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Bank adaptation to neighborhood change: Mortgage lending and the Community Reinvestment Act

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ABSTRACT

This research explores whether banks strategically leverage regulatory rules for the Community Reinvestment Act that fix a neighborhood's eligibility status over a decade based on a neighborhood's economic trajectory over that decade. Using 2004–2011 Home Mortgage Disclosure Act (HMDA) data, we find that banks approve loans more frequently in those neighborhoods that are most rapidly improving, and that this effect is stronger if the neighborhoods are CRA-eligible low- and moderate-income (LMI) tracts. We find the "moving up" CRA premium ranges in magnitude from a 2 to 13 percent reduction in the likelihood an application is not approved. These results suggest that banks learn which neighborhoods are most rapidly improving and funnel activity to those places to reduce default risk while complying with the fair lending regulation. The results imply a potential unanticipated consequence of the regulation is that it changes the distribution of resources *within* the target population.

1. Introduction

An extensive literature examines how people and institutions respond to a regulatory framework, and it has generated considerable evidence demonstrating there are often unintended consequences of regulation. In some cases, these consequences are such that regulations become less effective than they otherwise might be or sometimes even be detrimental relative to some of their objectives (see, for example, DeLeire, 2000; Blau, 2007). This literature suggests that considerable care must be taken when designing and implementing regulatory regimes.

Our research adds to this broad literature, but in a different way. It asks whether, given a level of compliance, there are mechanisms that drive responses such that some segments of the target population are favored while others are not. This type of consequence changes the distribution of resources within the target population. This is a different sort of unintended consequence, akin to the cream-skimming some have identified in other contexts (Koning and Heinrich, 2013; Heckman et al., 1997), and one that has not been a primary focus of the literature. Yet it is potentially quite important from a policy perspective.

The regulatory case we examine is the Community Reinvestment Act of 1977 (CRA), which was enacted to help promote credit flows to neighborhoods that had historically been disinvested, in that less credit was flowing into them relative to the level of deposits associated with their residents (Garwood and Smith, 1993; Essene and Apgar, 2009). The law does not stipulate any mandatory criteria that must be met, but rather allows depository institutions to develop their own strategies to expand access to mortgage and small business credit to historically underserved communities while adhering to regulatory safety and soundness guidelines. Bank compliance with the CRA is incentivized through provisions that establish an institution's CRA performance as a criterion for applications the institution makes for mergers and other activities.

The regulations that implement the CRA define locations that have historically been underinvested based in part upon whether their median incomes are low or moderate relative to the median income of the metropolitan area in which they are located. Because median income is measured using the decennial Census, these designations remain fixed for an entire decade. However, neighborhoods change over the course of a decade, with some improving and others remaining the same or falling behind relative to the metropolitan area. While changes in neighborhood status may imply changes in many attributes associated with the area (Galster, 2001; Ellen and Turner, 1997), in general, loans to neighborhoods that improve more will represent lower risk of loss. This dynamic raises an interesting behavioral question: do lending patterns among institutions covered by the CRA vary systematically across CRA-eligible locations, such that those doing better during the decade receive increasingly more credit?

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This paper seeks to answer this question. Using Home Mortgage Disclosure Act (HMDA) data files from 2004 to 2011 and other data sources, we track how institutions vary their lending patterns as neighborhoods evolve over the decade. We place particular emphasis on "moving-up" and "moving-down" neighborhoods, which we define as census tracts that either improved or declined significantly in terms of median family income between 2000 and 2010. Univariate analysis of HMDA data indicates that the share of loans originated in the moving-up (moving-down) neighborhoods increased (decreased) over the decade, with some acceleration after the financial crisis.

Our multivariate regression results suggest that concerns regarding unintended consequences of the CRA regulation may have some merit. We find that there are indeed distributional effects that arise from the CRA regulatory structure such that certain CRA-eligible populations fare better in terms of access to credit than others. In particular, we find that, even after controlling for individual and neighborhood characteristics, and even within a narrow range around the income threshold used under the CRA, loan applications in moving-up communities tend to have a greater probability of getting accepted by banks, with an added premium when the communities are CRA-eligible.

This finding introduces further nuance into our understanding of the lending behavior of banking institutions, with a nod to the unintended consequences of regulation literature. In our review of the CRA regulations and the history of the establishment of the CRA and subsequent design of its regulatory framework, we did not find discussions or concerns raised regarding this distributional possibility. We believe the relationships highlighted in this research are quite important in light of the CRA's primary objectives, and encourage policymakers to consider distributional issues such as these more explicitly as they contemplate revisions to the regulation.

2. Regulation and unintended consequences

It has been well-established in economics that markets can have imperfections that result in suboptimal outcomes for consumers and firms, and regulation has been recognized as a key tool for addressing market problems and producing outcomes closer to optimal potential (Bator, 1958; Arrow, 1963; Akerlof, 1970). The efficacy of regulation has been called into question, though, as regulations can often have impacts beyond their initial intent. In its discussion of campaign finance regulations designed to ensure political equity, Sunstein (1994) notes that the unintended consequences of regulations can render them either futile or self-defeating. Sunstein (1994) defines futile regulations as those "that do not bring about the desired consequences" (p. 1390) and self-defeating regulations as those "that actually make things worse from the standpoint of their strongest and most public-spirited advocates" (p. 1390).

Sunstein (1994) highlights many instances of futile regulation in the sphere of campaign finance. He argues that limits on individual contributions sparked a shift of political contributions to political action committees (PACs) that had far less restrictive rules. Similarly, he argues that limits on hard money contributions to particular candidates triggered rapid growth in contributions to soft money targets that were political but more loosely connected to specific candidates. In both cases, the regulatory remedies were not successful in limiting the influence of more monied interests.

As a further example, Blau (2007) examines trends to the inputs to child daycare centers as a function of regulations governing staff-child ratios, group sizes and staff qualifications. She finds no robust relationships between regulatory stringency and child care centers that suggests the regulations binded. She highlights, for example, that evidence suggests that daycare centers responded to higher staff qualification standards by employing fewer staff. This type of substitution pattern is the same one highlighted by Sunstein (1994) and implies there may be a "Sunstein-esque" futility in this regulatory context.

There are similarly many examples of self-defeating regulations. For example, DeLeire (2000) provides evidence suggesting that the Americans with Disabilities Act of 1990 (ADA) may have actually harmed the disabled by leading to less employment of disabled workers. Acemoglu and Angrist (2001) provide corroborating evidence by showing that negative employment effects for disabled workers were smaller among small firms that were exempt from the ADA and larger in states where more discrimination charges to the Employment Equal Opportunity Commission were filed. The former finding is consistent with the view that employers are sensitive to the costs of providing accommodations required to comply with the ADA's mandates. The latter suggests a sensitivity to the legal risks associated with having disabled workers.

Regulation can be counterproductive in other ways. For example, while they may be effective in shaping behaviors in the target market in desirable ways, there can be spillover effects that impose counterproductive costs. DiNardo and Lemieux (2001), for example, examines the effects of laws increasing the drinking age for young adults and, using data from a survey of college seniors, find a slight reduction in the use of alcohol but a slight increase in the consumption of marijuana. This "feedback" effect works against the desired goal of reducing the use of controlled substances by young adults.

The current research is related to this literature but differs in that the focus is not on regulatory effectiveness or spillover effects that reduce the regulation's net impact. Rather, we consider whether the regulatory framework creates a dynamic whereby some segments of the target beneficiary population fare better than others. In essence, we are exploring whether the regulatory framework inadvertently establishes a hierarchy among beneficiaries.

3. The CRA and neighborhood changes

We use the Community Reinvestment Act (CRA) of 1977 to explore this dynamic. The CRA was enacted as one response to evidence suggesting that credit flows to lower-income and minority neighborhoods continued to lag in the years after the enactment of laws in the 1960s designed to increase access to home mortgage and other credit for socioeconomically disadvantaged families (Munnell et al., 1996; Ross and Tootell, 2004; Garwood and Smith, 1993; Essene and Apgar, 2009).

The CRA aims to encourage depository institutions to originate home mortgages for properties in low- and moderate-income (hereafter, LMI) neighborhoods and to LMI borrowers, who have historically been underserved.[2] The CRA has two channels to incentivize bank compliance. First, regulators must consider an institution's CRA performance when evaluating an application by that institution for a merger or acquisition, formation of branch, or other business activity. Second, and more indirectly, the disclosure of loan-level data through the Home Mortgage Disclosure Act (HMDA) allows community activists and public interest groups to monitor banking institutions and provide an independent source of bank discipline where the CRA is concerned.[3]

The CRA is a focusing regulation, in that it causes banks to focus on a particular geographic area that is of policy concern. In this way, the CRA is like other regulations and requirements that focus the behavior of agents (see, for example, Coglianese and Lazer, 2003). A basic assumption underlying the CRA is that it will facilitate the discovery of positive information about places and the people that live in them. One should note, however, that this could uncover negative information as well.

Over the course of its existence, which has included several major revisions, the CRA's role in spurring the flow of credit to underserved

[2] Depository institutions include federally chartered financial institutions, such as national banks and savings associations, and state-chartered commercial and saving banks.

[3] This scrutiny has led banks to enter into so-called CRA agreements. Evidence suggests these agreements have influenced patterns of lending behavior (Bostic and Robinson, 2003; Schwartz, 1998).

neighborhoods has been the source of considerable scrutiny and debate. While some have argued that the CRA has been ineffective (for example, Dahl et al. (2002)), studies with more comprehensive data and rigorous identification strategies have generally found evidence of greater credit supply to disadvantaged areas and groups under the CRA (Bhutta, 2011; Avery et al., 2005; Gabriel and Rosenthal, 2009; Ding and Nakamura, 2017; Ringo, 2017). More recent critiques of the CRA have pointed to it as a primary driver of the subprime mortgage crisis and, as a result, the collapse of the housing market (Agarwal et al., 2012; Wallison, 2011). These claims have been subsequently refuted by analyses that provide empirical evidence that the CRA did not trigger higher probabilities of default and that highlight fallacies in the assumptions underlying the identification strategy used by Agarwal et al. (2012) (Avery and Brevoort, 2015; Ghent et al., 2015; Reid et al., 2013).

This research has a different focus from those studies in that it focuses more on *how* the regulatory framework has affected behavior than on *whether* it has. An important element of the regulation is how "CRA-eligible" neighborhoods are determined. The regulation established CRA-eligible neighborhoods to be LMI neighborhoods, which are defined as census tracts in which the median family income in the tract is less than 80 percent of the median income for the surrounding area (AMI).[4] The key insight driving this study is that calculations of the ratios of median family income are based on the last decennial census available. For example, ratios for the years from 1992 to 2002 are calculated based on the median income data from the 1990 Census; ratios for the years from 2003 to 2011 are based on the 2000 Census estimates; and ratios for the years between 2012 and 2016 are based on the 2010 Census and the 2010 American Community Survey (ACS) 5-year estimates.[5]

The CRA census tract eligibility rules introduce the possibility of a potential tension between the law's intent – service to LMI neighborhoods – and how things play out on the ground. This is because a tract's eligibility under the CRA is fixed for an entire decade, whereas the quality of neighborhoods changes over time.[6] Some tracts identified as CRA-eligible might improve over time, such that the credit risk associated with lending in those neighborhoods might be perceived as lower than the credit risk in neighborhoods that were comparable at the beginning of the period. To the extent that such tracts exist, they represent an opportunity for banking institutions to fulfill their CRA obligation while reducing the loss risks of lending. This is because improving neighborhoods will be stronger along dimensions, such as crime rate and house price appreciation, that are related to loss risk (Campbell et al., 2011; Harding et al., 2009; Ioannides, 2003; Chan et al., 2013).[7] Using a similar rationale, some tracts could decline such that they may be perceived as riskier than tracts that were comparable at the period's start, with the theoretical result of less lending in those communities. We refer to the former as "moving-up" tracts and the latter as "moving-down" tracts.[8]

While one might obviously expect banking institutions to shift their CRA-eligible loans towards moving-up communities, the implication with respect to moving-down communities is less clear. One should definitely expect lending to shy away from moving-down neighborhoods, generally. However, because lenders have CRA-related regulatory obligations, the expected response to CRA-eligible moving-down neighborhoods is less clear. On one hand, banking institutions might have a desire to prevent loan numbers in CRA-eligible communities from falling too much, for fear that it would garner the attention of regulators and community groups. In this sense, the CRA could mitigate the general moving-down effect. On the other hand, banking institutions could be fully aware of the moving-up tract dynamic for CRA-eligible neighborhoods and thus be less concerned about changes in volume in CRA-eligible moving-down neighborhoods. In this instance, the CRA would not influence the lending dynamic.

The normative implication of such behavior, if it exists, is unclear. Consider a heightened lender focus on moving-up neighborhoods as an example. On one hand, such lending could be interpreted as unleashing the potential of these neighborhoods, with the improvement signifying that credit constraints had been holding those neighborhoods back. By contrast, it could be that the improving neighborhoods were already poised to succeed and would have received enough mortgage credit without the added push of the CRA. If so, then the shift in the CRA-eligible lending towards the moving-up communities perpetuates the shortage of mortgage credit flowing to the persistently low- and moderate-income tracts.

To explore this issue, we first seek evidence consistent with the notion of moving-up and moving-down tracts and of banking institutions allocating mortgage credit more to the former and less to the latter as the decade progresses, which we will sometimes refer to as responding to contemporaneous change. To answer this question, we first report on the number of tracts with large percentage changes in their relative median income between 2000 and 2010. Relative median income here is defined as the ratio of the tract median family income and the local area median income (AMI). These are calculated for the two years using data from the 2000 decennial Census and the 2008–2012 American Community Survey (ACS) 5-year estimates.[9] We focus on large changes, because large changes are most likely to be noticed in real time by banking institutions operating in a service area. We set a 10 percentage point threshold to define a large change in either a positive or negative direction.

Table 1 shows that 22 percent of tracts experienced a large improvement, while 32 percent experienced a large decline. Low- and moderate-income tracts were less likely to improve than non-LMI tracts (18.1 versus 23.8 percentage points), but also were slightly less likely to experience a large decline (30.3 versus 32.9 percentage points).[10] These data show the dynamic nature of neighborhood change.

Turning to lending patterns, Fig. 1 presents the evolution of the loan approvals that were made in moving-up and moving-down neighborhoods (10 pp. or more) as a share of all approved loans (left panel) and

[4] The surrounding area for a census tract is either the metropolitan area or the non-metropolitan area of the state for those tracts not located in a metropolitan area. The regulation establishes a parallel structure for borrowers, with "CRA-eligible" borrowers being those borrowers with incomes less than 80 percent of the AMI.

[5] Given the availability of the ACS data, which is annual, the Federal Financial Institutions Examination Council (FFIEC) decided to update the census information every five years from 2010.

[6] This tension was noted in Avery, Calem, and Canner (2003): "This procedure has important implications because the income characteristics of a census tract may change greatly over the course of a decade as the composition of its population shifts, but the CRA review process largely ignores such changes." This issue is not CRA-specific, but holds for all programmatic definitions of geography that rely upon income based on decennial Census calculations. See, for example, the affordable goals established for Fannie Mae and Freddie Mac via the Federal Housing Enterprises Financial Safety and Soundness Act of 1992 (An and Bostic, 2008).

[7] In addition to using data from public sources, lending institutions can be expected to use any private information they accrue (Agarwal and Hauswald, 2010; Petersen and Rajan, 2002; Ergungor, 2010; Brevoort and Hannan, 2006).

[8] Our conception of "moving up" assumes tracts improve, but tracts could also move up if the metropolitan area median income falls.

[9] The 2008–2012 ACS 5-Year estimates were selected as an estimate of the middle year, 2010, based on the assumption that the trend over 5-year time period was linear. In addition, changes in census tract boundaries were adjusted, and the method is explained in detail in Appendix A.

[10] These numbers are comparable to the findings from Gleason and Foley (2012), which found that 18 percent of moderate-income tracts (50 to 79% of AMI) and 3 percent of low-income tracts (below 50% of AMI) in 2000 moved to upper-and middle-income classification in 2010. The shares found in Gleason and Foley (2012) are slightly different from those presented here because they used the 2006–2010 ACS and tracts that had little or no change in the boundaries between 2000 and 2010.

Table 1
Incidence of neighborhood status changes in 2000–2010 by income status in 2000.

	All	Changes in Median Family Income Ratio (Δ%AMI), 2000–2010				
	Tracts	$x < -20$ pp.	–20 to –11	–10 to 9	10 to 19	20 pp. $\leq x$
All 2000 Census Tracts	52,504	7264	9579	24,115	5712	5834
	100.0%	13.8%	18.2%	45.9%	10.9%	11.1%
LMI Tracts	16,243	1495	3432	8373	1556	1387
	100.0%	9.2%	21.1%	51.5%	9.6%	8.5%
0 ≤%AMI < 70%	11,121	839	2336	5950	1016	980
	100.0%	7.5%	21.0%	53.5%	9.1%	8.8%
70 ≤%AMI < 75%	2423	301	552	1148	229	193
	100.0%	12.4%	22.8%	47.4%	9.5%	8.0%
75 ≤%AMI < 78%	1627	218	323	783	190	113
	100.0%	13.4%	19.9%	48.1%	11.7%	6.9%
78 ≤%AMI < 80%	1072	137	221	492	121	101
	100.0%	12.8%	20.6%	45.9%	11.3%	9.4%
Non-LMI Tracts	36,261	5769	6147	15,742	4156	4447
	100.0%	15.9%	17.0%	43.4%	11.5%	12.3%
80 ≤%AMI < 82%	1103	140	222	521	125	95
	100.0%	12.7%	20.1%	47.2%	11.3%	8.6%
82 ≤%AMI < 85%	1731	206	348	809	202	166
	100.0%	11.9%	20.1%	46.7%	11.7%	9.6%
85 ≤%AMI < 90%	3179	358	626	1540	374	281
	100.0%	11.3%	19.7%	48.4%	11.8%	8.8%
90 ≤%AMI	30,248	5065	4951	12,872	3455	3905
	100.0%	16.7%	16.4%	42.6%	11.4%	12.9%

Note: The tracts are restricted to those with loan application records and within MSA/MDs. The neighborhood status in 2000 and 2010 were estimated using Census 2000 and 2008–2012 ACS 5-year estimates, respectively. For those census tracts that had experienced changes in their boundaries between two years, we estimated weighted averages of median family income of those census tracts using the number of families in a census block as weights. The detailed method is explained in Appendix A.

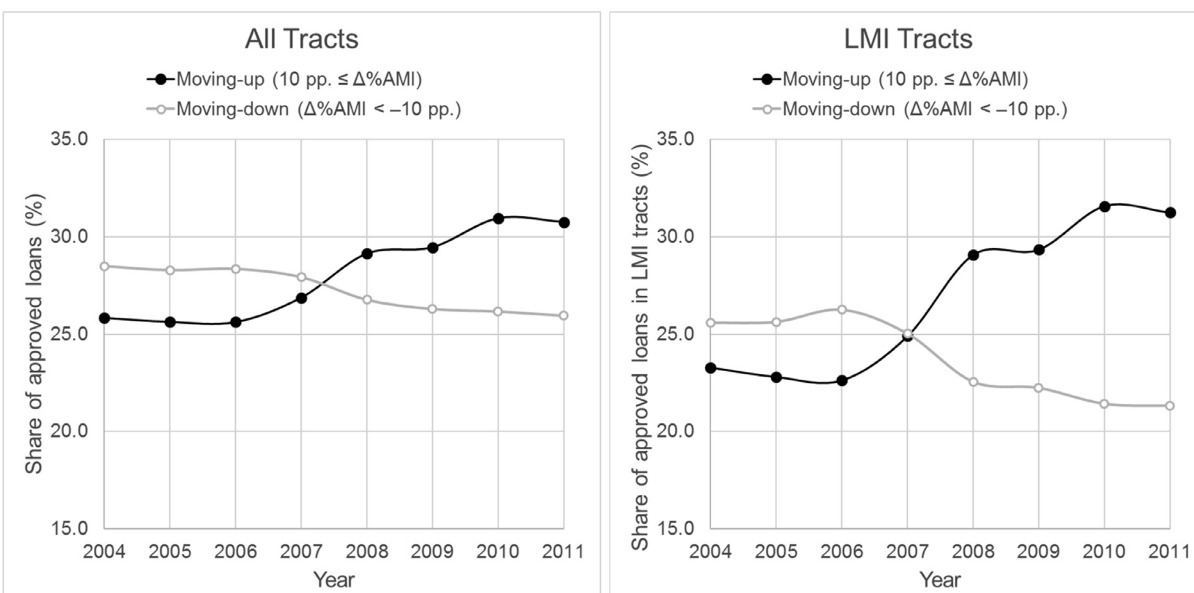

Fig. 1. Changes in approved loans in moving-up and moving-down neighborhoods as a share of total loan approvals (left) and as a share of loans approved in LMI tracts (right), 2004 to 2011.
Note: The "moving-up/down" tracts were defined as the census tracts that experienced increases/decreases in the tract income ratio by 10 percentage points or more from 2000 to 2010. The sample is restricted to the conventional loans for purchasing one-to-four family homes in the neighborhoods in MSA/MDs and within institution's assessment area. The sample includes loan approvals reported by banking institutions that are supervised by OCC, FRS, FDIC, and OTS/CFPB only. The loans purchased by reporting institutions or those with preapproval requests are excluded.
Source: Authors' analysis based on the 2004–2011 HMDA LAR files.

as a share of loan approvals made in LMI neighborhoods (right panel) annually from 2004 to 2011. The left panel shows that the share of all approved loans in the moving-up tracts increased, and the share in the moving-down tracts decreased over time, and this trend accelerated at the time of the housing crisis and Great Recession. The pattern is even more pronounced in LMI neighborhoods (right panel): banking institutions disproportionately approved more LMI loans in the moving-up tracts and less in the moving-down tracts over time.

We note that the literature has also identified this type of strategic behavior by banking institutions. For example, Ross and Tootell (2004) found a strategic response by lenders, who favored the mortgage applications with private mortgage insurance (PMI) in low-income neighborhoods. Calem et al. (2011) reported a similar strategic pattern in the secondary mortgage market, showing that banking institutions selectively sold risky subprime mortgage loans to investors to transfer their risk of default. In regards to the CRA, Evanoff and Segal (1997) examined strategic responses to the CRA and found that banks modify their behavior over the course of a year in order to hit a target denial rate for the year that is acceptable from a CRA perspective. Evanoff and Segal (1997) differs from the current work by focusing on within-year variation in lending activities rather than the between-year variation that is the subject of interest in this paper. Another paper showing a strategic response to the CRA is Bostic et al. (2005), which found that acquiring banks increase their CRA-eligible borrowing in the year preceding an acquisition to reduce the likelihood of a regulatory challenge on CRA grounds. However, that study focused on bank goals rather than on the geographic access to credit objectives of the CRA that are the concern of this research. In the context of the current research, Avery and Brevoort (2015) find evidence consistent with the idea that institutions shift mortgage lending towards the improving communities.[11]

4. Data

To examine the strategic response of banking institutions to the CRA, we construct a dataset that combines data from multiple sources. First, we compile mortgage application data from 2004 to 2011 collected pursuant to the Home Mortgage Disclosure Act (HMDA). HMDA data includes information about every application for a mortgage received by a lender required to report under the Act, including the applicant's race and ethnicity, sex, and income, the size of the loan, the loans' lien status, and whether the loan is a higher-priced loan, and the census tract in which the property to be purchased is located.

The HMDA data are restricted in several ways. Given our interest in responses to the CRA, we include only those applications made to banking institutions that are subject to the CRA and where the property is within the institution's assessment area.[12] We exclude any applications involving guarantee programs operated by the Federal Housing Administration (FHA), the Department of Veterans Affairs (VA), or the Department of Agriculture's Farm Service Agency or Rural Housing Service (FSA/RHS), to minimize the impact of any incentives these programs may have on observed patterns. Further, we consider only applications to purchase one-to-four family homes that will be the borrower's principal dwelling, fall below the conventional conforming loan limit, and are located in a metropolitan statistical area or metropolitan division (MSA/MD). Finally, loans purchased by reporting institutions and applications with preapproval requests are also excluded.[13] Table 2 summarizes the sample of HMDA loan applications included in the final dataset.

We supplement the HMDA data with Census data that provides information on the characteristics of the census tract in which the property to be purchased is located. We draw many of these data items from the Census and Demographics Files and Median Family Income Reports provided by Federal Financial Institution Examination Council (FFIEC) each year from 2004 to 2011. Use of these data allows us to use exactly the same census data that the lenders would have used to determine a neighborhood's eligibility for the CRA. The variables we use include the number of housing units, vacancy rate, homeownership rate, minority population share, share of the population 25 years and older with bachelor's degree or higher, share of the population with income below the poverty line, median family income as a share of area median income (AMI), median house value, and median gross rent.

Following Reid and Laderman (2011) and Apgar et al. (2007), we include a metropolitan statistical area or metropolitan division (MSA/MD) as a part of a bank's assessment areas if any of its branch offices is located in the MSA/MD.[14] We use the 2004–2011 HMDA Reporter Panel files to identify branch office locations.

5. Research design

We modify a standard model of loan decision-making to further understand the shift of lending towards moving-up neighborhoods. The standard model describing how a banking institution determines whether to approve or deny a mortgage loan is of the form in Eq. (1).

$$y_{ijklm} = \boldsymbol{\psi X_{ijklm}} + \boldsymbol{\omega N_{kl}} + BankFE_j + CountyFE_l + YearFE_m + \varepsilon_{ijklm} \tag{1}$$

Here, y_{ijklm} indicates whether a mortgage application of individual i was approved by bank j to purchase a property located in census tract k in county l in year m, and the vectors $\boldsymbol{X_{ijklm}}$ and $\boldsymbol{N_{kl}}$ are loan applicant and property neighborhood characteristics, respectively, that influence the likelihood that a loan application will be approved. For each observation, the loan approval variable was set equal to one if the mortgage application was approved and zero otherwise.[15] We recognize that using loan approval as a representation of lending activity has strengths and weaknesses. We believe loan approval is a strong option because it represents a lender's propensity to lend, which matches well with the notion of intent, which is important in the current context. In addition, our approach allows us to directly include applicant characteristics, which are widely recognized to be important for underwriting decisions. That noted, we recognize that some might take the view that an aggregate measure of activity might be preferred, as some might see this as a more "direct" measure of the level of lending. We consider this as a robustness check in a later section.

The standard model also typically includes banking institution, county, and year fixed-effects in acknowledgement that there may institution-, year-, or location-specific heterogeneity known to influence loan origination decisions that are not captured by the dataset being used (Harrison, 2001).

To this standard model, we include additional variables to examine the roles of the CRA and neighborhood change in home mortgage lending. This yields Eq. (2).

$$\begin{aligned} y_{ijklm} = {} & \boldsymbol{\psi X_{ijklm}} + \boldsymbol{\omega N_{kl}} + BankFE_j + County \times YearFE_{lm} + \boldsymbol{\alpha \Delta N_{kl}} \\ & + \beta LMI_{kl} + \boldsymbol{\gamma}\left(\boldsymbol{\Delta N_{kl}} \times LMI_{kl}\right) + \boldsymbol{\delta S_{jkl}} + \varepsilon_{ijklm} \end{aligned} \tag{2}$$

The first additional variable type is $\boldsymbol{\Delta N_{kl}}$, which captures the change in neighborhood status of a tract k in county l from a census to the successive Census by the change in its median family income ratio (Δ%AMI). For this vector we construct five categories: (1) –10 pp. ≤ Δ%AMI < 10 pp. (minor changes, reference group), (2) 10 pp. ≤ Δ%AMI

[11] While explaining why delinquency rate is positively associated with loan purchases as a share of lending in 2001 and is negatively correlated in 2004–2006 in their regression results, Avery and Brevoort (2015) states that "…This suggests that CRA-covered lenders *shifted their within-assessment-area purchases toward less risky census tracts* during the middle of the decade, which appears inconsistent with the CRA having induced depository institutions to purchase riskier loans during the run-up to the subprime crisis" (emphasis provided by authors, p. 358).

[12] These are the banking institutions that are supervised by Office of the Comptroller of the Currency (OCC), Federal Reserve System (FRS), Federal Deposit Insurance Corporation (FDIC), and Office of Thrift Supervision (OTS)/Consumer Financial Protection Bureau (CFPB). To deal with the changes in the agency and respondent ID codes between 2010 and 2011 due to the merger of the Office of Thrift Supervision (OTS), we used the RSSD ID in the HMDA Panel data to link those affected lenders.

[13] We test whether the results of analyses are sensitive to these sample restrictions. As will be shown in the robustness section, the findings are qualitatively unchanged.

[14] We also conducted the same analysis with actual assessment areas using a further restricted sample. The results are unchanged and are presented in the later section.

[15] We consider both applications that were originated and that were approved by the lender but not accepted as approved. Non-approved applications include those that were denied by the lender, withdrawn by the applicant, or closed for incompleteness.

Table 2
The number of the HMDA sample records by year (unit: thousands).

	2004	2005	2006	2007	2008	2009	2010	2011
HMDA Sample Selection								
(1) Original HMDA Records	33,608	36,439	34,105	26,606	17,392	19,493	16,718	14,873
(2) Exclude loans out of the territory of the US/outside of MSA/MDs/missing geographic information	28,926	31,529	29,429	22,553	14,372	16,436	14,260	12,658
(3) Reported by banks supervised by OCC, FRS, FDIC, and OTS/CFPB	16,382	18,378	18,242	16,610	10,747	12,118	9774	8997
(4) Conventional loans (any loan other than FHA, VA, FSA, or RHS loans) for home purchase	5982	7230	7366	5931	2798	1986	1526	1601
(5) One to four family that are the borrower's principal dwelling	4951	5941	6161	5010	2214	1619	1191	1228
(6) Exclude loans purchased by institution or applications with preapproval requests	3546	3989	3933	3326	1550	933	832	787
(7) Only within assessment areas	2555	2816	2869	2373	1012	689	678	640
(8) Exclude tracts with zero median family income in 2000/2010	2553	2815	2868	2372	1012	688	677	640
Final HMDA Sample								
Loan applications	2553	2815	2868	2372	1012	688	677	640
Loan approvals	2072	2200	2169	1743	724	518	517	489

Source: Authors' analysis based on 2004–2011 HMDA LAR files.

< 20 pp. (modest improvement), (3) 20 pp. ≤ Δ%AMI (substantial improvement), (4) –20 pp. ≤ Δ%AMI < –10 pp. (modest decline), and (5) Δ%AMI < –20 pp. (substantial decline).

The change in the median income ratio, $\boldsymbol{\Delta N_{kl}}$, is determined based on the 2000 Census and 2008–2012 ACS 5-year estimates.[16] Placing a tract in one of these categories is straightforward if that tract's boundaries do not change between Censuses. For tracts whose boundaries did change, we computed weighted averages of median family income using the number of families in a census block as weights and used these to make geographically consistent comparisons across Census years using the Census Bureau's 2010 Census Block Relationship Files.[17]

Regarding $\boldsymbol{\alpha}$, a significant positive coefficient on neighborhoods showing a large increase in relative median income would be consistent with the view that banks strategically shift lending to better performing neighborhoods holding all else equal. Similarly, a negative coefficient on neighborhoods showing a large drop in relative median family income would be consistent with banking institutions shying their lending activity away from neighborhoods in decline. However, this pattern would also be consistent with a CRA-independent notion that banking should generally shift lending in this way based on the more favorable neighborhood profiles of the improving tracts.

To isolate whether the effect is more strongly associated with the CRA, we distinguish between tracts that are CRA-eligible and those that are not (i.e., whether they are LMI neighborhoods or not). Because the CRA gives more weight to lending in LMI areas, banks should be strongly sensitive to whether neighborhood improvements occur in those LMI areas to reduce their default risk while complying with CRA regulations. We thus introduce LMI_{kl}, which equals one if tract k in county l is an LMI area and zero otherwise, and interact it with the neighborhood change identifiers. Significance of coefficients on the interaction terms, $\boldsymbol{\gamma}$, would support the idea that banks respond differently to the same level of neighborhood change between CRA-eligible LMI tracts and those that are not.

In executing this empirical approach, we further employ samples within a narrow range around the income threshold used under the CRA, in the spirit of a regression discontinuity (RD) design. One of the challenges in identifying causal relationships is that there might be omitted variables that are associated with both neighborhood changes and the approval decision. To mitigate this potential endogeneity problem,

Table 3
Results of balance test comparing neighborhood characteristics between LMI and non-LMI tracts, with varying bandwidths.

	All Tracts	[70%, 90%)	[75%, 85%)	[78%, 82%)
Neighborhood Characteristics in Census 2000				
Housing units	−281.4***	−73.7***	−50.0*	1.3
	(8.2)	(15.7)	(23.4)	(40.2)
Vacancy rate (%)	3.6***	1.0***	0.3	−0.2
	(0.1)	(0.1)	(0.2)	(0.3)
Homeownership (%)	−27.1***	−6.6***	−3.1***	−1.3
	(0.2)	(0.3)	(0.5)	(0.9)
Minority share (%)	32.5***	7.2***	3.7***	0.4
	(0.2)	(0.4)	(0.5)	(0.9)
Share with bachelor's degree or higher (%)	−18.1***	−2.7***	−1.6***	−0.9+
	(0.1)	(0.2)	(0.3)	(0.5)
Poverty rate (%)	16.6***	3.6***	1.7***	0.6*
	(0.1)	(0.1)	(0.1)	(0.3)
Median family income (in $1000 s)	−31.4***	−5.3***	−2.7***	−1.1***
	(0.1)	(0.0)	(0.0)	(0.0)
Median gross rent (in $1000 s)	−288.6***	−44.8***	−16.9***	3.7
	(2.4)	(2.8)	(4.1)	(7.5)
Median value (in $1000 s)	−103.0***	−15.3***	−6.6***	−2.1
	(1.0)	(1.1)	(1.7)	(3.6)
Number of census tracts	52,495	11,018	5307	1888

+ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$
Robust standard errors in parentheses. Each of these regression models include county-level fixed effects. The census tracts are restricted to those with at least one loan application in our sample. All figures are adjusted to 2018 dollars.

previous studies on the CRA have employed a regression discontinuity approach (Avery et al., 2003; Gabriel and Rosenthal, 2009; Avery and Brevoort, 2015; Bhutta, 2011). Following the previous studies, we limit our sample to narrow ranges around the CRA eligibility threshold of 80 percent of AMI. We use three ranges: (1) 70% ≦ x < 90%, (2) 75% ≦ x < 85%, and (3) 78% ≦ x < 82%.

This approach allows us to identify the causal effects of the regulation on the lending decision by comparing the outcomes in census tracts just below and above the 80 percent income threshold. The underlying assumption is that there is no systemic difference in observable and unobservable characteristics between the tracts that are just barely eligible to the CRA and those that are not. Table 3 presents the results of balance tests examining the differences between LMI and non-LMI tracts, with

[16] For the years 2012 and forward, the LMI status were updated based on the 2006–2010 American Community Survey (ACS), not the 2008–2012 ACS. We intentionally used the 2008–2012 ACS with the purpose of using the same 10-year interval.

[17] Appendix A provides a detailed description of the determination of median family income ratio changes.

varying bandwidths.[18] The differences in neighborhood characteristics generally become statistically insignificant as the bandwidth narrows. The two exceptions – median family income and poverty rate – are not surprising, given that relative income level is the varying dimension.

Our model acknowledges other research that has identified determinants of lending decisions. Lang and Nakamura (1993) argues that the volume of home sales is negatively related to uncertainty in home values, which is a disincentive for lending activity, and thus one should observe a positive association between home sales volume in a previous period and current lending activity. This has been consistently confirmed empirically (Harrison, 2001; Calem, 1996; Ling and Wachter, 1998). Along similar lines, Avery et al. (1999) and Blackburn and Vermilyea (2007) argue that there are economies of scale associated with processing loans in a local area, such that institutional uncertainty about the quality of neighborhoods and property values is reduced. This would give institutions an incentive to concentrate their provision of credit geographically. Both studies find support for this notion.

To control for these considerations, we introduce S_{jkl}. We use two measures of initial lending volume: (1) share of mortgage loans originated by a lender j in a tract k and (2) share of mortgage loans originated in a tract k by all lenders in 2000 to 2002.[19,20] These are calculated based on the 2000–2002 HMDA data and are linked to the records in later years using agency and bank respondent identifiers in the HMDA data. Though our discussion has focused on bank-level information effects, we also include an industry-level variable – share of mortgage loans originated in a census tract by all banks – because Harrison (2001), Ling and Wachter (1998), and Calem (1996) all point to the existence of industry-level information externalities.[21]

Finally, we augment the vector of controls in the basic model in two ways. First, we include the median family income of a census tract as a share of area median income, and its squared, cubic, and quartile terms into the model. Also, to account for substantial changes in market conditions within a housing submarket over time, we include year-county fixed effects.[22]

6. Results

Table 4 reports the results of the regressions from the 2004–2011 time period using the full sample of tracts. Starting with the control variables, most results for both individual and neighborhood characteristics conform with expectations and what has been found in prior research. Applications from females, ethnic minorities and people with lower incomes are less likely to be approved, as are those involving larger loan amounts and those for subordinate lien loans. At the neighborhood level, higher vacancy rates, minority shares, and poverty rates are all associated with lower approval probabilities. We also find that loans made in neighborhoods with larger college graduate population shares are more likely to be approved, while loans in neighborhoods with higher housing costs, measured by either median house value or median gross rent, are less likely to be approved.

Table 4
Mortgage approval regression using the 2004–2011 HMDA data, full sample tracts (dependent variable: whether a loan application is approved).

	Coef.	S.E.	Sig.
LMI	−0.009	(0.001)	***
Neighborhood Change (Ref. −10 ≤ Δ%AMI < 10 pp.)			
(20 pp. ≤ Δ%AMI)	0.009	(0.001)	***
(10 ≤ Δ%AMI < 20 pp.)	0.006	(0.000)	***
(−20 ≤ Δ%AMI < −10 pp.)	−0.005	(0.000)	***
(Δ%AMI < −20 pp.)	−0.007	(0.001)	***
LMI × Neighborhood Change			
LMI × (20 pp. ≤ Δ%AMI)	0.031	(0.001)	***
LMI × (10 ≤ Δ%AMI < 20 pp.)	0.011	(0.001)	***
LMI × (−20 ≤ Δ%AMI < −10 pp.)	−0.006	(0.001)	***
LMI × (Δ%AMI < −20 pp.)	−0.012	(0.002)	***
Share of loan originations in a tract, 2000–2002			
At industry-level (%)	0.925	(0.069)	***
At lender-level (%)	0.035	(0.007)	***
Individual applicant characteristics			
Sex composition (Ref: Male)			
Female	−0.001	(0.000)	***
Missing sex	−0.046	(0.001)	***
Race/ethnicity (Ref: NH-White)			
African American	−0.117	(0.001)	***
Asian & P.I.	−0.024	(0.001)	***
Hispanic	−0.078	(0.000)	***
Other	−0.073	(0.002)	***
Missing race/ethnicity	−0.050	(0.000)	***
Co–applicant	0.040	(0.000)	***
Income (in $1000,000 s)	0.016	(0.001)	***
Missing income	−0.108	(0.001)	***
Loan amount (in $1000,000 s)	−0.045	(0.002)	***
Lien status (Ref: First lien, not high-cost loan)			
Subordinate lien	−0.066	(0.001)	***
High-cost loan, first lien	0.402	(0.000)	***
High-cost loan, junior lien	0.408	(0.001)	***
Neighborhood characteristics in Census 2000			
Number of housing units (in 1000 s)	0.000	(0.000)	
% Vacancy (in basis points)	−0.099	(0.003)	***
% Homeownership (in basis points)	−0.019	(0.001)	***
% Minority (in basis points)	−0.043	(0.001)	***
% Bachelor's or higher (in basis points)	0.111	(0.002)	***
% Poverty (in basis points)	−0.102	(0.004)	***
Median gross rent (in $1000 s)	−0.005	(0.001)	***
Median value (in $1000,000 s)	−0.022	(0.003)	***
Median family income ratio	0.031	(0.010)	**
(Median family income ratio)^2	0.011	(0.008)	
(Median family income ratio)^3	−0.012	(0.003)	***
(Median family income ratio)^4	0.002	(0.000)	***
Adjusted R–squared	0.1684		
Number of observations	13,624,136		

$^+p < 0.1$.
$^*p < 0.05$.
$^{**}p < 0.01$.
$^{***}p < 0.001$.
Robust standard errors, clustered at bank-tract-year level, are in parentheses. The two-way high-dimensional fixed effects regression models were conducted using the REGHDFE, a user-written Stata program, with Stata 14.2. The sample is restricted to conventional home purchase loans for one-to-four family homes that will be the borrower's principal dwelling in MSA/MDs and within institution's assessment area. The sample includes loan applications reported by the lending institutions that are subject to the CRA, and the loans purchased by reporting institutions or those with preapproval requests are excluded.

[18] The results of the formal tests for continuity of observable variables are shown in Appendix Figure C-1 and support the key assumptions underlying the regression discontinuity analysis.

[19] Further, to account for nonlinearities found in Blackburn and Vermilyea (2007), we also tested this hypothesis by using an alternative measure, a tract k's loan origination quartile (with tracts without any loan origination serving as the omitted group). The results are robust to these tests, and we omit them for brevity.

[20] There remains a possibility that lending may be driving neighborhood level change rather than the other way around. The inclusion of lending activity in the first three years of the decade in our specifications is one proxy for this. We also ran all regressions that included two variables: the 1-year lagged share of loan originations in a tract (thus, industry-level) and the 1-year lagged share of loan originations in a tract by a bank (lender-level). The findings are fundamentally unchanged.

[21] The inclusion of these variables could also be justified via another body of research that shows that lending activities in LMI neighborhoods improve the neighborhood outcomes and characteristics (Avery, Calem, and Canner, 2003; Fitzgerald and Vitello, 2014). If true, then higher numbers of home mortgage originations in a neighborhood will spark larger community quality enhancement. The greater improvement will make subsequent mortgage applications from such neighborhoods more appealing, which should lead to even more lending, thereby generating a self-reinforcing pattern of lending.

[22] Given the large numbers of institutions and county-year pairs, we estimated two-way high-dimensional fixed effects models using REGHDFE, a user-written command for Stata 14.2 MP (Gormley and Matsa, 2014).

Table 5
Summarized results of regression analyses with varying bandwidths (dependent variable: whether a loan application is approved).

	All Tracts	[70%, 90%)	[75%, 85%)	[78%, 82%)
LMI	−0.009***	−0.004+	−0.003	−0.009
Neighborhood Change (Ref. −10 ≤ Δ%AMI < 10 pp.)				
(20 pp. ≤ Δ%AMI)	0.009***	0.013***	0.014***	0.013**
(10 ≤ Δ%AMI < 20 pp.)	0.006***	0.007***	0.010***	0.017***
(−20 ≤ Δ%AMI < −10 pp.)	−0.005***	−0.009***	−0.009***	−0.014***
(Δ%AMI < −20 pp.)	−0.007***	−0.013***	−0.011***	−0.009+
LMI × Neighborhood Change				
LMI × (20 pp. ≤ Δ%AMI)	0.031***	0.007**	0.005	0.012+
LMI × (10 ≤ Δ%AMI < 20 pp.)	0.011***	0.006*	0.007*	0.015*
LMI × (−20 ≤ Δ%AMI < −10 pp.)	−0.006***	0.002	0.003	0.012*
LMI × (Δ%AMI < −20 pp.)	−0.012***	0.001	−0.002	−0.006
Share of loan originations in 2000–02	Yes	Yes	Yes	Yes
Individual applicant char.	Yes	Yes	Yes	Yes
Neighborhood char. in 2000 Census	Yes	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
Adjusted R–squared	0.1684	0.1959	0.1981	0.1973
Number of observations	13,624,136	2,222,169	1,110,234	414,898

+ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Robust standard errors, clustered at bank-tract-year level, are in parentheses. The two-way high-dimensional fixed effects regression models were conducted using the REGHDFE, a user-written Stata program, with Stata 14.2. The sample is restricted to conventional home purchase loans for one-to-four family homes that will be the borrower's principal dwelling in MSA/MDs and within institution's assessment area. The sample includes loan applications reported by the lending institutions that are subject to the CRA, and the loans purchased by reporting institutions or those with preapproval requests are excluded.

Regarding our tests, we observe evidence consistent with the view that banking institutions respond to contemporaneous information and shift lending in response. Relative to the reference group of tracts that showed at most moderate change, tracts with more positive change showed elevated loan approval rates (by between 0.6 and 0.9 percentage points) and tracts with more negative change showed reduced approval rates (by between –0.7 and –0.5 percentage points). Moreover, coefficient magnitudes are monotonic in the expected direction, with the largest relationships associated with the greatest degree of neighborhood change.

Importantly, we observe an additional improvement (decline) in the likelihood of approval for loan applications from moving-up (moving-down) tracts that are LMI and thus CRA-eligible. The magnitude of the moving-up "premium" for LMI loans ranges from 1.1 to 3.1 percentage points, while modest or substantial decline in neighborhood status results in an additional penalty for LMI tracts (0.6 to 1.2 percentage points). Thus, the approval gradient is steeper for LMI neighborhoods than for non-LMI neighborhoods.

The overall magnitude of the effect is not negligible. Given that the share of loan applications that were not approved was about 23.4 percent in this time period, the non-approval rate for applications to purchase a property in a substantially improved LMI neighborhood (20 pp. or more) was 17 percent lower (4.0/23.4) than the rate for a LMI tract with minor neighborhood changes and even 9.4 percent lower (2.2/23.4) than the rate for a substantially improved non-LMI neighborhood. These represent about 9.4 and 5.1 percent of a standard deviation (42.4 percentage points) during the period, respectively. Similar calculations for the moderately improved tracts (10 to 20 pp.) indicate a relatively small reduction in the rate; nonetheless, the CRA premium persists.

Turning to moving-down tracts, we find the opposite relationships. The approval rates for applications in LMI moving-down tracts are consistently lower than those in LMI tracts with minor neighborhood changes (by 1.1 and 1.9 percentage points) or comparable non-LMI moving-down tracts (by 1.5 and 2.1 percentage points). Interestingly, the CRA relationship magnifies the moving-down tract relationship rather than mitigates it in this case. We will return to this in future tests to see if this result is robust.

Table 5 shows the results for the key variables when we account for potential unobservable variables by narrowing the sample bandwidth.[23] There are several main takeaways from the progressive limitation of the sample to include tracts with median incomes closer and closer to the CRA eligibility threshold.

First, as the bands narrow, the general neighborhood change relationships hold, and the loan applications in moving-up tracts that are CRA-eligible enjoy a "premium" from 2.0 to 13.3 percent, depending on the sample used. However, the distinction between changes of 10 to 19 percentage points and 20 or more percentage points weakens. This is true for both positive and negative changes. This is consistent with the notion of a threshold effect, beyond which distinctions in magnitude of change are perceived to be less significant. Second, the CRA premium largely holds for tracts with significant positive change, though the statistical significance of the relationship in substantially improving LMI tracts weakens in the narrowest sample bands. Third, the significant relationship for substantially moving-down LMI tracts effectively disappears as one limits the sample to those tracts with median incomes closest to the CRA threshold, and we even observe an instance of a slight CRA premium for the moderate negative movers when we apply the narrowest sample banks restriction.

7. Robustness and model validity

In this section, we explore whether the results in Table 5 are robust to choices we made regarding restricting the loans included in the sample and calculating the approval rate. The baseline analysis excludes applications for loans insured by the FHA from the sample because FHA loans feature a different risk and rate profile. However, FHA loans might plausibly be viewed as substitutes for conventional loans, especially among

[23] Control variable relationships were robust across the varying samples and so are not reported here. Full regression results are reported in Appendix Table B-1.

Table 6

Robustness and Model Validity Test 1: Summarized results based on the models with FHA loans, loans with preapproval requests, and without applications withdrawn by applicants or files closed for incompleteness (dependent variable: whether a loan application is approved).

	All Tracts	[70%, 90%)	[75%, 85%)	[78%, 82%)
A. With FHA loans				
LMI	−0.008***	−0.004*	−0.003	−0.010+
(20 pp. ≤ Δ%AMI)	0.009***	0.013***	0.014***	0.013**
(10 ≤ Δ%AMI < 20 pp.)	0.006***	0.006***	0.008***	0.015***
(−20 ≤ Δ%AMI < −10 pp.)	−0.005***	−0.008***	−0.009***	−0.013***
(Δ%AMI < −20 pp.)	−0.007***	−0.011***	−0.008**	−0.006
LMI × (20 pp. ≤ Δ%AMI)	0.030***	0.008***	0.006+	0.011+
LMI × (10 ≤ Δ%AMI < 20 pp.)	0.010***	0.006**	0.008*	0.015*
LMI × (−20 ≤ Δ%AMI < −10 pp.)	−0.005***	0.002	0.003	0.011*
LMI × (Δ%AMI < −20 pp.)	−0.011***	0.001	−0.002	−0.006
FHA loans	−0.007***	0.008***	0.008***	0.010***
Share of loan originations in 2000–02	Yes	Yes	Yes	Yes
Individual applicant char.	Yes	Yes	Yes	Yes
Neighborhood char. in 2000 Census	Yes	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
Adjusted R–squared	0.1539	0.1735	0.1753	0.1752
Number of observations	15,773,255	2,683,608	1,337,726	498,328
B. With loans with preapproval requests				
	All Tracts	[70%, 90%)	[75%, 85%)	[78%, 82%)
LMI	−0.009***	−0.003	−0.003	−0.008
(20 pp. ≤ Δ%AMI)	0.009***	0.012***	0.014***	0.014**
(10 ≤ Δ%AMI < 20 pp.)	0.006***	0.007***	0.010***	0.017***
(−20 ≤ Δ%AMI < −10 pp.)	−0.005***	−0.008***	−0.008***	−0.011**
(Δ%AMI < −20 pp.)	−0.007***	−0.012***	−0.010***	−0.009+
LMI × (20 pp. ≤ Δ%AMI)	0.030***	0.007**	0.005	0.011+
LMI × (10 ≤ Δ%AMI < 20 pp.)	0.011***	0.005*	0.007*	0.013*
LMI × (−20 ≤ Δ%AMI < −10 pp.)	−0.006***	0.001	0.002	0.009+
LMI × (Δ%AMI < −20 pp.)	−0.012***	0.000	−0.004	−0.007
Loans with preapproval requests	0.084***	0.093***	0.095***	0.094***
Share of loan originations in 2000–02	Yes	Yes	Yes	Yes
Individual applicant char.	Yes	Yes	Yes	Yes
Neighborhood char. in 2000 Census	Yes	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
Adjusted R–squared	0.1669	0.1939	0.1959	0.1952
Number of observations	14,721,000	2,395,177	1,195,529	447,356
C. Without applications withdrawn by applicants or files closed for incompleteness				
	All Tracts	[70%, 90%)	[75%, 85%)	[78%, 82%)
LMI	−0.009***	−0.005*	−0.004	−0.006
(20 pp. ≤ Δ%AMI)	0.009***	0.013***	0.017***	0.020***
(10 ≤ Δ%AMI < 20 pp.)	0.006***	0.007***	0.009***	0.015***
(−20 ≤ Δ%AMI < −10 pp.)	−0.005***	−0.008***	−0.008***	−0.009**
(Δ%AMI < −20 pp.)	−0.007***	−0.011***	−0.008**	−0.006
LMI × (20 pp. ≤ Δ%AMI)	0.032***	0.006*	0.001	0.002
LMI × (10 ≤ Δ%AMI < 20 pp.)	0.011***	0.005*	0.006*	0.013*
LMI × (−20 ≤ Δ%AMI < −10 pp.)	−0.006***	0.001	0.001	0.005
LMI × (Δ%AMI < −20 pp.)	−0.012***	−0.001	−0.004	−0.009
Share of loan originations in 2000–02	Yes	Yes	Yes	Yes
Individual applicant char.	Yes	Yes	Yes	Yes
Neighborhood char. in 2000 Census	Yes	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
Adjusted R–squared	0.1714	0.1943	0.1966	0.1957
Number of observations	12,286,278	1,990,509	993,483	371,380

Note: +: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$. Robust standard errors, clustered at bank-tract-year level, are in parentheses. The two-way high-dimensional fixed effects regression models were conducted using the REGHDFE, a user-written Stata program, with Stata 14.2. The sample is restricted to conventional home purchase loans for one-to-four family homes that will be the borrower's principal dwelling in MSA/MDs and within institution's assessment area. The sample includes loan applications reported by the lending institutions that are subject to the CRA. Loans purchased by reporting institutions are excluded. For Panels A and B, the sample includes applications for loans insured by the FHA and loans with preapprovals, respectively. The sample for Panel C excludes applicaions withdrawn by applicants or applications associated with files closed for incompleteness.

Table 7
Robustness and Model Validity Test 2: Summarized results based on the model without a fourth-order polynomial in income ratio and the model without neighborhood characteristics (dependent variable: whether a loan application is approved).

	All Tracts	[70%, 90%)	[75%, 85%)	[78%, 82%)
A. Without square, cubic, and quadratic terms of median family income ratio				
LMI	−0.014***	−0.002	−0.006*	−0.010*
(20 pp. ≤ Δ%AMI)	0.010***	0.013***	0.014***	0.013**
(10 ≤ Δ%AMI < 20 pp.)	0.006***	0.007***	0.010***	0.017***
(−20 ≤ Δ%AMI < −10 pp.)	−0.005***	−0.009***	−0.009***	−0.014***
(Δ%AMI < −20 pp.)	−0.007***	−0.013***	−0.011***	−0.009+
LMI × (20 pp. ≤ Δ%AMI)	0.030***	0.007**	0.005	0.011+
LMI × (10 ≤ Δ%AMI < 20 pp.)	0.010***	0.006*	0.007*	0.014*
LMI × (−20 ≤ Δ%AMI < −10 pp.)	−0.006***	0.002	0.003	0.011*
LMI × (Δ%AMI < −20 pp.)	−0.011***	0.001	−0.002	−0.006
MFI Ratio	Yes	Yes	Yes	Yes
(MFI Ratio)^2, (MFI Ratio)^3, (MFI Ratio)^4	No	No	No	No
Share of loan originations in 2000–02	Yes	Yes	Yes	Yes
Individual applicant char.	Yes	Yes	Yes	Yes
Neighborhood char. in 2000 Census	Yes	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
Adjusted R–squared	0.1684	0.1959	0.1981	0.1973
Number of observations	13,624,136	2,222,169	1,110,234	414,898
B. Without neighborhood characteristics observed in Census 2000				
	All Tracts	[70%, 90%)	[75%, 85%)	[78%, 82%)
LMI	−0.009***	−0.004+	−0.002	−0.006
(20 pp. ≤ Δ%AMI)	0.014***	0.022***	0.022***	0.021***
(10 ≤ Δ%AMI < 20 pp.)	0.008***	0.012***	0.016***	0.027***
(−20 ≤ Δ%AMI < −10 pp.)	−0.007***	−0.011***	−0.011***	−0.015***
(Δ%AMI < −20 pp.)	−0.010***	−0.015***	−0.014***	−0.016**
LMI × (20 pp. ≤ Δ%AMI)	0.036***	0.009***	0.009*	0.010
LMI × (10 ≤ Δ%AMI < 20 pp.)	0.014***	0.006**	0.006+	0.007
LMI × (−20 ≤ Δ%AMI < −10 pp.)	−0.008***	0.001	0.003	0.010+
LMI × (Δ%AMI < −20 pp.)	−0.015***	−0.002	−0.005	−0.005
MFI Ratio	Yes	Yes	Yes	Yes
(MFI Ratio)^2, (MFI Ratio)^3, (MFI Ratio)^4	Yes	Yes	Yes	Yes
Share of loan originations in 2000–02	Yes	Yes	Yes	Yes
Individual applicant char.	Yes	Yes	Yes	Yes
Neighborhood char. in 2000 Census	No	No	No	No
County × Year FEs	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
Adjusted R–squared	0.1675	0.1948	0.1969	0.1962
Number of observations	13,624,136	2,222,169	1,110,234	414,898

+ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Robust standard errors, clustered at bank-tract-year level, are in parentheses. The two-way high-dimensional fixed effects regression models were conducted using the REGHDFE, a user-written Stata program, with Stata 14.2. The sample is restricted to conventional home purchase loans for one-to-four family homes that will be the borrower's principal dwelling in MSA/MDs and within institution's assessment area. The sample includes loan applications reported by the lending institutions that are subject to the CRA, and the loans purchased by reporting institutions or those with preapproval requests are excluded.

LMI borrowers, and thus it could be appropriate to include applications for them in the sample (Ambrose et al., 2002; An and Bostic, 2008). As a consequence, we repeat our analyses using a dataset that includes FHA loan applications and adding an FHA dummy variable to the specification in Eq. (2). The results are shown in Panel A of Table 6.[24] We see some evidence supporting the view that the acceptance of FHA loan applications is greater in LMI neighborhoods, as we see that approval rates for those loans are higher for narrower bands after controlling for applicant and neighborhood characteristics. However, the inclusion of FHA loan applications does not materially change our key variables of interest; the estimated moving-up, moving-down, and interaction coefficients are largely unchanged.

Regarding calculation of the approval rate, there are several considerations. First, the data include loan applications that involved lender preapprovals, loan applications that were closed by the lender due to incompleteness, and loan applications that were withdrawn by the borrower. In the baseline analysis, we excluded applications with preapprovals, and considered closed and withdrawn loans to be non-approvals. To test sensitivity of the results to these choices, we estimated Eq. (2) on a sample where applications with preapprovals were included. The results, shown in the Panel B of Table 6, indicate that applications with preapprovals have higher approval rates, which is not surprising, and that the moving-up and moving-down relationships, as well as their relationships with LMI/CRA status are all robust to the inclusion of applications with preapprovals.

The baseline analysis treated applications that were closed by the lender due to incompleteness or those that were withdrawn by the ap-

[24] For brevity, only summarized regression results are shown in this section. Full regression results are reported in Appendix B, from Tables B-2 to B-10.

Table 8
Robustness and Model Validity Test 3: Summarized results based on the models with credit score and using the CRA reporting sample (dependent variable: whether a loan application is approved).

A. Without FICO Average Credit Score

	All Tracts	[70%, 90%)	[75%, 85%)	[78%, 82%)
LMI	−0.009***	−0.003	−0.004	−0.007
(20 pp. ≤ Δ%AMI)	0.010***	0.015***	0.017***	0.019***
(10 ≤ Δ%AMI < 20 pp.)	0.007***	0.008***	0.011***	0.021***
(−20 ≤ Δ%AMI < −10 pp.)	−0.006***	−0.010***	−0.009***	−0.013**
(Δ%AMI < −20 pp.)	−0.008***	−0.013***	−0.012***	−0.007
LMI × (20 pp. ≤ Δ%AMI)	0.031***	0.006+	0.003	0.005
LMI × (10 ≤ Δ%AMI < 20 pp.)	0.011***	0.005*	0.005	0.009
LMI × (−20 ≤ Δ%AMI < −10 pp.)	−0.006***	0.001	0.001	0.008
LMI × (Δ%AMI < −20 pp.)	−0.012***	0.001	−0.002	−0.007
FICO Average Credit Score	No	No	No	No
Share of loan originations in 2000–02	Yes	Yes	Yes	Yes
Individual applicant char.	Yes	Yes	Yes	Yes
Neighborhood char. in 2000 Census	Yes	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
Adjusted R–squared	0.1831	0.2147	0.2171	0.2158
Number of observations	10,979,708	1,781,173	890,022	330,915

B. With FICO Average Credit Score

	All Tracts	[70%, 90%)	[75%, 85%)	[78%, 82%)
LMI	−0.009***	−0.002	−0.002	−0.005
(20 pp. ≤ Δ%AMI)	0.009***	0.014***	0.016***	0.018***
(10 ≤ Δ%AMI < 20 pp.)	0.006***	0.007***	0.010***	0.021***
(−20 ≤ Δ%AMI < −10 pp.)	−0.005***	−0.009***	−0.008***	−0.010*
(Δ%AMI < −20 pp.)	−0.006***	−0.013***	−0.010**	−0.006
LMI × (20 pp. ≤ Δ%AMI)	0.028***	0.004	0.002	0.004
LMI × (10 ≤ Δ%AMI < 20 pp.)	0.010***	0.005+	0.005	0.007
LMI × (−20 ≤ Δ%AMI < −10 pp.)	−0.006***	0.001	0.000	0.004
LMI × (Δ%AMI < −20 pp.)	−0.011***	0.001	−0.002	−0.007
FICO Average Credit Score	Yes	Yes	Yes	Yes
Share of loan originations in 2000–02	Yes	Yes	Yes	Yes
Individual applicant char.	Yes	Yes	Yes	Yes
Neighborhood char. in 2000 Census	Yes	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
Adjusted R–squared	0.1835	0.2151	0.2174	0.2160
Number of observations	10,979,708	1,781,173	890,022	330,915

+ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** Robust standard errors, clustered at bank-tract-year level, are in parentheses. The two-way high-dimensional fixed effects regression models were conducted using the REGHDFE, a user-written Stata program, with Stata 14.2. The sample is restricted to conventional home purchase loans for one-to-four family homes that will be the borrower's principal dwelling in MSA/MDs and within institution's assessment area. The sample includes loan applications reported by the lending institutions that are subject to the CRA, and the loans purchased by reporting institutions or those with preapproval requests are excluded. The ZIP code-level credit scores, provided by the Fair Isaac Corporation, were converted to tract-level.

plicant as non-approved. However, these applications might actually reflect decisions made by the applicant rather than the lender. For example, incomplete files could be the by-product of applicants starting the process and then changing their mind about engaging a lender, perhaps because they found a more attractive product at another lender or had second thoughts about purchasing the home. We thus repeat the baseline analysis excluding incomplete or withdrawn applications from consideration. The results of this are shown in the final panel of Table 6. We see that, compared to the base case, the relationships are qualitatively the same, though they are a bit weaker in the narrowest sample band.

We also test for the robustness of our model specification. While it is conventional to include a fourth-order polynomial in the running variable, median family income ratio in our model, and a set of control variables in the RD approach, concerns may be raised that a high degree of collinearity might result. In their study with a similar framework, Gabriel and Rosenthal (2009) examined the effects of the multicollinearity on their estimates on the CRA effects and tested alternative specifications. Following their approach, Table 7 presents the regression results based on the model with only a linear term of median family income ratio (Panel A) and the model without a set of neighborhood attributes observed in Census 2000 (Panel B). In the table, we see that the coefficients on our variables of interest remain virtually identical to those in the baseline specifications shown in Table 7. We take this as evidence in support of the validity of the strategy of using the samples within an increasingly narrow range around the income threshold, and as further support of the main conclusions from the previous section.

Next, we add a measure of borrower credit quality to the specification. One weakness of the HMDA data is that it does not include information on the credit quality of borrowers submitting mortgage applications. Munnell et al. (1996) and Tootell (1996), among others, suggest that the omission of borrower creditworthiness can produce substantial bias in estimated coefficients. We do not have access to the credit scores of the applicants included in our data. However, we are able to proxy for these by incorporating the average credit score at the ZIP code level into our model. We obtained average ZIP code credit scores for 2005–2011 from the Fair Isaac Corporation, and follow Mian and Sufi (2009) in con-

Table 9
Robustness and Model Validity Test 4: Summarized results based on the model, with CRA reporting sample (dependent variable: whether a loan application is approved).

	All Tracts	[70%, 90%)	[75%, 85%)	[78%, 82%)
LMI	–0.011***	–0.002	–0.002	–0.019*
(20 pp. ≤ Δ%AMI)	0.010***	0.016***	0.019***	0.017*
(10 ≤ Δ%AMI < 20 pp.)	0.005***	0.007**	0.007*	0.015*
(–20 ≤ Δ%AMI < –10 pp.)	–0.005***	–0.007**	–0.006+	–0.010+
(Δ%AMI < –20 pp.)	–0.007***	–0.011***	–0.009*	–0.009
LMI × (20 pp. ≤ Δ%AMI)	0.032***	0.004	0.000	0.008
LMI × (10 ≤ Δ%AMI < 20 pp.)	0.013***	0.006+	0.007	0.018*
LMI × (–20 ≤ Δ%AMI < –10 pp.)	–0.010***	–0.002	–0.003	0.005
LMI × (Δ%AMI < –20 pp.)	–0.016***	–0.006	–0.008	–0.002
Share of loan originations in 2000–02	Yes	Yes	Yes	Yes
Individual applicant char.	Yes	Yes	Yes	Yes
Neighborhood char. in 2000 Census	Yes	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
Adjusted R–squared	0.0953	0.1063	0.1086	0.1112
Number of observations	5772,971	867,996	437,452	161,800

+ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Robust standard errors, clustered at bank-tract-year level, are in parentheses. The two-way high-dimensional fixed effects regression models were conducted using the REGHDFE, a user-written Stata program, with Stata 14.2 to account for county-year fixed effects and bank fixed effects. The sample is restricted to conventional home purchase loans for one-to-four family homes that will be the borrower's principal dwelling in MSA/MDs reported by the lending institutions that are subject to the CRA.

Table 10
Validating the mechanism 1: Summarized results of regression analyses for different number of loan applications thresholds.

A. Full sample				
	All Tracts	$N \geq 5$	$N \geq 10$	$N \geq 20$
LMI	–0.009***	–0.009***	–0.010***	–0.011***
(20 pp. ≤ ΔAMI)	0.009***	0.010***	0.010***	0.010***
(10 ≤ ΔAMI < 20 pp.)	0.006***	0.006***	0.006***	0.004**
(–20 ≤ ΔAMI < –10 pp.)	–0.005***	–0.005***	–0.005***	–0.006***
(ΔAMI < –20 pp.)	–0.007***	–0.006***	–0.006***	–0.006***
LMI × (20 pp. ≤ ΔAMI)	0.031***	0.030***	0.028***	0.027***
LMI × (10 ≤ ΔAMI < 20 pp.)	0.011***	0.012***	0.013***	0.010*
LMI × (–20 ≤ ΔAMI < –10 pp.)	–0.006***	–0.006***	–0.007*	–0.004
LMI × (ΔAMI < –20 pp.)	–0.012***	–0.008**	–0.008+	–0.006
Share of loan originations in 2000–02	Yes	Yes	Yes	Yes
Individual applicant char.	Yes	Yes	Yes	Yes
Neighborhood char. in 2000 Census	Yes	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
Adjusted R–squared	0.1684	0.1535	0.1514	0.1480
Number of observations	13,624,136	7,988,428	4,969,586	2,546,549
B. 78 to 82%				
	All Tracts	$N \geq 5$	$N \geq 10$	$N \geq 20$
LMI	–0.009	–0.009	–0.014	–0.044+
(20 pp. ≤ ΔAMI)	0.013**	0.016*	0.019+	0.021
(10 ≤ ΔAMI < 20 pp.)	0.017***	0.016*	0.023*	0.026
(–20 ≤ ΔAMI < –10 pp.)	–0.014***	–0.016**	–0.025**	–0.013
(ΔAMI < –20 pp.)	–0.009+	–0.016*	–0.036**	–0.077*
LMI × (20 pp. ≤ ΔAMI)	0.012+	0.017+	0.034*	0.037
LMI × (10 ≤ ΔAMI < 20 pp.)	0.015*	0.022*	0.038**	0.048+
LMI × (–20 ≤ ΔAMI < –10 pp.)	0.012*	0.015+	0.029*	0.033
LMI × (ΔAMI < –20 pp.)	–0.006	0.007	0.041*	0.078+
Share of loan originations in 2000–02	Yes	Yes	Yes	Yes
Individual applicant char.	Yes	Yes	Yes	Yes
Neighborhood char. in 2000 Census	Yes	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
Adjusted R–squared	0.1973	0.1971	0.2040	0.2040
Number of observations	414,898	210,086	113,972	47,937

+ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Robust standard errors, clustered at bank-tract-year level, are in parentheses. The two-way high-dimensional fixed effects regression models were conducted using the REGHDFE, a user-written Stata program, with Stata 14.2 to account for county-year fixed effects and bank fixed effects. The sample is restricted to conventional home purchase loans for one-to-four family homes that will be the borrower's principal dwelling in MSA/MDs reported by the lending institutions that are subject to the CRA.

Table 11
Validating the mechanism 2: Summarized results of regression analyses for different time periods (dependent variable: whether a loan application is approved).

	2004–2011	2004–2007	2008–2011
A. All Tracts			
LMI	−0.009***	−0.009***	−0.012***
(20 pp. ≤ Δ%AMI)	0.009***	0.009***	0.011***
(10 ≤ Δ%AMI < 20 pp.)	0.006***	0.006***	0.006***
(−20 ≤ Δ%AMI < −10 pp.)	−0.005***	−0.006***	−0.005***
(Δ%AMI < −20 pp.)	−0.007***	−0.007***	−0.008***
LMI × (20 pp. ≤ Δ%AMI)	0.031***	0.028***	0.043***
LMI × (10 ≤ Δ%AMI < 20 pp.)	0.011***	0.010***	0.016***
LMI × (−20 ≤ Δ%AMI < −10 pp.)	−0.006***	−0.005***	−0.010***
LMI × (Δ%AMI < −20 pp.)	−0.012***	−0.011***	−0.019***
Share of loan originations in 2000–02	Yes	Yes	Yes
Individual applicant char.	Yes	Yes	Yes
Neighborhood char. in 2000 Census	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes
Adjusted R–squared	0.1684	0.1898	0.1144
Number of observations	13,624,136	10,607,474	3,016,470
B. 70% ≤%AMI < 90%			
	2004–2011	2004–2007	2008–2011
LMI	−0.004+	−0.004+	−0.002
(20 pp. ≤ Δ%AMI)	0.013***	0.012***	0.017***
(10 ≤ Δ%AMI < 20 pp.)	0.007***	0.008***	0.002
(−20 ≤ Δ%AMI < −10 pp.)	−0.009***	−0.008***	−0.012***
(Δ%AMI < −20 pp.)	−0.013***	−0.011***	−0.021***
LMI × (20 pp. ≤ Δ%AMI)	0.007**	0.007*	0.007
LMI × (10 ≤ Δ%AMI < 20 pp.)	0.006*	0.004	0.014**
LMI × (−20 ≤ Δ%AMI < −10 pp.)	0.002	0.002	0.001
LMI × (Δ%AMI < −20 pp.)	0.001	0.000	0.004
Share of loan originations in 2000–02	Yes	Yes	Yes
Individual applicant char.	Yes	Yes	Yes
Neighborhood char. in 2000 Census	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes
Adjusted R–squared	0.1959	0.2162	0.1303
Number of observations	2,222,169	1,803,261	418,338
C. 75% ≤%AMI < 85%			
	2004–2011	2004–2007	2008–2011
LMI	−0.003	−0.003	0.000
(20 pp. ≤ Δ%AMI)	0.014***	0.015***	0.014*
(10 ≤ Δ%AMI < 20 pp.)	0.010***	0.011***	0.005
(−20 ≤ Δ%AMI < −10 pp.)	−0.009***	−0.009***	−0.011*
(Δ%AMI < −20 pp.)	−0.011***	−0.009**	−0.023***
LMI × (20 pp. ≤ Δ%AMI)	0.005	0.004	0.008
LMI × (10 ≤ Δ%AMI < 20 pp.)	0.007*	0.006	0.012+
LMI × (−20 ≤ Δ%AMI < −10 pp.)	0.003	0.005	−0.003
LMI × (Δ%AMI < −20 pp.)	−0.002	−0.003	0.007
Share of loan originations in 2000–02	Yes	Yes	Yes
Individual applicant char.	Yes	Yes	Yes
Neighborhood char. in 2000 Census	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes
Adjusted R–squared	0.1981	0.2182	0.1317
Number of observations	1,110,234	900,536	208,963
D. 78% ≤%AMI < 82%			
	2004–2011	2004–2007	2008–2011
LMI	−0.009	−0.004	−0.027*
(20 pp. ≤ Δ%AMI)	0.013**	0.016**	0.009
(10 ≤ Δ%AMI < 20 pp.)	0.017***	0.018***	0.013
(−20 ≤ Δ%AMI < −10 pp.)	−0.014***	−0.012**	−0.021*
(Δ%AMI < −20 pp.)	−0.009+	−0.008	−0.015
LMI × (20 pp. ≤ Δ%AMI)	0.012+	0.010	0.014
LMI × (10 ≤ Δ%AMI < 20 pp.)	0.015*	0.013+	0.020
LMI × (−20 ≤ Δ%AMI < −10 pp.)	0.012*	0.011+	0.013
LMI × (Δ%AMI < −20 pp.)	−0.006	−0.007	0.003
Share of loan originations in 2000–02	Yes	Yes	Yes
Individual applicant char.	Yes	Yes	Yes
Neighborhood char. in 2000 Census	Yes	Yes	Yes
County × Year FEs	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes
Adjusted R–squared	0.1973	0.2171	0.1325
Number of observations	414,898	334,495	79,683

Note: +: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$. Robust standard errors, clustered at bank-tract-year level, are in parentheses. The two-way high-dimensional fixed effects regression models were conducted using the REGHDFE, a user-written Stata program, with Stata 14.2. The sample is restricted to conventional home purchase loans for one-to-four family homes that will be the borrower's principal dwelling in MSA/MDs and within institution's assessment area. The sample includes loan applications reported by the lending institutions that are subject to the CRA, and the loans purchased by reporting institutions or those with preapproval requests are excluded.

verting these data into census tract measures.[25] In general, the average credit score increased rapidly in 2009–2011, reflecting tightened credit standards after the financial crisis (not shown).[26]

The addition of credit scores to the data resulted in the loss of about 20 percent of the observations, because data were not provided for all ZIP codes out of concerns for privacy. As a consequence, we are not able to directly compare the results of this analysis to those presented in Table 5. Instead, we replicate the analysis in Table 5 using the smaller sample and compare these results to the results obtained when the average credit score is added as a regressor. The product of this exercise is reported in Table 8. Panel A shows that coefficient point estimates are quite similar to those in Table 5, with the main difference being a lack of precision using the smaller sample, especially for the CRA relationships. Importantly, we do not observe a major change in the coefficient point estimates when the credit score variable is added (Panel B), which gives us some confidence that the omission of credit score information is not biasing our results.

Another potential issue is the definition of a banking institution's assessment area used in this study. While we defined an assessment area as the sum of the MSAs in which an institution had a branch, a banking institution can choose its assessment area in ways that do not necessarily align with MSA boundaries. Though banks usually define their assessment areas using MSA boundaries, we examined whether our more inclusive approach generates biased results. We re-estimated the relationships using the actual assessment area for each institution in each year based on the FFIEC's CRA Disclosure Report from 2004 to 2011. The cost of using this accurate definition of assessment area is sample size – only banks and savings associations of a certain asset size are required to collect and report these data. As a consequence, we lose about 60 percent of all observations.[27] Table 9 shows the results for key variables using the smaller sample restricted to those institutions that report their actual assessment area boundaries ("CRA Reporting sample"). The overall patterns persist, as we observe the same general relationships as before.

8. Validating the mechanism

In this section, we conduct several additional tests that seek to sharpen our understanding of the precise mechanisms that drive the observed relationships. First, if the effect is associated with familiarity

[25] We tested the robustness of the findings below by varying matching methods and thresholds and comparing results. They were qualitatively unchanged.

[26] The distribution of the credit scores by neighborhood status change categories is shown in Appendix Table B-7.

[27] All financial institutions regulated by the Office of the Comptroller of the Currency (OCC), Federal Reserve System (FRS), and the Federal Deposit Insurance Corporation (FDIC) that meet the asset size threshold are subject to data collection and reporting requirements. The asset size threshold is annually adjusted and is $1.252 billion as of January 1, 2018.

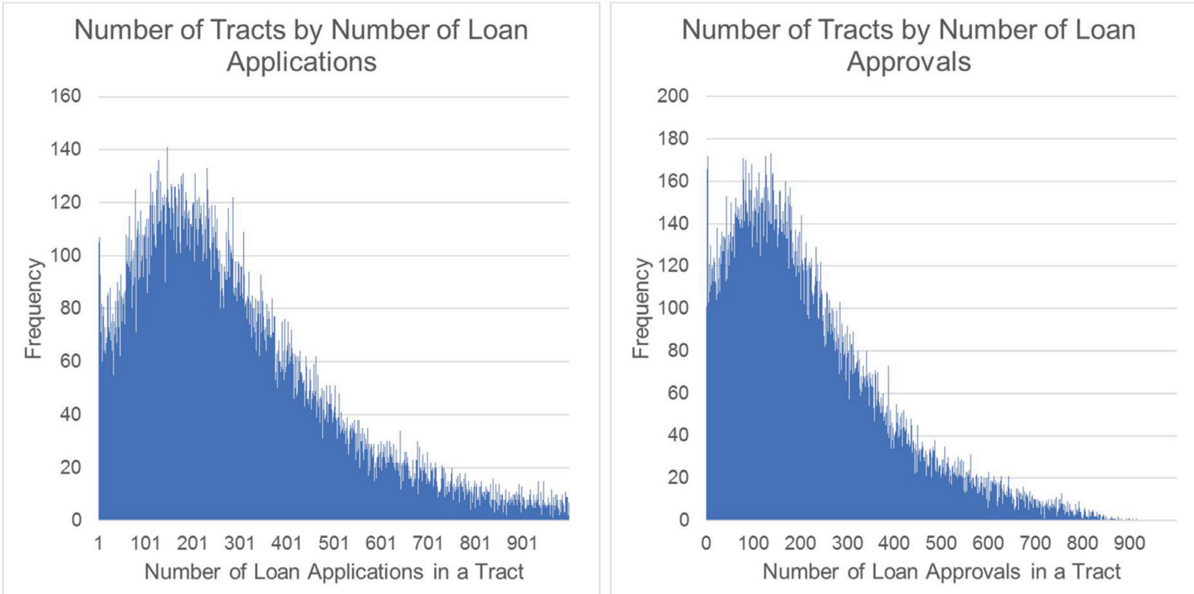

Fig. 2. Number of census tracts by number of loan applications (left) and number of loan approvals (right).
Note: The sample is restricted to the conventional loans for purchasing one-to-four family homes in the neighborhoods in MSA/MDs and within institution's assessment area. The sample includes loan approvals reported by banking institutions that are supervised by OCC, FRS, FDIC, and OTS/CFPB only. The loans purchased by reporting institutions or those with preapproval requests are excluded.
Source: Authors' analysis based on the 2004–2011 HMDA LAR files.

with developments in a neighborhood, then one might expect the relationships to be stronger if one focuses attention on those tracts that had higher levels of mortgage application activity. Lenders may not have an incentive to gain deeper knowledge about neighborhoods in which they only receive one or two applications. To test this hypothesis, we repeat the analysis limiting the sample to those tracts in which the number of applications for a lender in a year is greater than a threshold level. We use 5, 10, and 20 loan applications as thresholds.

This test provides an additional benefit, in that approval rates in tracts with small numbers of applications are quite sensitive to small variations in decisions. For example, in a tract with 2 applications, the change in the approval rate associated with switching the decision on a single loan is 50 percentage points. Clearly, the signal about a lender's perceptions of risk in a neighborhood is less robust in this case. Requiring a larger number of applications in a neighborhood reduces the potential bias associated with this and could represent a cleaner test of the underlying hypothesis.

Table 10 shows the results of this exercise. For parsimony, we present only the results for the key variables for the full sample (top panel) and the narrowest sample band (bottom panel).[28] The results for the full sample show few significant differences when one limits the sample to include only tracts whose number of applications exceeds some threshold. On balance, the basic pattern still holds.

When one looks at the results for the narrowest band, which is the approach most focused on the CRA dimension of the dynamic, we find that point estimates increase dramatically as one requires a tract have a threshold level of applications to be included. Point estimates for the LMI moving up tract interactions are up to three times larger in limited sample regressions than in the regressions including all tracts. Moving down tracts also show increases in point estimates for approval rate differences. There is an interesting pattern regarding statistical significance as well. Statistical significance increases for the LMI tracts as the threshold increases to 10 loans, but it degrades for all coefficients when the threshold is set at 20. This degradation could be due to the small number of LMI tracts and applications in the sample when the threshold is 20 loans.[29]

Another implication of our hypothesis is that the effects should strengthen as the decade progresses, because a neighborhood's relative improvement or decline should become more evident over time. We test this by separately estimating relationships for the first and second halves of the period. Table 11 presents the results of this exercise.[30] In the results for the full sample and 70 to 90% band, the magnitudes and statistical significances of the estimated coefficients on the interaction terms between LMI status and neighborhood improvement tend to be greater in the later years (2008–2011) compared to the earlier ones (2004–2007). This stronger CRA premiums during the later years could be explained by greater mismatch between the CRA eligibility and actual neighborhood status, longer exposure in time to learn such changes, and growing needs for default risk management after the subprime mortgage crisis in the later years. While the point estimates on the interaction terms are still greater in later years for the narrower 75% to 85% and 78% to 82% bands, they lose their statistical significance, which does not allow us to draw strong conclusion on this pattern. More research is warranted here.

Ultimately, the goal of the CRA is to increase the flow of credit to underserved neighborhoods. Our measure here - loan approval rate - may not fully capture this objective, as approval rates can increase at the same time that loan volumes fall. We thus augment this analysis by considering two other measures that we can glean from the HMDA data: (1) number of loan applications and (2) number of loan approvals. These tract-level statistics differ from the approval rate in that, as shown in Fig. 2, their distributions are both skewed. For this type of distribution, a negative binomial regression approach is more appropriate, and this is what we estimate. Since we aggregate loans in a tract across all lenders,

[28] Full regression results are reported in Appendix B, from Tables B-11 to B-13.

[29] For the narrowest band, the numbers of bank-census tracts that have at least 1, 5, 10, and 20 applications in a year are 144,705, 16,323, 5,459, and 1,303.

[30] Full regression results are reported in Appendix B, from Tables B-14 and B-15.

Table 12
Validating the mechanism 3: Summarized results of regression analyses with alternative dependent variables.

A. Dependent variable: number of loan applications in a census tract				
	All Tracts	[70%, 90%)	[75%, 85%)	[78%, 82%)
LMI	−0.064***	−0.024+	−0.007	−0.060*
(20 pp. ≤ Δ%AMI)	0.205***	0.279***	0.374***	0.303***
(10 ≤ Δ%AMI < 20 pp.)	0.094***	0.093***	0.067***	0.112***
(−20 ≤ Δ%AMI < −10 pp.)	−0.080***	−0.058***	−0.034**	0.014
(Δ%AMI < −20 pp.)	−0.138***	−0.092***	−0.078***	−0.061*
LMI × (20 pp. ≤ Δ%AMI)	0.299***	0.087**	−0.014	−0.051
LMI × (10 ≤ Δ%AMI < 20 pp.)	0.073***	0.008	0.056*	0.141***
LMI × (−20 ≤ Δ%AMI < −10 pp.)	−0.037***	−0.018	−0.019	−0.034
LMI × (Δ%AMI < −20 pp.)	−0.025**	−0.045**	−0.047*	−0.023
Share of loan originations in 2000–02	Yes	Yes	Yes	Yes
Neighborhood applicant char.	Yes	Yes	Yes	Yes
Neighborhood char. in 2000 Census	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Number of observations	401,164	85,791	42,604	16,734
B. Dependent variable: number of loan approvals in a census tract				
	All Tracts	[70%, 90%)	[75%, 85%)	[78%, 82%)
LMI	−0.078***	−0.030*	−0.016	−0.082**
(20 pp. ≤ Δ%AMI)	0.220***	0.306***	0.410***	0.329***
(10 ≤ Δ%AMI < 20 pp.)	0.102***	0.103***	0.082***	0.129***
(−20 ≤ Δ%AMI < −10 pp.)	−0.086***	−0.070***	−0.043**	−0.006
(Δ%AMI < −20 pp.)	−0.146***	−0.112***	−0.087***	−0.077*
LMI × (20 pp. ≤ Δ%AMI)	0.346***	0.096**	−0.014	−0.048
LMI × (10 ≤ Δ%AMI < 20 pp.)	0.089***	0.021	0.067**	0.169***
LMI × (−20 ≤ Δ%AMI < −10 pp.)	−0.049***	−0.018	−0.023	−0.019
LMI × (Δ%AMI < −20 pp.)	−0.047***	−0.044**	−0.047+	−0.022
Share of loan originations in 2000–02	Yes	Yes	Yes	Yes
Neighborhood applicant char.	Yes	Yes	Yes	Yes
Neighborhood char. in 2000 Census	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Number of observations	401,164	85,791	42,604	16,734

+ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Robust standard errors, clustered at tract-year level, are in parentheses. The sample is restricted to census tracts within MSA/MDs. The negative binomial regression models were conducted with Stata 14.2 to address the skewness in the numbers of loan applications and approvals across census tracts. The numbers of applications and approvals are aggregated at census tract-level, while the applicant characteristics are averaged at census tract-level.

we do not include bank fixed effects; rather, county and year fixed effects are included. Table 11 reports the result of this analysis.[31]

We see support for both the moving-up and moving-down narratives. The pattern of coefficients using the full sample offer strong support, and patterns for the narrowest sample band still offer some support for the hypothesis. In particular, the moving-up effect for LMI tracts showing moderate improvement more than offsets the general negative LMI effect for loan applications and approvals. Given the estimates based on the narrowest sample band, the numbers of loan applications in a modestly improving LMI tract in a year are about eight percent greater than the numbers in a comparably improving non-LMI tract. Similarly, the numbers of loan approvals in the modestly moving-up LMI tract compared to the modestly moving-up LMI tract are expected to be nine percent greater. Interestingly, the moving-down dynamic for LMI tracts largely disappears when the sample is narrowly restricted around the CRA threshold.

9. Conclusion

This paper contributes to the literature examining the unintended consequences of regulation, this time exploring whether a regulation's structure creates incentives such that some segments of the population the policy targets are favored relative to others. It uses the CRA as a case study and hones in on a key quirk of the regulation: though neighborhoods change continuously over the course of a decade, a neighborhood's eligibility under the CRA is determined by the decennial Census and remains fixed until the next Census. This raises an interesting behavioral question: do lending patterns among institutions covered by the CRA vary systematically across CRA-eligible locations such that those doing better during the decade receive increasingly more credit?

The answer to this question is yes. We find that the share of loans approved in improving neighborhoods increases over a decade, especially among the loans approved in LMI tracts. Moreover, the moving-up tracts that are CRA-eligible enjoy an approval premium on the order of 2.0 to 13.3 percent, depending on the sample used.

Sunstein (1994) notes that the unintended consequences of regulations can render them either futile or self-defeating. In the context of the CRA, it is clear that the regulation has proven to be neither (Avery et al., 2005; Gabriel and Rosenthal, 2009). Rather, the data are clear that the regulation has successfully channeled credit to communities that have been historically underserved.

What this research shows, however, is that it would be incorrect to conclude that there was not a feedback loop whereby the regulated firms responded to the presence of the regulation. Indeed, we demonstrate that financial institutions shift their lending within the universe of CRA-eligible tracts to those with the most favorable credit profiles. Thus, as in the case of other regulations, we see firms responding in ways that

[31] Full regression results are reported in Appendix B, from Tables B-16 and B-17.

maximize their interests such that there is an incidence to the regulation. The question is whether this incidence is an intended or an unintended consequence.

Some might argue that the evidence presented here is consistent with a story that, through bank lending activity, the CRA works to lift neighborhoods out of LMI status and then, in successive decades, turns to those neighborhoods that have been "left behind." This is certainly a viable strategic approach, but it is one that carries costs. Perhaps most significant among these is that those in the eligible population with the deepest needs (as measured by percentage of AMI) would receive the lowest CRA premia for many, many years. This increases the likelihood that such areas become nodes of isolation and poverty concentration, and there is a large literature that highlights the costs of concentrated poverty (Galster, 2002; Newburger et al., 2011; Chetty et al., 2016).

While the debate about whether to assist those closest to achieving self-sufficiency or those with the most acute needs is not new, it is important and one that policymakers focused on policies trying to promote access to amenities and resources to those who lack such access must recognize. In our reading of the CRA's history, we found no record of policymakers wrestling with this choice. Thus, the patterns arising from the CRA framework design that we observe here appear to have emerged organically rather than purposefully. Policymakers should change this and incorporate their thinking on this issue into future policy designs.

Finally, changes to the process by which the Census is conducted could have significant implications in the context of these issues. The implementation of more frequent updates via the American Community Survey has resulted in a regulatory change such that CRA eligibility will be determined every 5 years instead of every 10. This should, in theory, reduce the longer term effect of banking institutions responding to contemporaneous changes that can shift attention to a subset of CRA-eligible tracts. However, it does not diminish the larger question of whether the goal of the CRA is to incentivize capital flows to all underserved areas and communities or to those underserved areas and communities that are showing the most progress. Thus, this fundamental policy question remains.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jue.2019.103211.

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