total number of geographies in each income category within the assessment area(s);

    (d) The number and dollar amount of its home purchase, home refinancing, and home improvement loans, respectively, in each geography compared to the number of one-to-four family owner-occupied units in each geography;

    (e) The number and dollar amount of multifamily loans in each geography compared to the number of multifamily structures in each geography;

    (f) The number and dollar amount of small business and farm loans in each geography compared to the number of small businesses/farms in each geography;

    (g) Whether any gaps exist in lending activity for each income category, by identifying groups of contiguous geographies that have no loans or those with low penetration relative to the other geographies.

6. If there are groups of contiguous geographies within the institution's assessment area with abnormally low penetration, the examiner may determine if an analysis of the institution's performance compared to other lenders for home mortgage loans (using reported HMDA data) and for small businesses and small farm loans (using data provided by lenders subject to CRA) would provide an insight into the institution's lack of performance in those areas. Using the analysis from step number 6, form a conclusion as to whether the institution's abnormally low penetration in certain areas should constitute a negative consideration under the geographic distribution performance criteria of the lending test by considering:
   (a) The institution's share of reported loans made in low- and moderate-income geographies versus its share of reported loans made in middle- and upper-income geographies within the assessment area(s);
   (b) The number of lenders with assessment area(s) substantially overlapping the institution's assessment area(s);
   (c) The reasons for penetration of these areas by other lenders, if any, and the lack of penetration by the institution being examined that are developed through discussions with management and the community contact process;
   (d) The institution's ability to serve the subject area in light of (i) the demographic characteristics, economic condition, credit opportunities, and demand; and (ii) the institution's business strategy and its capacity and constraints;
   (e) The degree to which penetration by the institution in the subject area in a different reported loan category compensates for the relative lack of penetration in the subject area; and
   (f) The degree to which penetration by the institution in other low- and moderate-income geographies within the assessment area(s) in reported loan categories compensates for the relative lack of penetration in the subject area.
7. Review any analyses prepared by or for and offered by the institution for insight into the reasonableness of the institution's distribution of lending by borrower characteristics. Test the accuracy of the data and determine if the analyses are reasonable. If areas of low or no penetration were identified, review explanations and determine whether action was taken to address disparities, if appropriate.

8. Supplement with an independent analysis of the distribution of the institution's lending within the assessment area by borrower characteristics as necessary and applicable. Consider factors such as:

   (a) The number, dollar amount, and percentage of the institution's total home mortgage loans and consumer loans, if included in the evaluation, to low-, moderate-, middle-, and upper-income borrowers;

   (b) The percentage of the institution's total home mortgage loans and consumer loans, if included in the evaluation, to low-, moderate-, middle-, and upper-income borrowers compared to the percentage of the population within the assessment area who are low-, moderate-, middle-, and upper-income;

   (c) The number and dollar amount of small loans originated to businesses or farms by loan size of less than $100,000; at least $100,000 but less than $250,000; and at least $250,000 but less than or equal to $1,000,000;

   (d) The number and amount of the small loans to businesses or farms that had annual revenues of less than $1 million compared to the total reported number and amount of small loans to businesses or farms; and

   (e) If the institution adequately serves borrowers within the assessment area(s), whether the distribution of the institution's lending outside of the assessment area based on borrower characteristics would enhance the assessment of the institution's overall performance.

9. Review data on the institution's community development loans using information obtained in the performance context procedures, especially with regard to community credit needs and institutional capacity.

10. If the institution has been responsive to community development needs and opportunities in its assessment area(s) based on the analysis in step number 10, consider:

    (a) The number and dollar amount of community development loans in the broader statewide or regional area that includes the assessment area(s), but:

        (i) Will not benefit the assessment area(s); and

    (ii) Do not support organizations or activities with a purpose, mandate, or function that includes serving geographies or individuals located within the institution's assessment area(s).

  (b) The extent to which these loans enhance the institution's performance.

11. Evaluate whether the institution's performance under the lending test is enhanced by offering innovative loan products or products with more flexible terms to meet the credit needs of low-and moderate-income individuals or geographies.

12. Discuss with management the preliminary findings in this section.

13. Summarize your conclusions regarding the institution's lending performance under the following criteria:

    (a) Lending activity.

    (b) Geographic distribution.

    (c) Borrower characteristics.

    (d) Community development lending.

    (e) Use of innovative or flexible lending practices.

14. Prepare comments for the performance evaluation and the Compliance examination report. Refer to the appendix for guidance on addressing community development activities in the performance evaluation.

B Supplemental Materials to Section 2

B.1 Proof for Comparative Statics of $\Delta\pi$

Proof. Since branch closure occurs at the cutoff point where $\Delta\pi < 0$, understanding how parameters influence $\Delta\pi$ provides insights into their impact on CRA-induced branch closures.

Before delving into specific cases, it is important to note that the cost of failing to meet CRA requirements in Eqn. (2) is positive only if $\eta_1(\bar{L} - L_{lmi}) + \eta_2(L_{hmi} - L_{lmi}) > 0$. Our analysis focuses on the corresponding parameter regime that satisfy this condition. Outside this parameter regime, the bank incurs no cost and always retains the branch in the model.

The effect of δ: We have

$$\begin{aligned}\frac{\partial \Delta\pi}{\partial \delta} &= -\eta_1(\bar{L} - \frac{\alpha + \alpha_l + \gamma + \delta}{2\beta}) - \eta_2 \frac{\alpha_h - \alpha_l - \delta(1 + \eta_2)}{2\beta} \\ &= -\eta_1(\bar{L} - L^*_{lmi}|_{b=1}) - \eta_2(L^*_{hmi}|_{b=1} - L^*_{lmi}|_{b=1}) < 0.\end{aligned}$$

Thus, a larger δ results in branch closure under CRA regulation. The result remains unchanged regardless of whether $\eta_1 = 0$ or $\eta_2 = 0$.

The effect of β: First, we can rewrite $\Delta\pi$ as follows:

$$\Delta\pi = \frac{\gamma(2\alpha + \alpha_l + \alpha_h + \gamma) + \delta\eta_1(\alpha + \alpha_l + \gamma + \delta\eta_1/2) - \delta\eta_2(\alpha_h - \alpha_l - \delta)}{2\beta} - \delta\eta_1\bar{L}$$

To simplify the notation, let $\Delta\pi = \frac{Z_1 - Z_2}{2\beta} - \delta\eta_1\bar{L}$. Clearly, when $Z_1 > Z_2$, we have $\frac{\partial\Delta\pi}{\partial\beta} < 0$. In this parameter regime, weaker fundamentals lead to a lower $\Delta\pi$, and when $\Delta\pi$ falls below zero, the bank closes its branch. In the remaining regimes where $Z_1 < Z_2$, $\Delta\pi$ is always less than zero, meaning the bank does not establish a branch, irrespective of the fundamentals. Therefore, in the regime where β influences the branch closure decision, we find that $\frac{\partial\Delta\pi}{\partial\beta} < 0$. The result remains consistent when $\eta_2 = 0$. However, when $\eta_1 = 0$, $\Delta\pi$ has the same sign with $Z_1 - Z_2$, meaning that changes in β no longer influence the bank's decision to maintain branches.

The effect of α: We have

$$\frac{\partial \Delta\pi}{\partial \alpha} = \frac{2\gamma + \delta\eta_1}{2\beta} > 0.$$

Hence, a small α results in branch closure under CRA regulation. The result remains unchanged regardless of whether $\eta_1 = 0$ or $\eta_2 = 0$.

The effect of $\alpha_h - \alpha_l$: We have

$$\frac{\partial \Delta\pi}{\partial(\alpha_h - \alpha_l)} = \frac{\delta\eta_2}{2\beta} > 0.$$

Hence, a large dispersion $\alpha_h - \alpha_l$ results in branch closure under CRA regulation. The result remains unchanged regardless of whether $\eta_1 = 0$ or $\eta_2 = 0$. □

B.2 Proof for Comparative Statics of β^*

Proof. Let β^* denote the threshold where $\Delta\pi(\beta^*) = 0$. Our objective is to investigate how β^* shifts in response to changes in other parameters.

The effect of δ: Take the derivative of $\Delta\pi(\beta^*) = 0$ with respect to δ, we can get

$$\frac{\partial \beta^*}{\partial \delta} = \frac{\delta^2(1+\eta_2^2) - \gamma(4\alpha + 2\alpha_l + 2\alpha_h + 2\gamma)}{4\bar{L}\delta^2\eta_1} < 0.$$

The last inequality arises because given $\delta\eta_1 \times (\bar{L} - L^*_{lmi}|_{b=1}) + \delta\eta_2 \times (L^*_{hmi}|_{b=1} - L^*_{lmi}|_{b=1}) > 0$ in Eqn. (5), we must have $\frac{\gamma(2\alpha+\alpha_l+\alpha_h+\gamma)}{2\beta} > \delta^2\frac{1+\eta_2^2}{4\beta}$ when $\Delta\pi = 0$. Hence, $\frac{\partial 1/\beta^*}{\partial\delta} > 0$.

The effect of α: Take the derivative of $\Delta\pi(\beta^*) = 0$ with respect to α, we can get

$$\frac{\partial \beta^*}{\partial \alpha} = \frac{2\gamma + \delta\eta_1}{2\delta\eta_1\bar{L}} > 0.$$

Hence, $\frac{\partial 1/\beta^*}{\partial\delta} < 0$.

The effect of $\alpha_h - \alpha_l$: Take the derivative of $\Delta\pi(\beta^*) = 0$ with respect to $\alpha_h - \alpha_l$, we can get

$$\frac{\partial \beta^*}{\partial \alpha_h - \alpha_l} = -\frac{\eta_1}{2\eta_1 \bar{L}} < 0.$$

Hence, $\frac{\partial 1/\beta^*}{\partial \alpha_h - \alpha_l} > 0$. □

B.3 Counterfactual Cutoff $\beta^{*\prime}$

In this section, we derive the CRA-induced branch closure cutoff in the counterfactual, where $\alpha + \alpha_1$ changes to $\alpha + \alpha_1 + \Delta\alpha$. We will show that cutoff $\beta^{*\prime}$ can be fully pinned down given our estimates in Table 5 and does not depend on the exact value of η_2. Therefore, while η_2 cannot be identified in our estimation, we can still determine how the marginal county shifts as $\alpha + \alpha_1$ varies in the counterfactual.

At the CRA-induced branch closure cutoff, $\frac{1}{\beta^{*\prime}}$, banks are indifferent about maintaining local branches or not. Therefore, the new cutoff must solve the following break-even condition as $\alpha + \alpha_1$ varies in the counterfactual:

$$\Delta\pi(\frac{1}{\beta^{*\prime}}|\Delta\alpha) = 0 \tag{B1}$$

where $\Delta\pi(\cdot)$ represents the difference between banks' profits with and without local branches, and $\Delta\alpha$ represents the change in $\alpha + \alpha_l$. Eqn. (B1) yields the following:

$$\Delta\pi = \frac{2\delta\eta_1\bar{L}\beta^* + \Delta\alpha(2\gamma + \delta\eta_1)}{2\beta^{*\prime}} - \delta\eta_1\bar{L} = 0 \Longrightarrow (\frac{1}{\beta^{*\prime}}) = \frac{2\delta\eta_1\bar{L}}{\frac{2\delta\eta_1\bar{L}}{1/\beta^*} + \Delta\alpha(2\gamma + \delta\eta_1)} \tag{B2}$$

Next, we show the above expression can be entirely expressed in terms of our model estimates in Table 5 and thus, $\frac{1}{\beta^{*\prime}}$ does not vary with η_2. From Eqn. 5, we obtain the following:

$$\begin{aligned}\frac{2\delta\eta_1\bar{L}}{(1/\beta)^*} &= \gamma(2\alpha + \alpha_l + \alpha_h + \gamma) + \delta\eta_1(\alpha + \alpha_l + \gamma + \delta\eta_1/2) - \delta\eta_2(\alpha_h - \alpha_l - \delta) \\ &= (2\gamma + \delta\eta_1)(\alpha + \alpha_l) + (\gamma - \delta\eta_2)(\alpha_h - \alpha_l) + (\gamma + \delta)(\gamma - \delta\eta_2) + \frac{(\delta(1 + \eta_2))^2}{2}.\end{aligned} \tag{B3}$$

From Eqn. (14) and (18), we have the following relationships:

$$\gamma + \delta = 2\hat{\kappa}_1^l, \quad \gamma - \delta\eta_2 = 2\hat{\kappa}_1^h, \quad \alpha + \alpha_l = 2\hat{\kappa}_2^l, \quad \alpha + \alpha_h = 2\hat{\kappa}_2^h.$$

Thus, given our estimates in Table 5, $\frac{2\delta\eta_1\bar{L}}{(1/\beta)^*}$ and $2\delta\eta_1\bar{L}$ are fully determined, which means that all terms in the function of $\frac{1}{\beta^{*\prime}}$ defined in Eqn. B2 are constant, independent of η_2.

C Estimating Bank-Specific Compliance Costs

Although Equation (11) provides a straightforward formula to estimate $\frac{\delta(1+\eta_2)}{2\beta}$ using a RD design, the coefficient on $\mathbb{1}(\text{LMI}_{i,t})$ from Specification (11) does not yield a direct estimate of δ that is comparable across different banks. This is primarily because banks operate in different sets of locations, each with varying price sensitivity β. Consequently, directly comparing these coefficients across banks without adjusting for these differences may lead to biased conclusions.

To obtain accurate and comparable estimates of the bank-specific compliance cost δ for each bank, we outline the correct estimation procedure below. For simplicity, we abstract from the RD design and assume that we directly observe the lending difference between LMI and non-LMI neighborhoods for Bank A across its assessment areas (AAs). Let this lending difference be represented by the vector $\{y^A\}$, where N_A is the total number of assessment areas for Bank A, and each area is indexed by m. Each element y_m^A is given as $y_m^A = \frac{\delta_A(1+\eta_2)}{\beta_m^A}$, where δ_A is a constant representing Bank A's CRA compliance cost, β_m^A is the price sensitivity in assessment area m, and η_2 reflects the relative weight assigned to the lending dispersion penalty.

To estimate δ_A, we perform a weighted regression of y_m^A on a constant term, using weights $w_m^A = \beta_m^A$. The choice of weights is crucial, as it accounts for the heterogeneity in price sensitivity across different assessment areas. Under this specification, the estimated coefficient yields:

$$\tilde{\delta}_A = \frac{\sum_{m=1}^{N_A} w_m^A y_m^A}{\sum_{m=1}^{N_A} w_m^A} = \frac{\sum_{m=1}^{N_A} \beta_m^A \left(\frac{\delta_A(1+\eta_2)}{\beta_m^A}\right)}{\sum_{m=1}^{N_A} \beta_m^A} = \frac{N_A\delta_A(1+\eta_2)}{\sum_{m=1}^{N_A} \beta_m^A} = \frac{\delta_A(1+\eta_2)}{\bar{\beta}_A}, \tag{C4}$$

where $\bar{\beta}_A = \frac{1}{N_A} \sum_{m=1}^{N_A} \beta_m^A$ is the average price sensitivity across Bank A's assessment areas. Then, we can recover an estimate of δ_A as:

$$\delta_A(1 + \eta_2) = \tilde{\delta}_A \times \bar{\beta}_A. \tag{C5}$$

This estimation procedure effectively adjusts for the variation in price sensitivity across different assessment areas by weighting each observation proportionally to β_m^A. By doing so, we ensure that areas with higher price sensitivity contribute appropriately to the estimation. Applying the same methodology to other banks, we can obtain estimates $\delta_A(1 + \eta_2)$ for each bank b. This enables a meaningful comparison of CRA compliance costs across banks, even when they operate in different sets of locations with varying characteristics.

In the analysis, we use the invserse of log income per capita, $\frac{1}{log(PCI_m)}$, for assessment area m) to proxy for β_m and weight each assessment area by $\frac{1}{log(PCI_m)}$.

D Risk-Adjusted Price of Lending

Is compliance with CRA regulation costly? To address this question, we analyze whether risk-adjusted loan rates for loans extended to underserved neighborhoods are significantly lower than those for loans in non-underserved neighborhoods. If this is the case, high-δ banks, which lend more to underserved neighborhoods to meet CRA requirements, would incur reduced profit margins compared to a counterfactual scenario where they allocate lending to non-underserved regions.[30]

We apply the same RD design around the 80% policy cutoff, leveraging CoreLogic LLMA data, which offers loan-level rate information from 2005 to 2008. Unlike the HMDA database, CoreLogic LLMA lacks lender identities, and the most granular geographic detail available is the zip code, thereby constraining our analysis to the following specification:

$$r_{i,z,t} = \kappa_0 \mathbb{1}(\text{lmi}_z) + \kappa_1(\text{MFI}_z - 80\%) + \kappa_2 \mathbb{1}(\text{lmi}_z) \times (\text{MFI}_z - 80\%) + X_{i,t}\Gamma + \epsilon_{i,z,t}. \quad \text{(D6)}$$

$r_{i,z,t}$ represents the mortgage rate for loan i, extended to zip code z in year t. The set $X_{i,t}$ includes a comprehensive set of controls to approximate default risk, such as credit score, loan-to-value ratio, debt-to-income ratio, their squared terms, origination month fixed effects, loan type (e.g., conventional, FHA/VA, and RHS loans) interacted with year fixed effects, and assessment area-by-year fixed effects. Given that the most granular geographic detail available is at the zip code level, we aggregate MFI from the census tract to the zip code level using a weighted average, with weights determined by the proportion of residential and business addresses. To ensure comparability of loan prices, we restrict our analysis to a standardized set of loans with full documentation. Specifically, we focus on 30-year fixed-rate mortgages with full documentation and exclude loans with missing data on interest rate, FICO score, loan-to-value ratio, or debt-to-income ratio.

Table E4 shows the results. Like before, we identify the optimal bandwidth with minimized mean square error, which ranges from 7% to 15%. To ensure robustness, we employ three distinct bandwidths in our local polynomial regression estimates: ±10%, ±15%, and the optimal two separate MSE-optimal bandwidths. 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

[30] 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.

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).[31]

The estimates across columns consistently show that risk-adjusted mortgage rates are 1.5%-3% lower in census tracts with MFI just below the 80% threshold compared to those just above, supporting the model's premise that CRA regulation reduces profit margins on loans to underserved neighborhoods. This pronounced discontinuity effect is closely tied to the 80% policy cutoff as before. Placebo tests in Table E5, using alternative MFI thresholds of 60% and 100%, reveal no significant differences in loan rates at these thresholds.[32]

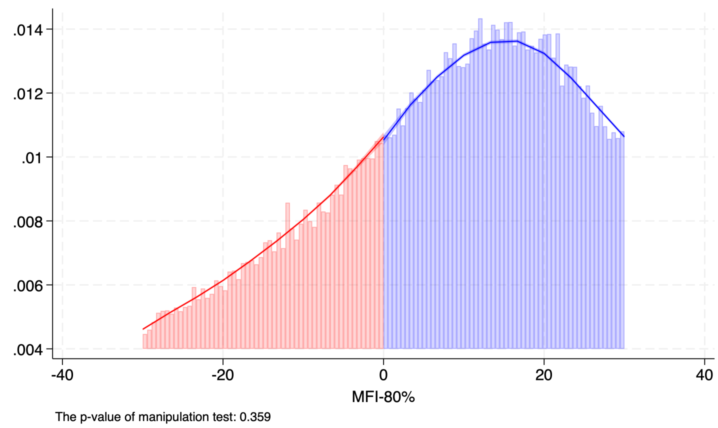
[31]We calculate residuals of the raw mortgage rate regressed on origination year-month, loan type, loan default risk measures (i.e., FICO, ltv, dti, and their squared terms), and two-way interactions between these three sets of covariates. Since we already residualized the mortgage rates, we do not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

[32]The placebo cutoff points are selected to ensure that the estimation window does not overlap with the 80% cutoff and that a sufficient number of observations are available around each chosen cutoff. Unlike the placebo cutoffs in Table E3, we select different thresholds here to account for the fact that the unit of observation is at the zip code level, leaving too few observations to estimate reliably at the 50% cutoff.

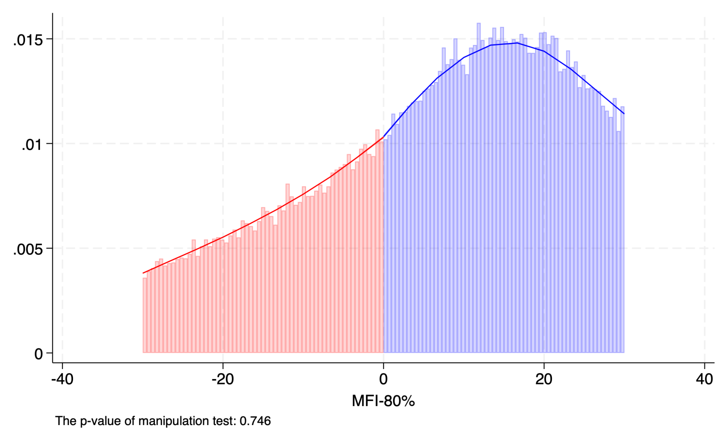
E Additional Tables and Figures

Figure E1. Histograms and Densities of the Running Variable

The figure illustrates the density distribution of census tracts around the 80% MFI threshold for the years 2005-2017. Panel A shows the unweighted count of census tracts within each 1% bin, with each bar representing the raw number of tracts. Panel B, in contrast, adjusts each bar to reflect the total population within each 1% bin, effectively weighting by census tract population. The histograms employ the density test for breaks in the running variable as proposed by Cattaneo et al. (2020), utilizing procedures detailed in Cattaneo et al. (2018). The p-value for the density test is noted in the figure's note.



(a) Baseline



(b) Baseline

Figure E2. Discontinuity Around the CRA Eligibility Threshold: Loan Pricing

This figure demonstrates the discontinuity in loan pricing around the 80% MFI threshold using a non-parametric regression discontinuity (RD) plot based on 2005-2008 CoreLogic LLMA loan-level data. The y-axis represents the residuals from the regression:

$$\log(\text{Residualized Rate}_{b,z,t}) = \alpha(\text{MFI}_{z,t} - 80\%) + \text{FEs} + \epsilon_{b,z,t}.$$

Here, residualized mortgage rates are adjusted for default risk measures (FICO, LTV, DTI, and their squared terms), along with their two-way interactions. The running variable, $(\text{MFI}_{z,t} - 80\%)$, quantifies the MFI ratio deviation in zipcode z from the 80% threshold. Fixed effects (FEs) include origination month, loan type by year, and assessment area by year. The plot features circles that represent average values within each of six bins, which contain equal numbers of observations. The solid lines denote fitted values employing triangular weights, with the shaded area reflecting the 90% confidence interval.

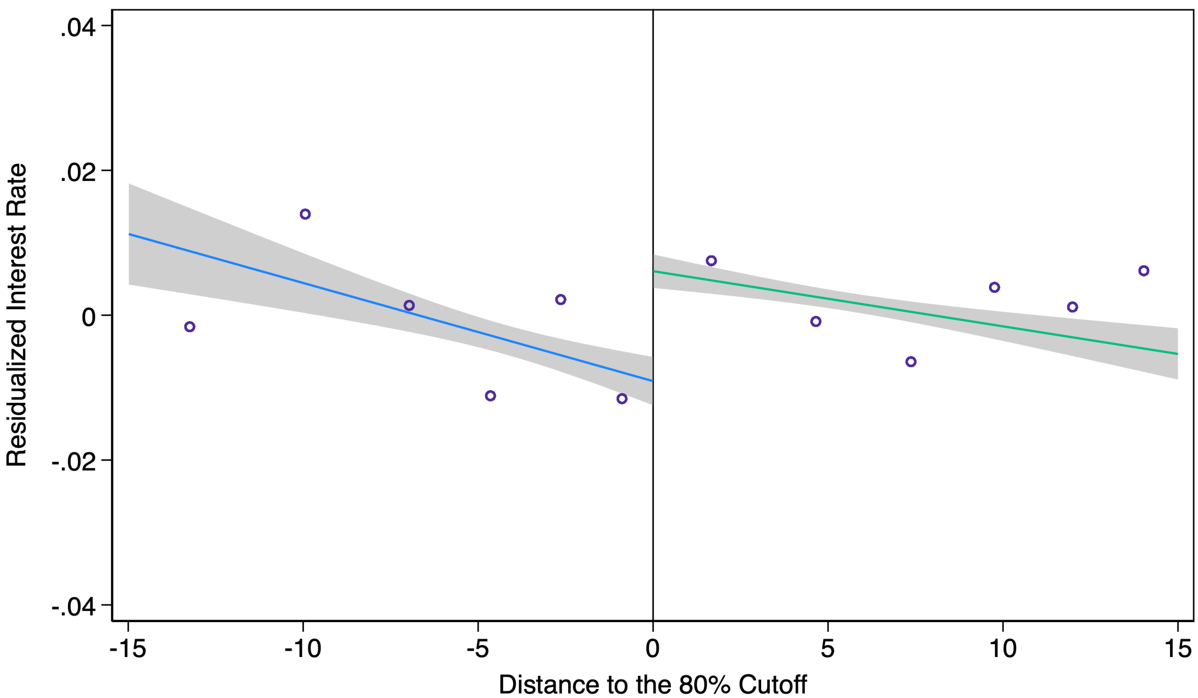


Figure E3. Quantification Illustration

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

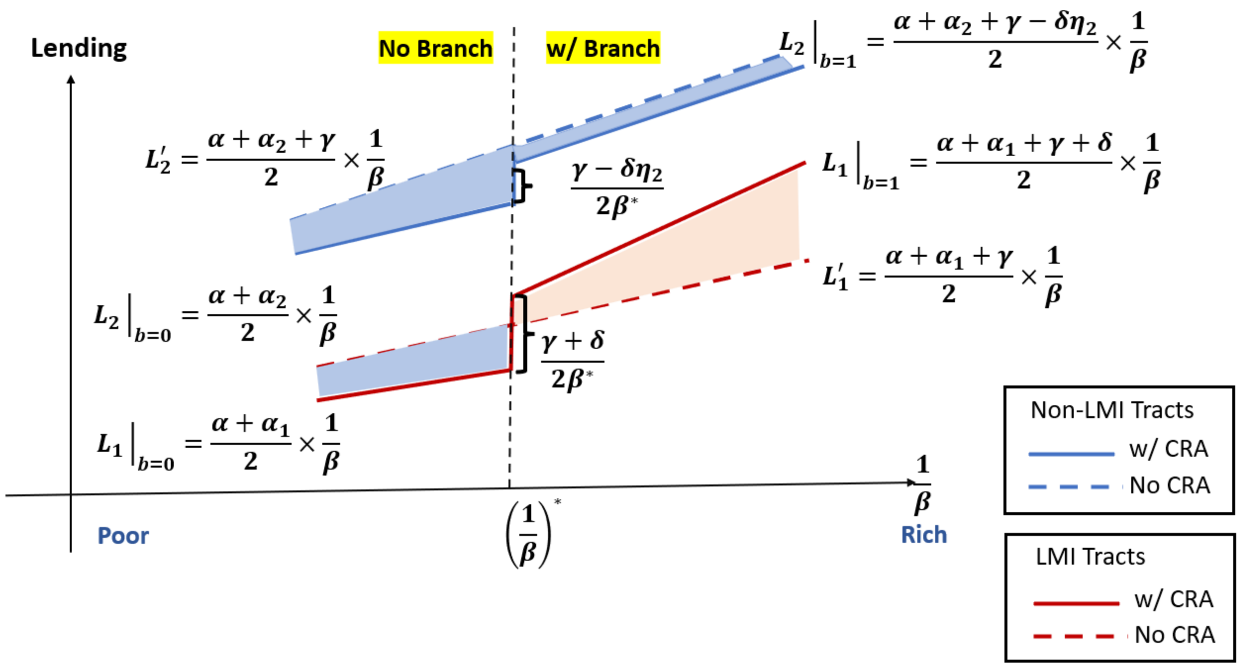


Table E1 Test of Discontinuities in Covariates before the Threshold Implementation

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

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

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

	[-20,20]	[-15,15]	[-10,10]
	(1)	(2)	(3)
% Vacancy	0.003	0.005	0.008
	(0.004)	(0.006)	(0.006)
Num. rooms	-0.007	0.027	-0.008
	(0.040)	(0.049)	(0.055)
ln(Rent)	-0.002	0.003	-0.012
	(0.012)	(0.014)	(0.015)
ln(Home value)	0.019	0.006	-0.009
	(0.019)	(0.020)	(0.026)
ln(Population)	-0.037	-0.019	0.010
	(0.049)	(0.054)	(0.073)
% Black	-0.017	-0.020	-0.012
	(0.016)	(0.016)	(0.022)
% Non-white	-0.020	-0.023	-0.016
	(0.016)	(0.016)	(0.023)
Age	-0.075	-0.040	-0.118
	(0.400)	(0.446)	(0.567)
% Social Security inc.	0.007	0.011	0.010
	(0.007)	(0.008)	(0.010)
ln(Inc. per capita)	0.002	-0.003	-0.020
	(0.018)	(0.021)	(0.024)
% Employed	0.004	-0.003	-0.003
	(0.006)	(0.007)	(0.008)
% Renters	-0.003	-0.008	-0.003
	(0.012)	(0.014)	(0.016)
% College degree	0.006	0.003	-0.005
	(0.007)	(0.008)	(0.009)
ln(Loan applications)	-0.007	0.002	0.007
	(0.032)	(0.033)	(0.040)
ln(Count loan applications)	-0.006	0.000	-0.002
	(0.025)	(0.028)	(0.033)

Table E2 Test of Discontinuities in Covariates within Sample Period

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

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

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

	[-20,20]	[-15,15]	[-10,10]
	(1)	(2)	(3)
ln(Rent)	-0.008	-0.005	-0.007
	(0.011)	(0.013)	(0.017)
ln(Home value)	0.028	0.030	0.023
	(0.026)	(0.030)	(0.040)
ln(Population)	-0.002	0.006	0.008
	(0.011)	(0.013)	(0.017)
% Black	-0.001	-0.000	0.001
	(0.004)	(0.005)	(0.006)
% Non-white	-0.001	-0.001	0.003
	(0.004)	(0.005)	(0.006)
Age	0.052	0.217	0.103
	(0.149)	(0.172)	(0.235)
ln(Loan applications)	-0.001	-0.005	-0.035
	(0.025)	(0.027)	(0.032)
ln(Count loan applications)	0.001	-0.009	-0.026
	(0.020)	(0.023)	(0.027)

Table E3 Placebo Tests for Table 2

This table presents the results of regression discontinuity (RD) designs replicating the analysis from Table 2, employing placebo thresholds of 110% (Panel A) and 50% (Panel B). These thresholds are chosen to maintain the sample distinct from the main 80% CRA threshold used in earlier analyses. The methodologies are identical to the original except for the adjusted treatment cutoffs. Standard errors are clustered at the assessment area-year level. Values in parentheses denote standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Placebo test with 110% as the cutoff

	[-20,+20]		[-15,+15]		Optimal Bindwidth	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(LMI)	-0.007*	-0.007	-0.009*	-0.008	-0.008*	-0.008*
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
MFI-110	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
$\mathbb{1}$(LMI)×(MFI-110)	0.002***	0.002***	0.001	0.001	0.001***	0.002***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓	
Market FE	✓		✓		✓	
Market×Year FE		✓		✓		✓
Adjusted R^2	0.435	0.450	0.435	0.450	0.435	0.450
Observations	2,139,520	2,137,575	1,646,933	1,644,840	1,960,893	1,958,891

Panel B: Placebo test with 50% as the cutoff

	[-20,+20]		[-15,+15]		Optimal Bindwidth	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(LMI)	-0.004	-0.004	0.001	0.002	0.007	0.010
	(0.008)	(0.008)	(0.009)	(0.009)	(0.012)	(0.012)
MFI-50	0.014***	0.015***	0.015***	0.015***	0.016***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
$\mathbb{1}$(LMI)×(MFI-50)	-0.006***	-0.005***	-0.005***	-0.004***	-0.005**	-0.004*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓	
Market FE	✓		✓		✓	
Market×Year FE		✓		✓		✓
Adjusted R^2	0.400	0.411	0.402	0.414	0.405	0.419
Observations	750,410	749,279	552,507	551,695	361,815	361,206

Table E4 Costly CRA Compliance—Lower Risk-Adjusted Loan Pricing

This table presents the results from a regression discontinuity (RD) analysis on bank loan pricing. Since the loan pricing data records only zip code information, we aggregate census tract MFI to zip code level by taking the average, weighted by the proportion of residential and business addresses. TThe running variable is the deviation of the MFI ratio in zip code z from the 80% threshold, with $\mathbb{1}(\text{LMI}_{z,t})$ indicating zip codes where the MFI falls below this threshold. We employ the following RD specification using CoreLogic LLMA loan-level data from 2005 to 2008:

$$r_{b,z,t} = \kappa_0 \mathbb{1}(\text{LMI}_{z,t}) + \kappa_1(\text{MFI}_{z,t} - 80\%) + \kappa_2 \mathbb{1}(\text{LMI}_{z,t}) \times (\text{MFI}_{z,t} - 80\%) + X_{b,t}\Gamma + FEs + \epsilon_{b,z,t}.$$

Our analysis focuses on a subset of standardized loans: 30-year fixed-rate mortgages with full documentation. We exclude loans lacking data on interest rate, FICO score, loan-to-value ratio, or debt-to-income ratio and remove outliers at the 1st and 99th percentiles for interest rates and loan-to-value ratios. Columns 1, 3, and 5 display results using raw mortgage rates, while columns 2, 4, and 6 use residualized mortgage rates from a regression adjusted for default risk measures (FICO, LTV, DTI, and their squared terms), along with their two-way interactions. This comprehensive model also incorporates a saturated set of default risk measures, origination month fixed effects, loan type-year fixed effects, and assessment area-year fixed effects. To ensure robust estimation, we utilize three distinct bandwidths around the 80% threshold for local polynomial regression: 15%, 10%, and an average optimal bandwidth minimizing squared error loss, as suggested by Calonico et al. (2017). A triangular kernel is used to construct the local estimator. Standard errors are clustered at the assessment area-year level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	[-15,+15]		[-10,+10]		Optimal Bandwidth	
	Raw Rate	Residualized Rate	Raw Rate	Residualized Rate	Raw Rate	Residualized Rate
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(LMI)	-0.019***	-0.019***	-0.025***	-0.025***	-0.024***	-0.024***
	(0.007)	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)
MFI-80	-0.004***	-0.004***	-0.006***	-0.006***	-0.006***	-0.006***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
$\mathbb{1}$(LMI)×(MFI-80)	-0.001	-0.001	0.001	0.002	0.001	0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Assessment Area ×Year FE	✓	✓	✓	✓	✓	✓
Loan Type ×Year FE	✓	✓	✓	✓	✓	✓
Origination Month FE	✓	✓	✓	✓	✓	✓
Default Risk Controls	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.317	0.062	0.316	0.063	0.316	0.063
Observations	534,946	534,946	345,121	345,121	339,411	339,411

Table E5 Placebo Tests for Table E4

This table presents the results of regression discontinuity (RD) designs replicating the analysis from Table E4, employing placebo thresholds of 100% (Panel A) and 60% (Panel B). These thresholds are selected to ensure the sample remains distinct from the primary 80% CRA threshold utilized in earlier analyses, while still retaining sufficient observations for robust statistical analysis. The methodologies are identical to the original except for the adjusted treatment cutoffs. Standard errors are clustered at the assessment area-year level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Placebo test with 100% as the cutoff

	[-15,+15]		[-10,+10]		Optimal Bindwidth	
	(1)	(2)	(3)	(4)	(5)	(6)
	Raw Rate	Residualized Rate	Raw Rate	Residualized Rate	Raw Rate	Residualized Rate
$\mathbb{1}$(LMI)	0.003	0.003	0.001	0.001	0.000	0.001
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
MFI-100	-0.002***	-0.002***	-0.001***	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
$\mathbb{1}$(LMI)×(MFI-100)	-0.001	-0.000	-0.002*	-0.002*	-0.002**	-0.002**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Assessment Area ×Year FE	✓	✓	✓	✓	✓	✓
Loan Type ×Year FE	✓	✓	✓	✓	✓	✓
Origination Month FE	✓	✓	✓	✓	✓	✓
Default Risk Controls	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.356	0.058	0.358	0.060	0.358	0.060
Observations	874,324	874,324	622,703	622,703	666,489	666,489

Panel B: Placebo test with 60% as the cutoff

	[-15,+15]		[-10,+10]		Optimal Bindwidth	
	(1)	(2)	(3)	(4)	(5)	(6)
	Raw Rate	Residualized Rate	Raw Rate	Residualized Rate	Raw Rate	Residualized Rate
$\mathbb{1}$(LMI)	0.007	0.003	-0.008	-0.010	-0.010	-0.012
	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
MFI-60	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
$\mathbb{1}$(LMI)×(MFI-60)	-0.007***	-0.007***	-0.013***	-0.012***	-0.013***	-0.013***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
Assessment Area ×Origination Month FE	✓	✓	✓	✓	✓	✓
Loan Type ×Origination Month FE	✓	✓	✓	✓	✓	✓
Default Risk Controls	✓	✓	✓	✓	✓	✓
Origination Month FE	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.287	0.097	0.288	0.101	0.288	0.101
Observations	157,141	157,141	98,344	98,344	96,074	96,074

Table E6 CRA Effect on Lending Standard

This table presents the results from a regression discontinuity (RD) analysis on banks' lending standards. Since the loan pricing data records only zip code information, we aggregate census tract MFI to zip code level by taking the average, weighted by the proportion of residential and business addresses. TThe running variable is the deviation of the MFI ratio in zip code z from the 80% threshold, with $\mathbb{1}(\text{LMI}_{z,t})$ indicating zip codes where the MFI falls below this threshold. We employ the following RD specification using CoreLogic LLMA loan-level data from 2005 to 2008:

$$Y_{b,z,t} = \kappa_0 \mathbb{1}(\text{LMI}_{z,t}) + \kappa_1(\text{MFI}_{z,t} - 80\%) + \kappa_2 \mathbb{1}(\text{LMI}_{z,t}) \times (\text{MFI}_{z,t} - 80\%) + X_{b,t}\Gamma + FEs + \epsilon_{b,z,t}.$$

Columns 1-4 focus on zip codes within a 15% bandwidth around the 80% threshold, while Columns 5-8 target zip codes within a 10% bandwidth. A triangular kernel is employed for constructing the local estimator. The outcome variables differ across columns: Columns 1 and 5 assess the presence of balloon mortgages, a notable type of Alternative Mortgage Product (AMP) classified in the literature. Columns 2 and 6 examine whether loan applications are fully documented. The FICO scores are analyzed in columns 3 and 7, while the original loan-to-value ratios are assessed in columns 4 and 8, restricting these analyses to fully documented loans. All columns incorporate origination month fixed effects, loan type-year fixed effects, and assessment area-year fixed effects, with standard errors clustered at the assessment area-year level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	[-15,+15]				[-10,+10]			
	(1) Balloon	(2) Full Doc	(3) FICO	(4) LTV	(5) Balloon	(6) Full Doc	(7) FICO	(8) LTV
$\mathbb{1}$(LMI)	-0.000	-0.003	0.936	0.011	-0.002	-0.003	1.605	0.043
	(0.001)	(0.003)	(1.032)	(0.121)	(0.001)	(0.003)	(1.409)	(0.157)
MFI-80	-0.000*	-0.001***	0.511***	-0.040***	-0.000	-0.002***	0.671***	-0.036*
	(0.000)	(0.000)	(0.065)	(0.009)	(0.000)	(0.000)	(0.147)	(0.020)
$\mathbb{1}$(LMI)×(MFI-80)	-0.000***	-0.000	0.276*	-0.049***	-0.001***	0.001	0.200	-0.050*
	(0.000)	(0.000)	(0.147)	(0.017)	(0.000)	(0.001)	(0.235)	(0.027)
Assessment Area ×Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Loan Type ×Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Origination Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.022	0.084	0.139	0.248	0.023	0.085	0.144	0.243
Observations	3,592,661	3,592,661	1,365,336	1,605,058	2,319,694	2,319,694	882,137	1,035,984

Table E7 First-stage of IV Regression

The table presents the first-stage results of the IV regression, where the change in non-bank market share from 2010 to year t is regressed on the NBank Shock variable constructed as defined in Eqn. (13). Standard errors are clustered at the assessment-area level. Numbers in parentheses are standard errors. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	ΔNBank Share$_{2010,t}$	
	(1)	(2)
NBank Shock	0.196***	0.535***
	(0.02)	(0.05)
Constant	0.046***	-0.037***
	(0.00)	(0.01)
Assessment Area FE		✓
Year FE	✓	✓
Adjusted R^2	0.310	0.621
Observations	16,465	16,465

Table E8 Test for Exclusion Restriction of Bartik IV

This table presents tests for the exclusion restriction of the Bartik IV. Column 1 reports estimates from a regression of the average non-bank share observed in the focal assessment area m from 2005 to 2008 on contemporaneous average market-level covariates. Column 2 reports estimates from a regression of branch count changes during 2005–2008, scaled by the local area's population (in millions), on non-bank share and local covariates. Robust standard errors are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	$s_{m,0508}$	$\frac{\Delta \text{Branch}_{0508}}{\text{Pop}_{2010}}$	
	(1)	(2)	(3)
$s_{m,0508}$		-49.131	-38.688
		(37.31)	(39.49)
log(PCI)	-0.024***		-12.370
	(0.01)		(15.15)
log(Pop)	0.012***		6.508***
	(0.00)		(2.09)
Minor Share	-0.011		-19.902
	(0.01)		(19.22)
Unemployment Rate	0.003***		-6.945***
	(0.00)		(1.66)
Age	0.000		-0.822
	(0.00)		(1.11)
FHA Share	0.003***		-1.900***
	(0.00)		(0.56)
Constant	0.351***	29.952***	211.763
	(0.09)	(6.72)	(170.80)
Adjusted R^2	0.112	0.000	0.019
Observations	2,409	2,384	2,384

Table E9 Robustness of Table 3: Placebo Test

This table presents the results of placebo tests for the effect of CRA regulation on banks' branching decisions. The variable construction mirrors that of Table 3, except that branch changes and NBank Shock are constructed for the period from 2005 to 2008, a time when non-bank market share experienced minimal growth. Standard errors (in parentheses) are clustered at the county level. *, **, *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	$\frac{\Delta\#\text{Branch}}{\text{Pop}_{2010}}$	$\frac{\Delta\#\text{Branch}}{\text{Pop}_{2010}}\vert_{\#\text{Branch}\neq 0}$	Δ I(Branch=1)
	(Total Effect) (1)	(Intensive Margin) (2)	(Extensive Margin) (3)
NBank Shock × High-δ_b	-3.193	-2.030	-0.046
	(5.34)	(2.42)	(0.07)
Bank FE	✓	✓	✓
County × Year FE	✓	✓	✓
Adjusted R^2	0.341	0.257	0.219
Observations	52,610	35,615	54,038