Finance and Economics Discussion Series

Federal Reserve Board, Washington, D.C.
ISSN 1936-2854 (Print)
ISSN 2767-3898 (Online)

Does Giving CRA Credit for Loan Purchases Increase Mortgage Credit in Low-to-Moderate Income Communities?

Kenneth P. Brevoort

2022-047

Please cite this paper as:
Brevoort, Kenneth P. (2022). "Does Giving CRA Credit for Loan Purchases Increase Mortgage Credit in Low-to-Moderate Income Communities?," Finance and Economics Discussion Series 2022-047. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2022.047.

Does Giving CRA Credit for Loan Purchases Increase Mortgage Credit in Low-to-Moderate Income Communities?

Kenneth P. Brevoort*
Federal Reserve Board

June 07, 2022

Abstract

Under the Community Reinvestment Act (CRA) banks can fulfill their affirmative obligation to meet local credit needs by lending in low-to-moderate-income (LMI) communities or by purchasing loans made by others. This paper evaluates whether giving CRA credit for purchases has had its intended effect of increasing LMI credit availability by making LMI loans more liquid. Analyses using a regression discontinuity design show that CRA increases loan purchases without affecting LMI originations. Instead, banks purchase loans that are temporarily diverted from the Government Sponsored Enterprises, which provides little benefit to the communities the CRA is meant to help.

Keywords: Community Reinvestment Act (CRA); Mortgage lending; Redlining; Low- and moderate income (LMI)

JEL Classification: G21, G28, R38

*Email: kenneth.p.brevoort@frb.gov. The views expressed in this paper are those of the author and do not necessarily represent those of the Federal Reserve Board or its staff. I would like to thank Bob Avery, Glenn Canner, and Ian Keith for helpful discussions (some going back many years) about the issues covered in this paper. I would also like to thank Lei Ding, Jeff Larrimore, David Silberman, Anna Tranfaglia, Mark Willis, and participants at the Consumer Finance Round Robin for thoughtful feedback about this paper.

1. Introduction

Policy concerns about redlining have been long standing. Believed to have been widely used by mortgage lenders in the past, *redlining* is a practice where lenders limit mortgage credit to creditworthy borrowers in particular neighborhoods, most often those with high concentrations of lower-income or minority residents. Interest in redlining has been renewed by the rediscovery of the Residential Security maps produced by the Home Owners' Loan Corporation in the 1930s. Recent research using these maps has tied historical redlining to an array of adverse present-day outcomes that include continued segregation and inequality (Mitchell and Franco, 2018), reduced economic opportunity (Aaronson et al., 2021), less greenspace (Nardone et al., 2021), higher land-surface temperatures (Wilson, 2020), and worse health outcomes (Nardone et al., 2020; Collin et al., 2021).[1]

Among the most important laws passed to combat redlining is the Community Reinvestment Act (CRA) of 1977. Passage of the CRA was motivated by concerns that deposits collected in lower-income neighborhoods by commercial banks and thrifts (hereafter *banks*) were funding loans in higher-income areas, which was causing capital flight out of distressed communities and contributing to urban decay (Canner and Cleaver, 1980). The CRA reaffirmed banks' affirmative obligation to help meet the credit needs of their entire local communities, including low- and moderate-income (LMI) neighborhoods, and tasked federal banking agencies with encouraging banks, during regular examinations, to meet their CRA obligations in a manner consistent with safe and sound banking practice. The agencies were also instructed to take CRA ratings into account when evaluating applications for new branch locations or bank mergers.

For the past 25 years, a central component of CRA exams for large banks has been a retail *lending test* that assesses each bank's record of lending to LMI borrowers and in LMI neighborhoods (collectively, *LMI communities*). Instead of establishing quotas on lending

[1] While recent research on the effects of redlining has focused on the HOLC maps, which are the only redlining maps still in existence, the accumulated evidence clearly shows that the practice of redlining predated these maps and that the maps were not used by HOLC or others in making credit decisions (Hillier, 2003; Fishback et al., Forthcoming).

amounts, the lending test focuses on the share of a bank's retail lending made in LMI communities.

Since its inception, the lending test has allowed banks to meet the credit needs of their local communities either by originating loans themselves or by purchasing loans originated by others. Loan purchases were included because it was believed this would increase the liquidity of LMI loans and, thus, make credit more widely available in LMI communities.[2] This approach, however, has not been universally supported. Opponents of giving originations and purchases equal treatment, which have generally included community groups, have argued that equal treatment may incentivize banks to purchase loans solely to improve their CRA rating and that this might cause banks to sell the same loans repeatedly among themselves, a practice called *churning* (Community Reinvestment Act Regulations, 2001; Community Reinvestment Act Regulations, 2004). Additionally, some have argued that because originating loans requires more effort on the part of the bank, originations should count more towards meeting a bank's CRA obligations.

To date, there has been no evaluation of the extent to which giving banks equal credit on their CRA exams for originating and purchasing LMI loans has affected the liquidity of these loans and, if so, whether it has made credit more widely available. This paper seeks to fill this gap by evaluating loan origination and purchasing behavior in the U.S. mortgage market since the Great Recession. I focus on mortgages because of the central role that mortgage lending plays in CRA examinations, the more active secondary markets for mortgages (which makes large-scale purchasing more feasible than it is for small-business or other consumer lending), and the importance of homeownership in wealth building among lower-income households.

I examine public mortgage data collected pursuant to the Home Mortgage Disclosure Act (HMDA) from years since 2013. Using the CRA's bright-line definitions of LMI borrowers

[2]This justification for allowing loan purchases comes from the Advanced Notice of Proposed Rulemaking published ahead of the 2004 CRA rule changes, which considered, but ultimately decided against, altering uniform treatment of originations and purchases (Community Reinvestment Act Regulations, 2001). No explanation for the equal treatment was provided in the Federal Register notices that preceded the 1995 CRA rules that established the lending test.

and LMI neighborhoods, I identify four different thresholds where the CRA's treatment of a borrower or a neighborhood changes abruptly and use regression discontinuity at these thresholds to identify any causal effects of the CRA on lending activity.

The results of the analysis show that banks operating within their CRA assessment areas significantly increase their loan purchases at the LMI thresholds, suggesting that the CRA enhances the liquidity of LMI loans. However, this additional liquidity appears to have no effect on lending in LMI communities. There is no indication of a material increase in originations at the LMI thresholds. Moreover, lenders do not appear to retain fewer originations on their portfolio, which might have been used to to expand lending away from the LMI threshold.

Instead, the analysis suggests that the CRA-induced loan purchases by banks within their assessment areas have been fueled by loans that otherwise would have been sold to Government Sponsored Enterprises (GSEs). The share of originations sold directly to the GSEs drop significantly at LMI thresholds, with even larger declines observed for resold loan purchases. Significant discontinuities in the sale of originations and purchases to the GSEs are observed for multiple lender types, including banks outside of their assessment areas and independent mortgage banks. The magnitude of the decline in GSE loans sales appears large enough to account for all of the CRA-induced loan purchases at the LMI thresholds.

Despite the decline in loan sales to the GSEs, supplementary analysis of conventional loans using the National Mortgage Database suggests that the CRA has no effect on the share of loans ultimately acquired by the GSEs. Instead, the CRA only appears to affect the speed with which the GSEs acquire loans. The share of GSE acquisitions that are made within 60 days of origination drops significantly at the LMI thresholds. In contrast, the CRA appears to have little or no effect on the share of loans acquired within 120 days, implying that CRA-induced loan purchases only temporary diverts loans from the GSEs by a few months at most.

Together, these results suggest that the CRA's equal treatment of originations and purchases increase the liquidity of LMI loans, but otherwise confers little benefit on LMI com-

munities. In contrast, providing CRA credit for both originations and purchases increases banks' LMI shares substantially, with the largest gains being realized by banks whose originations-only LMI shares are lowest.

The results of this analysis have clear implications for our understanding how the CRA is affecting mortgage availability among LMI households. It also contributes our understanding of the effectiveness of public policies aimed at improving homeownership opportunities for lower-income households by increasing secondary market support for mortgage lending (Ambrose and Thibodeau, 2004; Bostic and Gabriel, 2006; An and Bostic, 2008; Bhutta, 2012)

The rest of the paper documents the analysis and the evidence used to reach these conclusions. The next section begins by providing background information on the CRA and the state of existing research. Sections 3 and 4 discuss the empirical approach and the data used in the analysis. Results are documented in Section 5 with robustness checks in Section 6. Section 7 concludes.

2. Background

The CRA is best understood in context as the fourth in a sequence of laws passed by Congress aimed at eliminating discrimination in mortgage and consumer credit markets following the passage of the Civil Rights Act in 1964. The first of these laws, the Fair Housing Act (FHAct) of 1968, banned discrimination in all aspects of real-estate-related transactions, including mortgage lending. This prohibited neighborhood-based discrimination such a redlining. It was followed by the Equal Credit Opportunity Act (ECOA) in 1974 which outlawed discrimination in all credit transactions, not just those involving real estate. While ECOA originally only banned discrimination on the basis of sex or marital status, its protections were expanded in 1976 to cover other bases. The third law, the Home Mortgage Disclosure Act (HMDA), was passed in 1975 to provide greater transparency around mortgage lending by mandating the collection and reporting of mortgage data to help policymakers and the

public determine whether lenders were serving the housing needs of their local communities. Two years later, Congress passed the CRA.

The CRA was passed to address persistent concerns about redlining (Barr, 2005). In particular, some expressed concerns that banks were collecting deposits in lower-income neighborhoods that were being used to fund loans in higher-income areas, which was resulting in capital flight out of distressed areas and contributing to urban decay (Canner and Cleaver, 1980). Unlike the FHAct, which told lenders what they could not do (discriminate based on race or other protected class status), the CRA established that banks have an affirmative obligation to meet the credit needs of their entire local communities including low- and moderate-income (LMI) neighborhoods. It was no longer enough that banks treat applicants fairly, they now had to be proactive about offering services and soliciting business from both lower- and higher-income areas. Federal banking agencies were tasked with encouraging banks to meet these obligations, consistent with safe and sound business practices, as part of regular bank examinations.

In 1993, President Clinton requested that federal banking agencies reform the CRA's implementing regulations to make them more objective and performance-based, while reducing banks' compliance costs. He also asked the agencies to develop a specialized staff of CRA bank examiners and to more effectively sanction lenders who consistently failed to meet their CRA obligations. Revisions to the CRA Regulations were finalized in 1995 (Community Reinvestment Act Regulations, 1993).

Among the changes made was the introduction of CRA's *lending test*. Applied only to large banking institutions with assets of at least $250 million, the lending test evaluates the share of a bank's mortgage lending made to low- or moderate-income borrowers or neighborhoods (*LMI-lending share*), compared to the LMI-lending shares of other financial institutions.[3] The regulation focuses on LMI lending shares because drafters of the CRA wanted to avoid establishing quotas for the amount of credit banks had to make available. The lending test is conducted in bank-specific *assessment areas*. Each bank designates its own assess-

[3]The lending test also applies to other types of retail credit including small business, small farm, and consumer loans. It also evaluates a bank's record of community development lending.

ment areas around its bank branch network that represents the local communities within which its lending is evaluated.

Since the introduction of the lending test, banks have been able to include both loans they originate and those they purchase from other lenders as part of their local lending activity. In 2001, the federal banking agencies solicited public comment on proposed changes to the CRA's regulations that included distinguishing between originations and purchases. Consumer groups responded favorably to the proposed change, arguing that originations should receive more weight because they require more effort and because banks could purchase loans solely to improve their CRA ratings. However, industry commentators were against the change, arguing that the uniform treatment improved the liquidity of LMI loans and consequently made credit more available (Community Reinvestment Act Regulations, 2004). Ultimately, the federal banking agencies retained the equal treatment of originations and purchases.

Since its inception, the CRA has been a controversial policy that has caused a lot of debate (particularly in law review articles around the 1995 revisions),[4] but relatively little empirical research on its effects. The papers that have evaluated the CRA's effects on mortgage lending (which include Ross and Tootell (2004), Avery et al. (2005), Bhutta (2011), Butcher and Muñoz (2017), Lee and Bostic (2020), and Ding and Nakamura (2021)) have generally found small and inconsistent effects of the CRA on mortgage lending.

Since the Great Recession, a second strand of literature has explored the CRA's role in triggering the mid-2000s housing bubble and causing the collapse of the subprime mortgage market in 2007. Despite the previous literature having found only modest effects of CRA, these papers, starting with early work by Pinto (2010) and Wallison (2011), argue that the CRA (along with the GSE goals) caused lenders to lower their lending standards to make mortgages available to lower-income borrowers who were unlikely to repay. On balance, most studies that look at these claims find that the CRA's role in the subprime collapse was minimal (Bhutta and Canner, 2009; Avery and Brevoort, 2015; Bhutta and Ringo, 2015; Ghent

[4]See for example, Fishbein (1992), Macey and Miller (1993), Swire (1993), Bierman et al. (1994), Barr (2005).

et al., 2015). Nevertheless, a few studies have continued to claim that the CRA caused the subprime crisis, largely based on incorrect information about the CRA.[5]

Across both strands of the literature, most studies that have examined the CRA's effects on mortgage lending have largely ignored the role of loan purchases (except for Avery and Brevoort (2015)). Most also limit their analysis to the effects of CRA on lending in LMI tracts without examining lending to LMI borrowers and without differentiating the behavior of banks within and outside of their assessment areas.

3. Empirical Approach

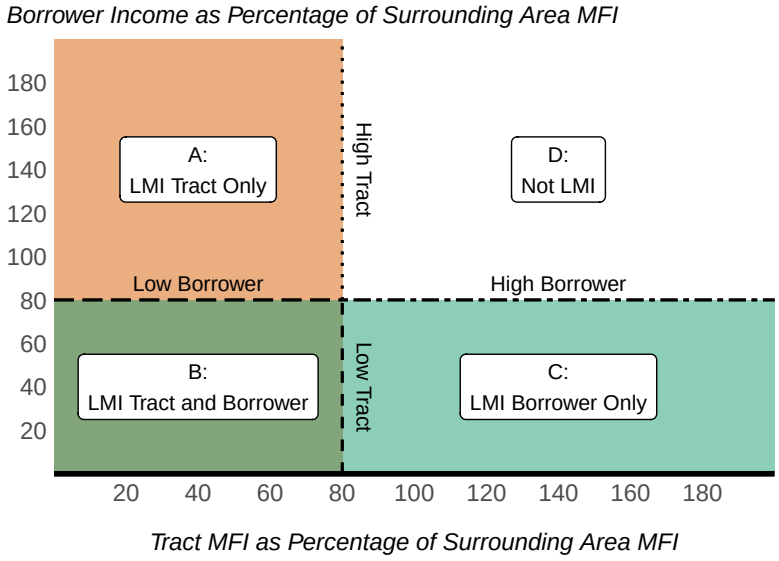
For purposes of the lending test, the CRA uses bright-line definitions of *LMI borrowers* and *LMI neighborhoods*. Both terms are defined similarly. LMI borrowers have incomes that are less than 80% of the median family income (MFI) of the surrounding area. LMI neighborhoods are census tracts whose MFI is less than 80% of the MFI of the surrounding area. Both definitions define *surrounding area* the same way. In urban areas, the *surrounding area* is the Metropolitan Statistical Area or, in large urban areas, Metropolitan Division. In rural areas, it is the non-metropolitan portion of the state where the borrower or tract is located.

Figure 1 depicts how loans are designated using the CRA's definitions of LMI neighborhoods and LMI borrowers. Any loan can be represented on the figure as a single point based on the borrowers' income as a percentage of the surrounding area MFI (the y-axis) and the its census tract's MFI as a percentage of the surrounding area MFI (the x-axis). Loans in the three shaded quadrants meet the definition of one (areas A and C) or both (area B) of CRA's LMI definitions and thus help banks on the lending test. Loans in quadrant D, which ac-

[5] See, for example, Agarwal et al. (2012) whose misunderstanding about the CRA are documented by Reid et al. (2013).

Figure 1: Thresholds Used to Designate LMI Borrowers or LMI Neighborhoods

Figure illustrates the delineations of LMI neighborhoods and LMI borrowers used by the CRA and the resulting thresholds where CRA's treatment of loans changes. LMI neighborhoods are those where the median family income (MFI) of the tract is less than 80 percent of the MFI of the surrounding area. LMI borrowers are those whose incomes are less than 80 percent of the MFI of the surrounding area.



count for two-thirds of HMDA originations from 2010 to 2020, are non-LMI loans under both definitions.[6]

The lines that delineate LMI neighborhoods and LMI borrowers each contain two segments. The upper portion of the line that defines LMI neighborhoods, the *high tract* threshold, separates areas A and D in Figure 1. Along this threshold loans to middle- or upper-income borrowers go from being in LMI neighborhoods to being in higher-income neighborhoods. Along the lower segment of this line, the *low tract* threshold, loans to LMI borrowers go from also being in LMI tracts, in which case they help the lender meet both its obligations to LMI borrowers and LMI tracts, to no longer being in LMI tracts. I distinguish the high and low tract thresholds because the marginal value to lenders should differ across the two segments which might have different effects on lending activities. The line delineating LMI borrowers is similarly subdivided into *high* and *low borrower* thresholds.

Because treatment at these thresholds change abruptly, the causal effects of CRA can be estimated using a regression discontinuity design (RDD). This study uses RDD to estimate local average treatment effects (LATEs) around the four thresholds shown in Figure 1 (Imbens and Angrist, 1994).

In modelling lending at the LMI neighborhood thresholds (the low- and high-tract thresholds), I aggregate annual lending activity to the census tract level and use that as the unit of observation. I define the *tract relative income* of each observation as the difference between a tract's MFI and the MFI of the surrounding area. Similarly, when modelling lending activity at the LMI borrower thresholds, I aggregate all loans to borrowers with the same income (which HMDA rounds to the nearest $1,000) within each MSA/MD and use that as the unit of observation. For each of these observations, I define the *borrower relative income* as the difference between the borrower's income and the MFI of the surrounding area.

Several different lending outcomes are evaluated around each LMI threshold, including loan purchases as a share of lending activity, loan originations, and the share of loans sold to

[6]This calculation uses the same loan definition used throughout this paper. It is based on first-lien mortgages originated for home purchase or refinance backed by single-family homes located in urban areas. Only 6 percent of loans over this period were to LMI borrowers in LMI tracts.

different purchasers. Using i to index each observation and t to index the observation's year, I generically refer to each of these dependent variables as y_{it}^k where k indicates which of the four thresholds are being examined. I specify two different models of lending outcomes.

First, using r_{it}^k to represent the tract or borrower relative income, I specify an *unadjusted model* as

$$y_{it}^k = f^k(r_{it}^k) + \epsilon_{it}^k \tag{1}$$

where

$$f^k(x) \equiv \begin{cases} f_+^k(x) & x \geq 0 \\ f_-^k(x) & x < 0. \end{cases} \tag{2}$$

I estimate this model using local-linear polynomials for $f^k(x)$ where the bandwidth is selected using the method suggested by Imbens and Kalyanaraman (2012). The estimation is restricted to observations where the value of the running variable, r_{it}^k, is between -$20,000 and $20,000. The estimation results from this model are used to calculate the threshold effect as $\tau \equiv f_-^k(0) - f_+^k(0)$. Positive values of this estimated threshold effect indicate that lending outcomes were higher on the LMI side of the threshold, suggesting that CRA increased those outcomes.

Because this analysis combines data from different time periods and across a wide array of Metropolitan Statistical Areas or Metropolitan Divisions ("MSA/MDs"), I also estimate an *adjusted model*. Using the same notation as above, I specify this model as

$$y_{it}^k = \alpha_m + \gamma_t + f^k(r_{it}^k) + \epsilon_{it}^k \tag{3}$$

where α_m and γ_t are MSA/MD-specific and yearly fixed effects, respectively. I estimate this model using the method developed by Calonico et al. (2019) with a bias-correction and implemented in Calonico et al. (2015). The threshold effect from this estimated model, τ_M, is

defined similarly to the unadjusted model and calculated with robust ("hc3") standard errors that are clustered at the MSA/MD level.

In discussing the results of the analyses, I focus on the threshold effects produced from the estimation of the adjusted model. I primarily use the estimation results from the unadjusted model to graphically display $\widehat{f^k}(x)$ and as a sanity check on the results of the adjusted model.

3.1. Overlap with the GSE Affordable Housing Goals

In order to identify policy effects around a sharp threshold, nothing else can change discontinuously at that threshold. The Affordable Housing Goals established for Fannie Mae and Freddie Mae (*GSE goals*) present a challenge in this respect.

Since the passage of the Federal Housing Enterprises Safety and Soundness Act of 1992, Fannie Mae and Freddie Mac have been required to devote a minimum percentage of their purchases to loans made to historically underserved groups. The GSE goals establish targets for the share of single-family home-purchase loans going to low-income borrowers or backed by properties in low-income areas. They also include a target for the share of refinance-loan purchases going to low-income borrowers.

Revisions to the GSE goals enacted by the Housing and Economic Recovery Act of 2008, which went into effect in 2010, changed the definitions of *low-income borrowers* and *low-income areas* in ways that closely resemble the CRA's definitions of LMI borrowers and LMI neighborhoods. The remainder of this section discusses the overlap between the GSE goal designations and the CRA's LMI borrower and neighborhood thresholds.

3.1.1. LMI Neighborhoods and Low-Income Areas

For the purposes of the GSE goals, a *low-income area* is defined as a census tract whose MFI is less than 80% of the MFI of the surrounding area. Like the CRA, tract and surrounding area MFIs are taken from the American Community Survey.

There are, however, two important differences in how the thresholds are calculated between the CRA and the GSE goals. First, the two programs use different *surrounding areas* in large metropolitan areas comprised of multiple metropolitan divisions. An example of such an area is the Dallas-Fort Worth-Arlington TX MSA, which has two metropolitan divisions, one covering Dallas and the other Fort Worth. In designating tracts as low-income areas in this MSA, the GSE goals use the MFI of the entire MSA, so that Dallas and Fort Worth share the same threshold for a tract to be considered low-income. In contrast, the CRA uses the MFI for each metropolitan division, which results in Dallas and Fort Worth having different thresholds used to define LMI neighborhoods. In smaller MSAs that do not have metropolitan divisions, the two programs use the same surrounding area definition.

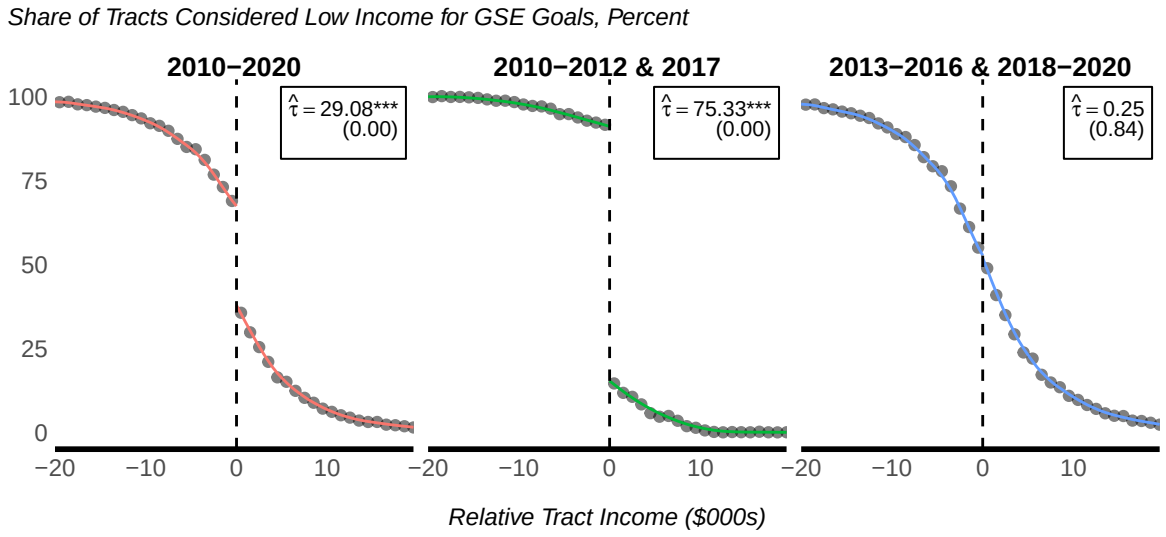
Second, while the CRA and GSE goals both use MFIs from the 5-year ACS, the two programs often use information from different survey years. Since 2012, LMI designations in the CRA have been based on MFIs that are updated every 5 years.[7] LMI designations for 2012-2016 used MFIs from the 2006-2010 ACS and designations for 2017-2021 used the 2011-2015 ACS. Before 2012, LMI neighborhood designations used MFIs from the Decennial Census and were updated every 10 years. In contrast, MFIs for the GSE goals are updated annually to reflect the latest ACS data. This means that in designating LMI neighborhoods and low-income tracts for 2012, both programs relied on MFIs from the 2006-2010 ACS making the designations almost exact. But for the next four years, 2013-2016, the programs used ACS data from different survey years.

Because of the close relationship between the definitions used, there is a discontinuous increase in the likelihood that a tract would be designated as a low-income area for GSE goal purposes at the CRA's LMI threshold. This can be seen in the left-panel of Figure 2. Over the 2010-2020 period, the probability of a census tract being low-income under the GSE goals jumps 29 percentage points at the CRA LMI threshold. This discontinuity is entirely

[7] While the source of MFI data is only updated every 5 years, the FFIEC updates LMI neighborhood status annually to reflect changes in MSA/MD definitions. If the definition of an MSA/MD changes within one of these 5-year stretches, the MFI of the surrounding area will be updated to reflect the new MSA/MD boundaries but will remain based on information from the same ACS. Ding and Nakamura (2021) exploit such a change to metropolitan divisions in the Philadelphia MSA to gauge CRA's effects.

Figure 2: The Extent of Overlap Between the Definitions of CRA's LMI Neighborhoods and the GSE Goals' Low-Income Tracts Varies By Year

This figure shows the likelihood that a census tract is considered to be low-income for GSE goal purposes using data from 3 different time periods: (a) the entire 2010-2020 period; (b) 2010-2012 and 2017, which are the years where the CRA and GSE goals used identical data sources about median family incomes (MFIs); and (c) 2013-2016 and 2018-2020, when the CRA and GSE goals used MFI data from different years of American Community Survey. Points show the share of observations in evenly spaced relative tract income buckets that were classified as low-income tracts for GSE goal purposes. The solid lines show local-linear approximations of the relationship using triangular kernals and the optimal bandwidth suggested by Imbens and Kalyanaraman (2012). The linear approximations are estimated separately for the negative and non-negative relative tract income levels. The estimated coefficient $\hat{\tau}$ is the threshold effect with robust standard error. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.



caused by years where both programs established their respective thresholds based on the same survey data. These years include (a) 2010-2011, when both programs used the 2000 Decennial Census; 2012 when they both used the 2006-2010 American Community Survey; and (c) 2017 when they both used the 2011-2015 ACS. During these four years, as shown in the middle panel, the discontinuity of being considered a low-income area increases by 75 percentage points at the LMI threshold. However, in years where the two programs used different ACS surveys, there is little evidence of a statistically significant discontinuity in treatment under the GSE goals at CRA's LMI threshold, as shown in the right panel of Figure 2. The estimated threshold effect is small at 0.3 percentage points and statistically insignificant.

Because of the substantial evidence of a discontinuity in treatment of tracts under the GSE goals at the CRA's LMI threshold in 2010-2012 and 2017, I limit the analysis to years where the CRA and GSE goals relied on different years of ACS data (2013-2016 and 2018-2020). As an additional robustness check, I also repeat the analysis using data from 2004-2009, a period when the GSE goals defined low-income tracts as those where the tract's MFI was less than 90% of the the MFI of the surrounding area and thus had little overlap with CRA's LMI neighborhood definition.

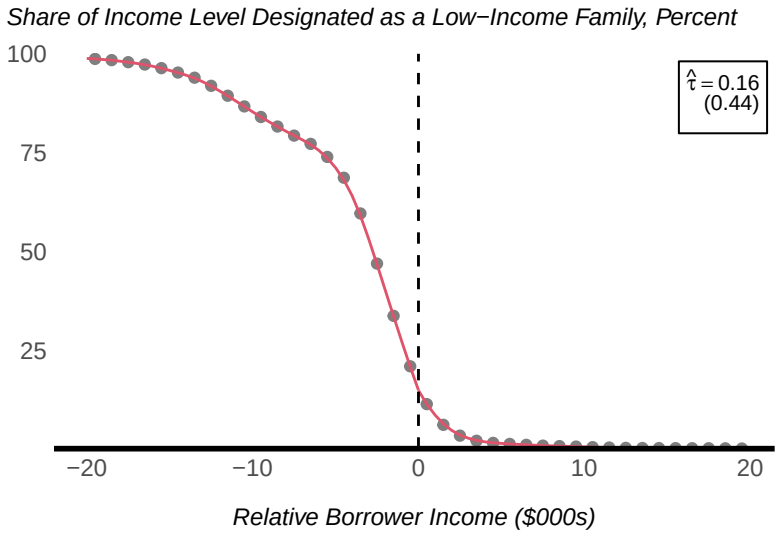
3.1.2. LMI Borrowers and Low-Income Borrowers

Both the CRA and the GSE goals define their concepts of an LMI borrower and a low-income family, respectively, as a borrower whose income is less than 80% of the MFI of the surrounding area. As with the census-tract-based designations, the definitions differ in how they define the surrounding area in large metropolitan areas with metropolitan divisions. However, both programs update these definitions annually.

Despite the similar definitions, and the fact that both programs rely on the same borrower incomes, there is little overlap between the thresholds because the programs use different sources of MFIs for the surrounding areas. The GSE goals use MFIs from the most-recently published 5-year American Community Survey. So for 2012, GSE goal thresholds

Figure 3: The Likelihood of being Considered a Low-Income Family for Purposes of the GSE Goals is Not Discontinuous at CRA's LMI Borrower Threshold

This figure shows the likelihood that a borrower income level meets the definition of a low-income family under the GSE affordable housing goals using data from 2010-2020. Points show the share of each relative borrower income level that met the GSE definition at evenly spaced $1,000 buckets. The solid line shows local-linear polynomials estimated separately for the negative and non-negative relative income levels using a triangular kernel and the optimal bandwidth suggested by Imbens and Kalyanaraman (2012). The estimated coefficient $\hat{\tau}$ is the threshold effect with robust standard error. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.



were calculated based on data for the 2006-2010 ACS and for 2013 they used 2007-2011 ACS MFIs. In contrast, the CRA uses forecasts of area MFIs produced by the FFIEC (or HUD prior to 2012). FFIEC-forecasted MFIs skew notably higher than the ACS MFIs used in the GSE goals, suggesting little relationship between the borrower-based thresholds used by the two programs.

Consistent with their use of different data sources, there is little indication of a discontinuous jump in the likelihood that a borrower is a low-income family for GSE goal purposes at CRA's LMI borrower threshold (Figure 3). Using data from 2010-2020, only about 15 percent of borrowers at the borrower LMI threshold meet the GSE definition of a low-income family. Additionally, the effect at the CRA's LMI-borrower threshold is small at 0.16 percentage points which is not statistically significant.

While there is no evidence of a discontinuity in the treatment of borrowers at the CRA LMI borrower threshold during the 2010-2020 period, analyses of the low- and high-borrower thresholds are conducted using only data from 2013-2016 and 2018-2020 to match the approach being used for the tract-based thresholds.

4. Data

The primary source of data used in this paper are collected pursuant to the Home Mortgage Disclosure Act (HMDA). The HMDA data provide loan-level information about mortgage originations and purchases made each year. HMDA reporting applies to most depository and nondepository institutions with offices in Metropolitan Statistical Areas. For each origination or purchase, the data include the lender who originated or purchased the loan, its purpose (e.g., home purchase, refinance), lien status, the type of property backing the loan, the borrower's income, the type of institution to whom the loan was sold (e.g., Fannie Mae, commercial bank), and the census tract of the property being financed. The HMDA data are an ideal source for studying the effects of the CRA because they are used in conducting the CRA's lending test.

The institution type of each HMDA reporter is assigned using the HMDA Lender File, also referred to as the "Avery file" (Avery et al., 2007). Banks are matched to information about their CRA assessment areas published annually by the FFIEC. For banks that declare assessment areas, a lender type is assigned based on where the loan was made. Loan originates or purchases by a bank that are within its assessment area are classified as having been made by an "inside assessment area" bank; otherwise, they were made by an "outside assessment area" bank. Loan originations or purchases by banks without assessment areas, which predominantly are small lenders who are not covered by the lending test, are classified as "other banks." Non-bank institution types include independent mortgage banks and credit unions.

The proximity of loans to their LMI thresholds was determined using the threshold values published annually by the FFIEC. A loan's proximity to the LMI neighborhood threshold is measured using the *tract relative income* which is the difference between the corresponding LMI neighborhood threshold and median family income of the loan's census tract. A loan's proximity to the LMI borrower threshold is given by the *borrower relative income* which is defined similarly as the difference between the LMI borrower threshold and the borrower's income.

From these data, I generate four (non-mutually-exclusive) datasets. Each dataset contains all of the loans within $20,000 of one of the four LMI thresholds (shown earlier in Figure 1). For example, the high-tract dataset includes all loans where the tract MFI is within $20,000 of the threshold (a tract relative income between -$20,000 and $20,000) and the borrower's income exceeded the LMI borrower threshold (the borrower relative income is non-negative).

The assembled data include information about both loan originations and purchases. The sample is restricted to first-lien mortgages for home-purchase or refinancing that are backed by single-family homes in Metropolitan Statistical Areas, where HMDA reporting is more comprehensive. Data in the high- and low-tract datasets are aggregated annually to the census tract level. Data in the high- and low-borrower datasets are aggregated annually for each MSA/MD to the borrower income level. Because borrower incomes in HMDA are reported to the nearest $1,000, all loans with borrower incomes of $51,000 in the Columbus, Ohio MSA, for example, are aggregated into a single observation in the high- and low-borrower datasets that records the number of loans and averages of other lending metrics. Summary statistics on each of the four datasets are provided in Table 1.

Supplementary analysis of conventional loan sales to Fannie Mae or Freddie Mac, conducted in Section 5.4, relies on a different dataset, the National Mortgage Database (NMDB). Jointly produced by the Federal Housing Finance Agency and the Consumer Financial Protection Bureau, the NMDB is a nationally representative, 1-in-20 random sample of mortgage loans that were drawn from de-identified credit records and merged with administra-

Table 1: Summary Statistics

Table shows summary statistics for the four datasets used to examine changes in lending activity at the high-tract, low-tract, high-borrower, and low-borrower LMI thresholds. *Loans* and *Purchases* show the average number of loan originations and purchases per observation. *Purchase Share (%)* = *Purchases* / (*Purchases* + *Loans*). *Retained (%)* is the share of originations that remained unsold at the end of the year the loan was originated. *Direct* and *Indirect GSE Sales* are the share of loan originations and purchases, respectively, that were sold to the GSEs conditional on the loan having been sold by the end of the calendar year. The *Lender Type* and *Loan Type* Distributions* are the share of *Loans* plus *Purchases* accounted for by each lender or loan type. Other variables are as defined in the text. Sample means for variables expressed as percentages are weighted by their denominators.

	Thresholds			
	Tract		Borrower	
	High	Low	High	Low
Observations	223,523	220,125	111,943	107,462
Sample Means				
Loans	56.5	31.4	111.7	28.2
Purchases	7.8	5.0	4.4	4.6
Purchase Share (%)	12.2	13.7	3.8	14.0
Retained (%)	20.4	18.8	16.9	18.3
Direct GSE Sales (%)	65.9	60.8	63.0	60.9
Indirect GSE Sales (%)	93.7	91.9	89.8	89.8
Tract Relative Income ($000s)	1.7	1.8	NA	NA
Borrower Relative Income ($000s)	NA	NA	0.0	-0.1
Lender Type Distribution (Percent)				
Inside AA	27.6	28.1	23.5	27.2
Outside AA	8.9	7.6	7.8	7.5
Credit Union	8.0	7.5	8.2	7.3
Ind. Mort. Bank	48.3	49.9	53.2	52.3
Other	7.2	6.9	7.3	5.6
Loan Type Distribution (Percent)				
Conventional	76.3	64.1	70.0	65.3
Nonconventional	23.7	35.9	30.0	34.7

tive data from government agencies and private data providers.[8] The resulting dataset provides detailed information about each loan, including its origination date, loan type, borrower income, and the census tract of the property backing the loan. The NMDB also reports whether each loans was acquired by Fannie Mae or Freddie Mac and, if so, the date of acquisition. The NMDB data do not contain information about the lenders who originated the loans, so they cannot be used to examine lending by banks within their assessment areas, for example. Nor do they indicate which loans were in Ginnie-Mae-guaranteed securitizations. However, they provide a more complete depiction of loan acquisitions by Fannie Mae and Freddie Mac than the direct- or indirect-to-GSE sales data available in HMDA.

5. Analysis

5.1. Does the CRA Increase the Purchase of Mortgages?

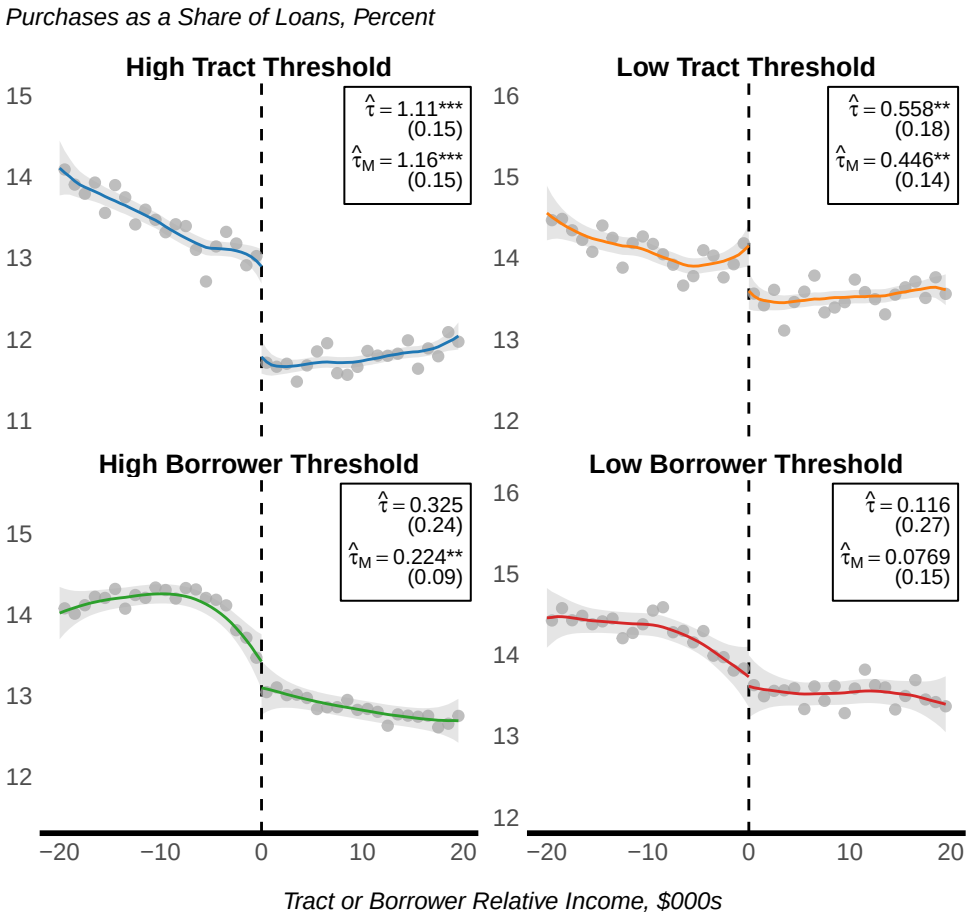
The first step in assessing whether the CRA's equal treatment of loan originations and purchases increased liquidity for LMI loans is determining whether the CRA increased loan purchases. For each observation, I calculate loan purchases as a percentage of CRA lending activity (defined as originations plus purchases) for each of the four LMI thresholds and use this measure as the dependent variable, y_{it}^k, in estimations of the adjusted and unadjusted models (equations (1) and (3), respectively).

Results from these estimations confirm that the CRA increases loan purchases at the LMI thresholds (Figure 4). Loan purchases jump as a share of lending activity by statistically significant amounts at both tract-based thresholds and at the high-borrower threshold, with larger effects at the tract thresholds than at the borrower thresholds. The largest discontinuity occurs at the high-tract threshold, where lending jumps by 1.2 percentage points, an increase in purchase activity of 9.5%. Tract threshold effects are also larger among high-income borrowers, and the borrower threshold effects are larger among those in high-income

[8] For more information about how the NMDB is constructed and the sources of data that it contains, see Avery et al. (2021).

Figure 4: Loan Purchases Increase Discontinuously at the LMI Thresholds

Figure shows the estimation results of the adjusted and unadjusted models using purchases as a share of CRA lending activity as the dependent variable. Each panel shows one of the four LMI thresholds. Points show purchases as a share of loans at evenly spaced relative income levels. The solid lines show a local linear approximation of the dependent variable. The local linear approximation is estimated separately for the negative and non-negative values of the applicable relative income levels. The approximations use a triangular kernel and the optimal bandwidth for the unadjusted model. Estimated parameters $\hat{\tau}$ shows the threshold effect fom the unadjusted model. Parameter $\hat{\tau_M}$ shows the threhold effect from the adjusted model with robust standard errors clustered at the MSA/MD level. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.



tracts. This suggests that when making marginal purchases of loans in LMI tracts, banks disproportionately buy loans to middle- or upper-income borrowers. And when making marginal purchases of loans to LMI borrowers, bank disproportionately acquire loans in middle- or upper-income tracts.

Since the CRA does not distinguish between conventional and nonconventional mortgages, one might expect effects at the LMI thresholds for both loan types. To test this, I estimated separate versions of the adjusted models, with purchases as a share of CRA lending activity as the dependent variable, using only conventional or unconventional loans respectively (Table 2). The results confirm that lenders increase their purchases of both loan types in response the CRA. The threshold effects are statistically significant at the 0.1 percent level for both conventional and nonconventional loans at the high-tract threshold, with statistically significant increases at the 5% level for conventional loans at the high-borrower threshold and at the low-tract threshold for nonconventional loans.

Because the lending test only applies to large banks within their assessment areas, threshold effects should only be observed for those banks. Using the same dependent variable used elsewhere in this section, I estimate separate versions of the adjusted and unadjusted models for each lender type (also shown in Table 2). Results from these models confirm that that the increase in purchasing activity is only observed for banks within their assessment areas. The threshold effects estimated for these banks (*Inside AA*) is positive and statistically significant at the 1% level for all but the low-borrower threshold. Among the other lender types, which include banks outside of their assessment areas (*Outside AA*) and banks not covered by the CRA (*Other Banks*), there is no evidence of a statistically significant jump in purchases at the LMI thresholds.

The smaller jumps at the borrower thresholds could be explained in a number of ways. For example, banks may have an easier time originating a sufficient number of loans to LMI borrowers without supplementing those numbers with additional purchases. But it is notable that, in addition to the jumps at the borrower thresholds, there is also an apparent inflection in the rate of loan purchases that starts at the low- and high-borrower thresholds.

Table 2: Threshold Effects for Loan Purchases

Table shows the estimation results from the adjusted model using purchases as a share of CRA lending activity (originations plus purchases) as the dependent variable. Each column shows estimated threshold effects one of the four LMI thresholds. Each parameter in the table displays the threshold effect estimated using the full sample ('All') or a sample limited to each loan or lender type. All estimations are weighted by the denominator of the dependent variable (CRA lending activity). Robust standard errors are clustered at the MSA/MD level and are shown in parentheses. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels, respectively.

	Thresholds			
	Tract		Borrower	
	High	Low	High	Low
All	1.164***	0.446**	0.224**	0.077
	(0.15)	(0.14)	(0.09)	(0.15)
Loan Type				
Conventional	1.311***	0.243	0.249*	0.107
	(0.16)	(0.16)	(0.10)	(0.19)
Nonconventional	0.891***	0.553*	0.141	0.023
	(0.22)	(0.22)	(0.17)	(0.22)
Lender Type				
Inside AA	2.719***	1.528***	0.710**	0.321
	(0.53)	(0.44)	(0.22)	(0.44)
Outside AA	0.487	-1.190*	-0.545	-0.192
	(0.51)	(0.59)	(0.34)	(0.53)
Other Bank	-0.384*	-0.224	-0.068	0.218
	(0.18)	(0.21)	(0.11)	(0.19)
Credit Union	0.014	0.062	-0.163*	0.020
	(0.11)	(0.14)	(0.07)	(0.13)
Ind. Mortgage Bank	0.121	-0.054	0.130	0.210
	(0.20)	(0.21)	(0.13)	(0.33)

By itself, there is no reason that I am aware of why the CRA should have increased loan purchases gradually just below the LMI threshold. And by itself, RD designs have poor external validity so they cannot reliably detect policy responses away from a treatment threshold, so these increases in purchases below the high- and low-borrower thresholds could reflect factors other than the CRA.

However, when the estimations are conducted by lender type (as shown for the high borrower threshold in Figure 5), only banks operating within their assessment areas exhibit an inflection point in loan purchases at the threshold. Results from estimations at the low borrower threshold (not shown) are similar, though more muted. This comparison of purchases above and below the LMI thresholds across lenders, which is essentially a difference-in-differences result, suggests that the increase in purchases of loans to LMI borrowers away from the LMI threshold is a response to the CRA. Section 6.2 explores the possibility that this and other results at the LMI borrower thresholds may result from uncertainty about the thresholds.

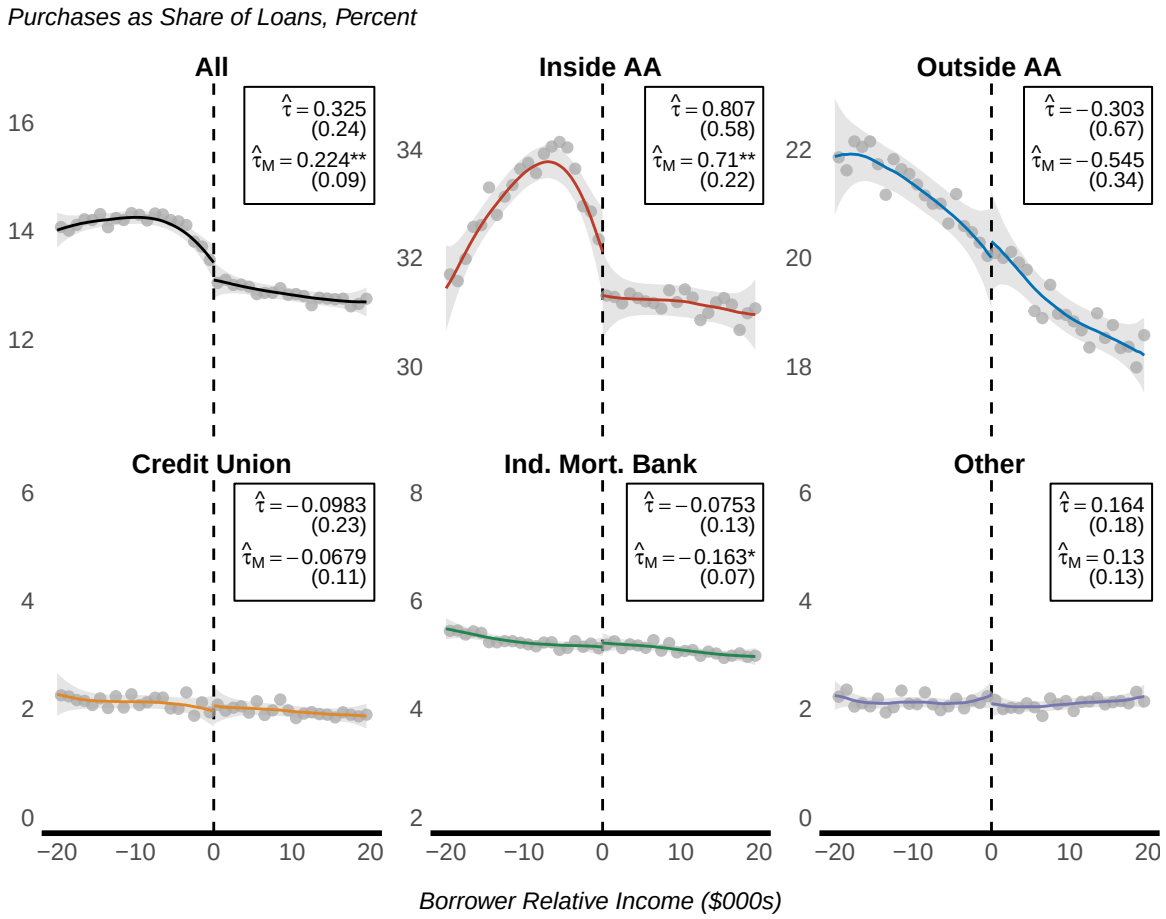
5.2. Does the CRA Increase Loan Originations?

The results of the previous section show that banks within their assessment areas significantly increase LMI loan purchases below CRA thresholds. The increase in purchases reflects an increased demand for CRA-qualifying loans that should increase the liquidity of LMI loans, consistent with the predicted liquidity increase that motivates CRA's equal treatment of originations and purchases. In this section, I examine the evidence on whether the increase in LMI loan liquidity at the thresholds results in more originations.

Enhanced LMI-loan liquidity should benefit all mortgage lenders and not just banks within their assessment areas. In fact, one might expect the benefits to be most pronounced for independent mortgage banks, for example, who generally lack sufficient capital to retain loans on their balance sheets long term and instead rely on selling the loans they originate. Their originations will ultimately be limited by what they can sell on the secondary market,

Figure 5: Purchases Around the High Borrower Threshold

Figure shows the estimation results of the adjusted and unadjusted models using purchases as a share of CRA lending activity as the dependent variable. Each panel shows one of the four LMI thresholds. Points show the average of the dependent variable at evenly spaced relative income levels. Solid lines show a local linear approximation of the relationship between the dependent variable and relative income, using a triangular kernel and the optimal bandwidth from the unadjusted model. The local linear approximations are estimated separately for the negative and non-negative relative-income ranges. Estimated parameter $\hat{\tau}$ is the estimated threshold effect from the unadjusted model. Parameter $\hat{\tau_M}$ is the threshold effect from the adjusted model with robust standard errors clustered at the MSA/MD level. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.



while depository institutions can make and retain profitable loans if willing buyers cannot be found.

If banks expand their lending because of an increase in LMI-loan liquidity, loan originations should increase at the LMI thresholds. Increases by independent mortgage banks or other institutions not covered by the CRA would be particularly compelling evidence of such an effect. The evidence would be less clear for banks within their assessment areas for whom the CRA provides incentives to increase their originations at the LMI thresholds, making it difficult to determine whether such an increase in originations was a direct result of CRA or an indirect effect caused by CRA's effect on LMI-loan liquidity.

I estimate the adjusted and unadjusted models using the number of mortgage originations from each observation as the dependent variable. The estimation results provide no evidence that the average number of originations per observation (tract or MSA-specific relative borrower income level) is affected by the CRA (Figure 6). None of the threshold effects are positive and statistically significant at the 5% level, despite statistically significant increases in loan purchase at three of the four thresholds (shown earlier in Figure 4). The estimated effects from the adjusted model at the borrower thresholds are both significant at the 5% level; however, neither jump is apparent in the unadjusted model and there is little reason why a decrease should have occurred. Also notable about the borrower thresholds is that neither exhibits the same inflection point at the CRA threshold observed for loan purchases.

Similar results are observed for each lender type (Table 3). Consistent with the overall lending patterns, there is little evidence that any lender type increases its originations at the LMI thresholds, despite an apparent increase in the liquidity of these loans. Along the borrower-based thresholds, some estimated threshold effects are negative and statistically significant at the 5% level, though the results are inconsistent within lender types and never statistically significant at the 1% level. The lack of an effect on origination activity at the high tract threshold is particularly notable given that is the threshold with the largest increase in purchase activity.

Figure 6: Loan Originations Do Not Increase at the CRA Threhsold

Figure shows the estimation results of the adjusted and unadjusted models the number of loan originations as the dependent variable. Each panel shows one of the four LMI thresholds. Points show the average of the dependent variable at evenly spaced relative income levels. Solid lines show a local linear approximation of the relationship between the dependent variable and relative income, using a triangular kernel and the optimal bandwidth from the unadjusted model. The local linear approximations are estimated separately for the negative and non-negative relative-income ranges. Estimated parameter $\hat{\tau}$ is the estimated threshold effect from the unadjusted model. Parameter $\hat{\tau_M}$ is the threshold effect from the adjusted model with robust standard errors clustered at the MSA/MD level. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.

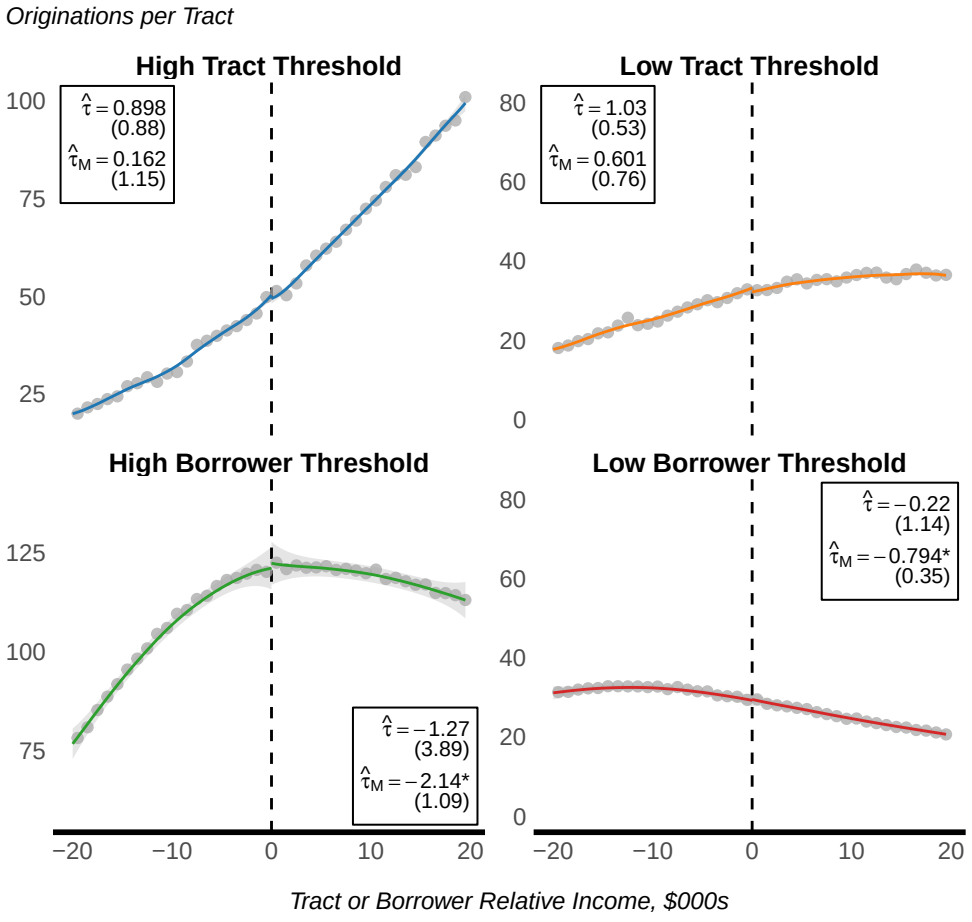


Table 3: Threshold Effects For Loan Originations

This figure shows estimated threshold effects for the adjusted model , $\hat{\tau}_M$, at each of the four LMI thresholds. Each coefficient was estimated separately using the number of loan originations for a specific type of loan ('Loan Type') or lender ('Lender Type') as the dependent variable. Results are also shown from estimations using originations of all loan and lender types ('All'). These coefficients are identical to the ones shown in Figure 6. Robust standard errors are clustered at the MSA/MD level and shown in parentheses. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.

	Thresholds			
	Tract		Borrower	
	High	Low	High	Low
All	0.162	0.601	-2.143*	-0.794*
	(1.15)	(0.76)	(1.09)	(0.35)
Loan Type				
Conventional	0.228	0.063	-1.464	-0.616*
	(1.05)	(0.46)	(0.95)	(0.30)
Nonconventional	-0.170	0.538	-0.638*	-0.123
	(0.35)	(0.38)	(0.25)	(0.10)
Lender Type				
Inside AA	0.358	0.137	0.054	-0.047
	(0.42)	(0.19)	(0.25)	(0.08)
Outside AA	0.018	0.169*	0.064	-0.067
	(0.14)	(0.07)	(0.10)	(0.05)
Other Bank	-0.110	0.063	-0.213*	-0.087*
	(0.11)	(0.09)	(0.11)	(0.04)
Credit Union	-0.135	0.125	-2.038*	-0.529
	(0.67)	(0.49)	(0.87)	(0.27)
Ind. Mortgage Bank	0.085	0.126	-0.026	0.013
	(0.14)	(0.09)	(0.09)	(0.03)

In summary, the data analyzed in this section suggests that the increase in loan liquidity just beyond the LMI thresholds did not significantly increase mortgage credit availability in those same neighborhoods.

5.3. Are Banks Retaining Fewer Loans?

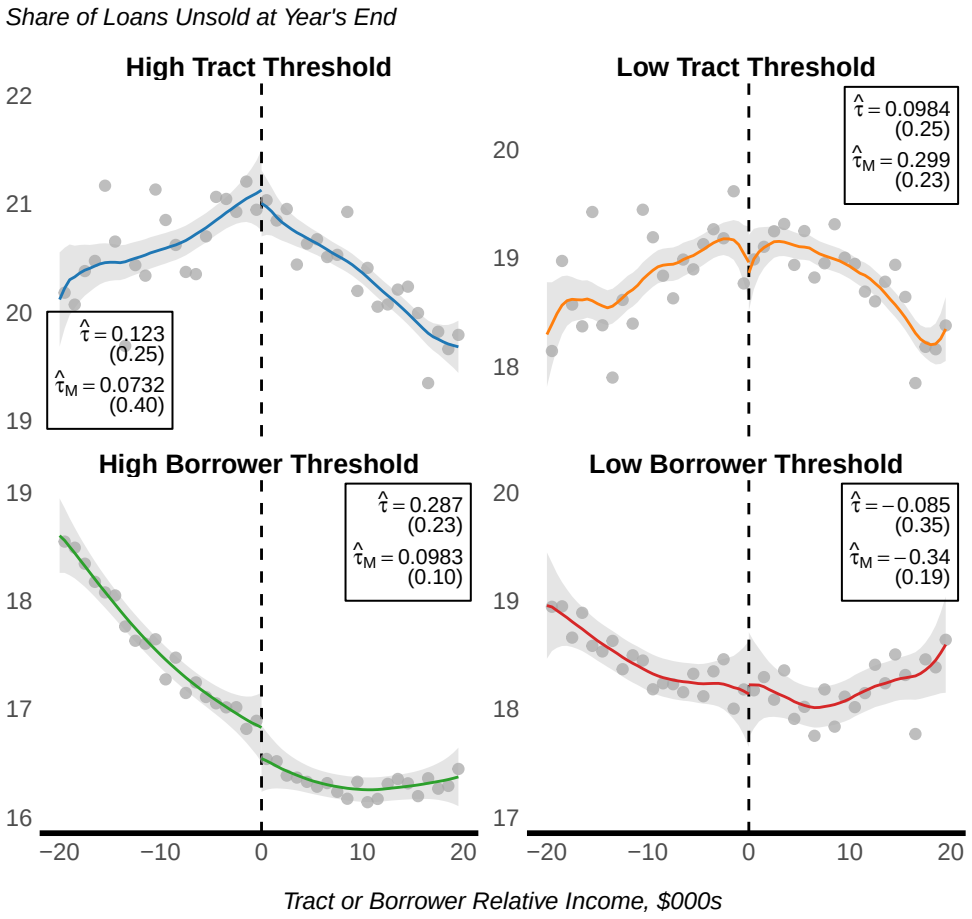
An increase in loan originations at the LMI threshold is not the only way that enhanced LMI loan liquidity at those same thresholds might increase lending in LMI communities. If the increased liquidity allows banks to retain fewer originations in their own portfolios, this could free up capital that could be redeployed to make more loans in LMI communities farther below the thresholds (i.e., in neighborhoods with MFIs that are 75% of area median income).

For example, a depository institution can make loans to creditworthy borrowers that it does not expect to be able to sell on the secondary market if it is willing to hold those loans on its own balance sheet. With sufficient capital a bank might retain enough loans to satisfy the demand from all creditworthy applicants at prevailing market prices at LMI thresholds. If so, additional loan liquidity would not be expected to increase originations at those thresholds. However, if additional liquidity allows banks to retain fewer of the loans they originate, it could free up capital to support additional LMI lending away from the threshold. That loan liquidity might have this affect is among the arguments that have been made to support the equal treatment of originations and purchases (Community Reinvestment Act Regulations, 2001).

I investigate this possibility by looking at the share of loans that lenders retain at the LMI thresholds. In the HMDA data, lenders report whether an originated loan was sold before year's end and, if so, the type of institution that purchased the loan. If depositories are retaining fewer loans on their balance sheets because of the additional liquidity generated by the CRA, there should be a decrease in the share of loans that remain unsold at the LMI threshold.

Figure 7: Share of Loan Originations Unsold at Year's End

Figure shows the estimation results of the adjusted and unadjusted models using the share of loans that remained unsold at the end of the calendar year of origination as the dependent variable. Each panel shows one of the four LMI thresholds. Points show the average of the dependent variable at evenly spaced relative income levels. Solid lines show a local linear approximation of the relationship between the dependent variable and relative income, using a triangular kernel and the optimal bandwidth from the unadjusted model. The local linear approximations are estimated separately for the negative and non-negative relative-income ranges. Estimated parameter $\hat{\tau}$ is the estimated threshold effect from the unadjusted model. Parameter $\hat{\tau_M}$ is the threshold effect from the adjusted model with robust standard errors clustered at the MSA/MD level. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.



I estimate version of the adjusted and unadjusted models using the share of loan originations remaining unsold at year's end as the dependent variable (Figure 7). The results give little indication that fewer loans are being retained in portfolio. None of the estimated threshold effects at the four LMI thresholds is large enough to suggest that the increased liquidity from CRA-induced loan purchases has affected the share of loans that are being sold.

Similar results are observed when estimating separate models based on the type of loan or lender (Table 4). None of the estimated threshold effects are significant at the 1% level and only one is both negative and significant at the 5% level. The one marginally-significant negative coefficient is found for banks outside of their assessment areas at the low borrower threshold. Since that is the only threshold where CRA does not increase purchasing activity, it is unlikely to be the result of enhanced LMI loan liquidity. There appears to be very little evidence, therefore, that enhanced LMI loan liquidity is causing lenders to reduce the share of loans they retain on their own balance sheets that might have freed up capital to boost lending away from the LMI thresholds.

5.4. Where are Banks' Additional Loan Purchases Coming From?

The increase in loan purchases by banks within their assessment areas appears to be fueled neither by an increase in originations nor by a decrease in loans retained on balance sheet. The remaining possibility is that the increase in purchases by banks within their assessment areas crowds out purchases by other institutions. In this section, I examine whether the CRA alters to whom loans are sold.

Most sales of originated loans reported in the HMDA data are to the GSEs, defined broadly to include Fannie Mae, Freddie Mac, Ginnie Mae, and Farmer Mac.[9] I start by examining

[9] I use this broad definition of *GSEs* because most of the analysis combines conventional and nonconventional loans. While Ginnie Mae does not actually purchase loans, the rules governing HMDA reporting record loan sales into a Ginnie-Mae-backed securitization as a purchase by Ginnie Mae. For simplicity, I also refer to these loans as Ginnie Mae sales.

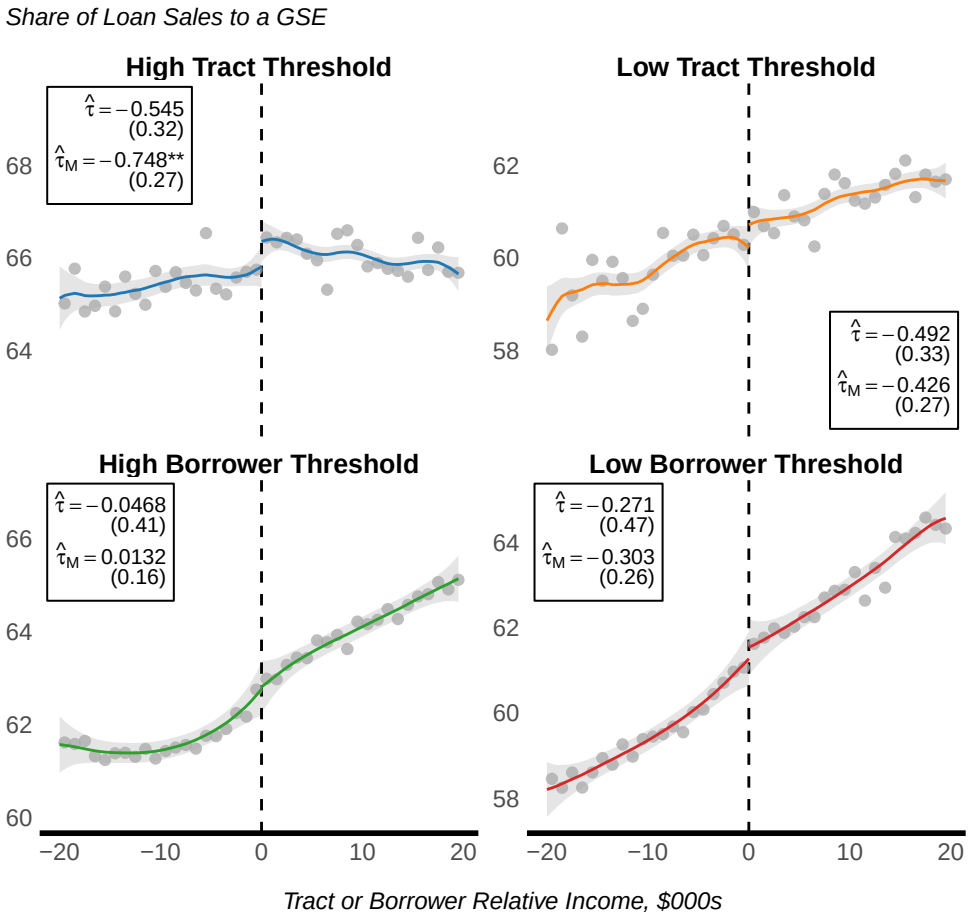
Table 4: Threshold Effects for Share of Originations that Remain Unsold

This figure shows estimated threshold effects for the adjusted model, $\hat{\tau}_M$, at each of the four LMI thresholds. Each coefficient was the produced by a separate estimation using the number of share of loan originations that remained unsold at the end of the year of origination as the dependent variable. Separate estimations were conducted for each type of loan ('Loan Type') or lender ('Lender Type'). Results are also shown from estimations using originations of all loan and lender types ('All'). These coefficients are identical to the ones shown in Figure 7. Robust standard errors are clustered at the MSA/MD level and shown in parentheses. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.

	Thresholds			
	Tract		Borrower	
	High	Low	High	Low
All	0.073	0.299	0.098	-0.340
	(0.40)	(0.23)	(0.10)	(0.19)
Loan Type				
Conventional	0.129	0.525	0.096	-0.371
	(0.46)	(0.30)	(0.12)	(0.28)
Nonconventional	-0.205	0.017	-0.108	-0.266
	(0.18)	(0.16)	(0.13)	(0.25)
Lender Type				
Inside AA	1.246	0.293	0.634*	0.554
	(0.86)	(0.43)	(0.26)	(0.52)
Outside AA	-0.850	-0.829	-0.376	-1.459*
	(0.73)	(0.59)	(0.31)	(0.70)
Other Bank	-0.947	-0.051	0.262	0.267
	(0.66)	(0.62)	(0.33)	(0.71)
Credit Union	-0.177	-0.090	0.047	-0.058
	(0.17)	(0.21)	(0.08)	(0.15)
Ind. Mortgage Bank	-1.311	1.891	-0.608	-0.850
	(0.92)	(1.28)	(0.40)	(0.93)

Figure 8: Direct GSE Loan Sales at the LMI Thresholds

Figure shows the estimation results of the adjusted and unadjusted models using the share of loans sold to the GSEs conditional on having been sold by the end of the calendar year of origination as the dependent variable. Each panel shows one of the four LMI thresholds. Points show the average of the dependent variable at evenly spaced relative income levels. Solid lines show a local linear approximation of the relationship between the dependent variable and relative income, using a triangular kernel and the optimal bandwidth from the unadjusted model. The local linear approximations are estimated separately for the negative and non-negative relative-income ranges. Estimated parameter $\hat{\tau}$ is the estimated threshold effect from the unadjusted model. Parameter $\hat{\tau_M}$ is the threshold effect from the adjusted model with robust standard errors clustered at the MSA/MD level. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.



the share of originations that were directly sold to a GSE, conditional on having been sold during the origination year.

The results of the adjusted and unadjusted model estimations (Figure 8) suggest that direct-to-GSE sales decline by a statistically significant amount along the high-tract threshold where purchases jump the most. A smaller decline is also observed at the low-tract threshold though it is not statistically significant.

Along the tract-based thresholds, declines in direct-to-GSE sales are observed for multiple lender types (Figure 9). Banks within their assessment area decrease their direct-to-GSE sales the most by -0.7 percentage points, which is significant at the 0.1% level. Outside of their assessment areas, the declines are of similar magnitude but are not statistically significant. Independent mortgage banks also reduce their direct-to-GSE loan sales at the high-tract threshold by -0.7 percentage points, which is significant at the 5% level.

Along the borrower-based thresholds, there is less evidence of a sudden decrease in direct-to-GSE loan sales, though the threshold effect for banks within their assessment areas is significant at the 5% level (Figure 10). The lack of effects at the borrower thresholds is consistent with the smaller increase in loan purchases at these thresholds observed earlier. However, it is notable that direct-to-GSE sales dip just below the borrower LMI thresholds. This mirrors the inflection in loan purchases by banks within their assessment areas at these same thresholds (shown earlier in Figure 5). While the inflection in purchases is only observed for banks within their assessment areas, the dip in direct-to-GSE sales is observed for multiple lender types.

CRA-induced purchases by banks within their assessment areas need not come directly from loan originators. They can also come from institutions that purchased the loans. Like direct-to-GSEs sales, I estimate versions of the adjusted and unadjusted models using the share of purchases that were resold to the GSEs, conditional on having been resold in the year of purchase (“indirect GSE sales”).

A substantial majority, 90% or more, of resold purchases around the LMI thresholds are sold to the GSEs. Like originations, the CRA appears to reduce the share of GSE loan sales

Figure 9: Direct GSE Loan Sales at the High Tract Threshold by Lender Type

Figure shows the estimation results of the adjusted and unadjusted models using the share of loan originations that are sold to the GSEs conditional on having been sold before the end of the calendar year of origination as the dependent variable. Each panel shows one of the four LMI thresholds. Points show the average of the dependent variable at evenly spaced relative income levels. Solid lines show a local linear approximation of the relationship between the dependent variable and relative income, using a triangular kernel and the optimal bandwidth from the unadjusted model. The local linear approximations are estimated separately for the negative and non-negative relative-income ranges. Estimated parameter $\hat{\tau}$ is the estimated threshold effect from the unadjusted model. Parameter $\hat{\tau_M}$ is the threshold effect from the adjusted model with robust standard errors clustered at the MSA/MD level. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.

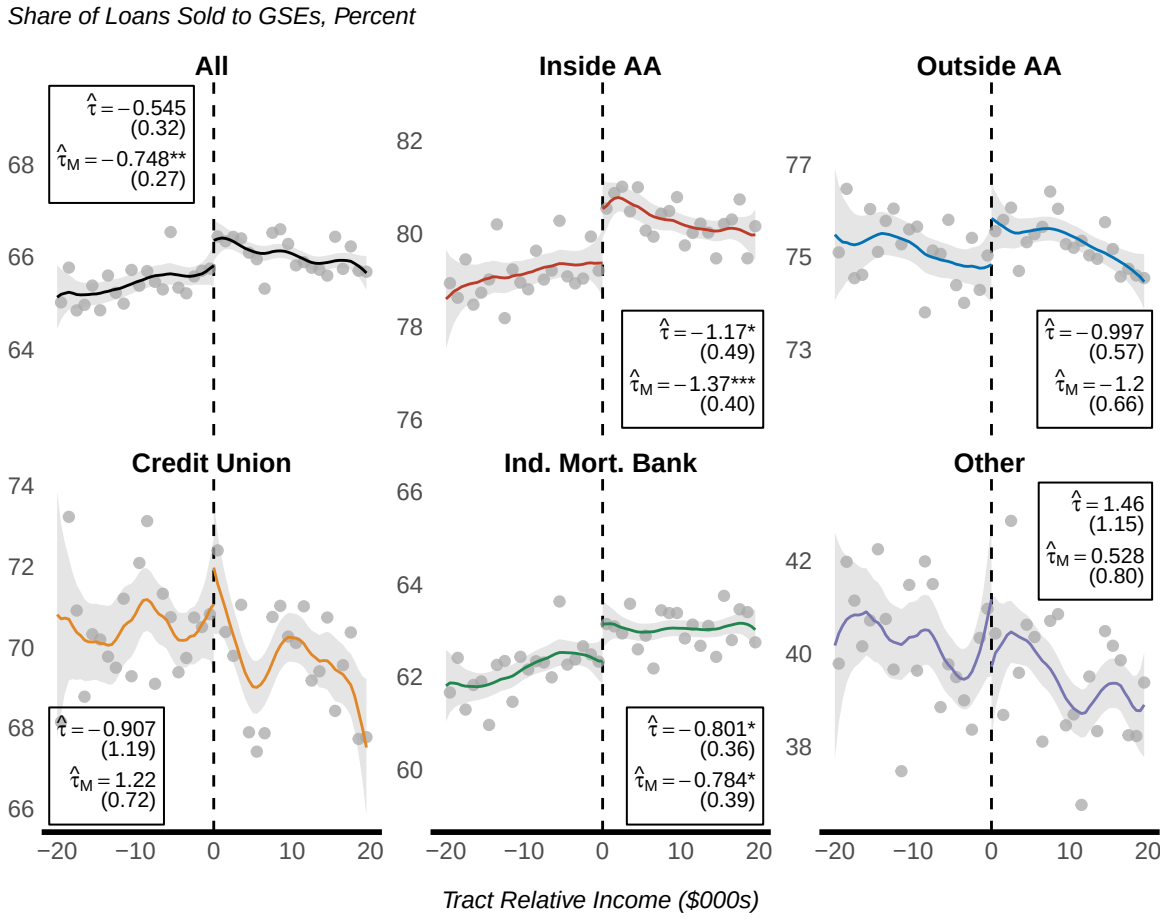


Figure 10: Direct GSE Loan Sales at the High Borrower Threshold by Lender Type

Figure shows the estimation results of the adjusted and unadjusted models using the share of originated loans that were sold to the GSEs conditional on having been sold by the end of the calendar year of origination as the dependent variable. All panels show results at the High Borrower threshold for all lenders ('All') or for one of five lender types. Points show the average of the dependent variable at evenly spaced relative income levels. Solid lines show a local linear approximation of the relationship between the dependent variable and relative income, using a triangular kernel and the optimal bandwidth from the unadjusted model. The local linear approximations are estimated separately for the negative and non-negative relative-income ranges. Estimated parameter $\hat{\tau}$ is the estimated threshold effect from the unadjusted model. Parameter $\hat{\tau_M}$ is the threshold effect from the adjusted model with robust standard errors clustered at the MSA/MD level. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.

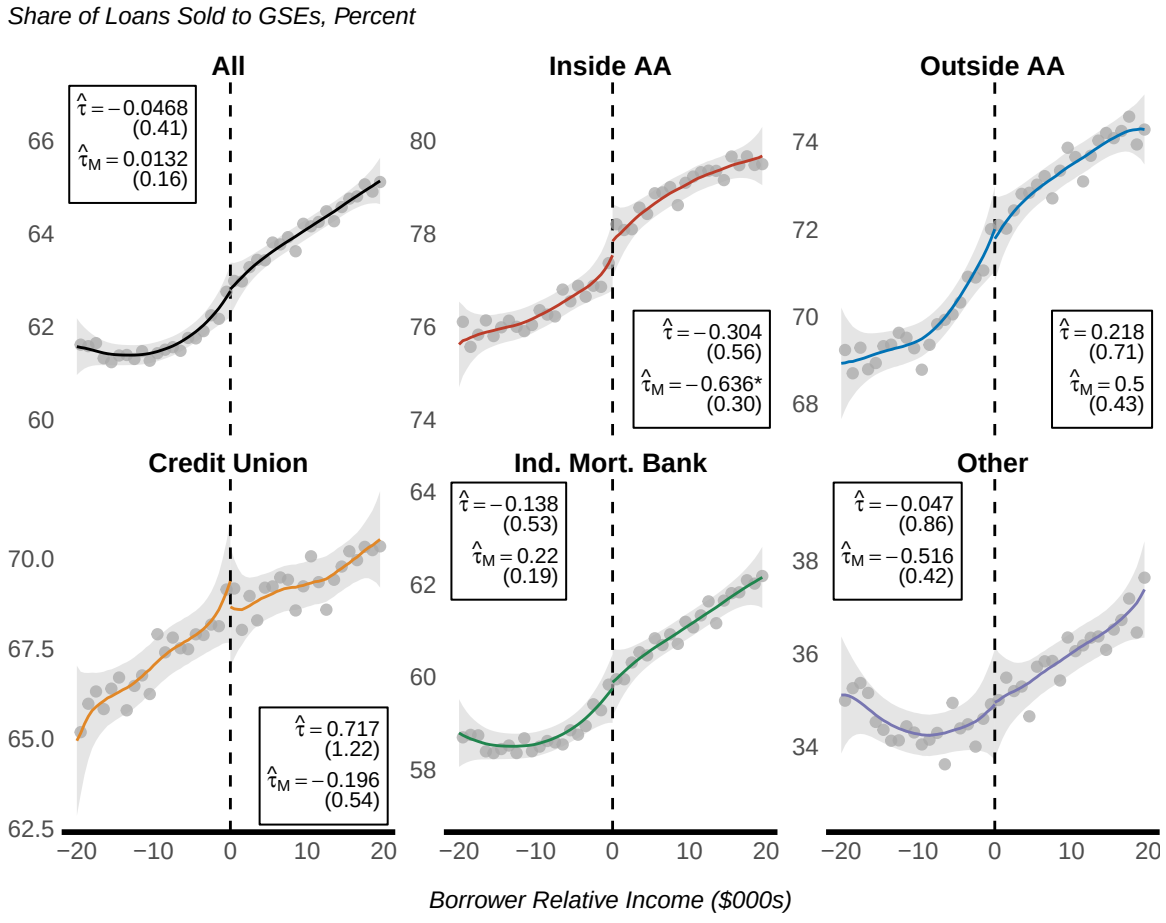
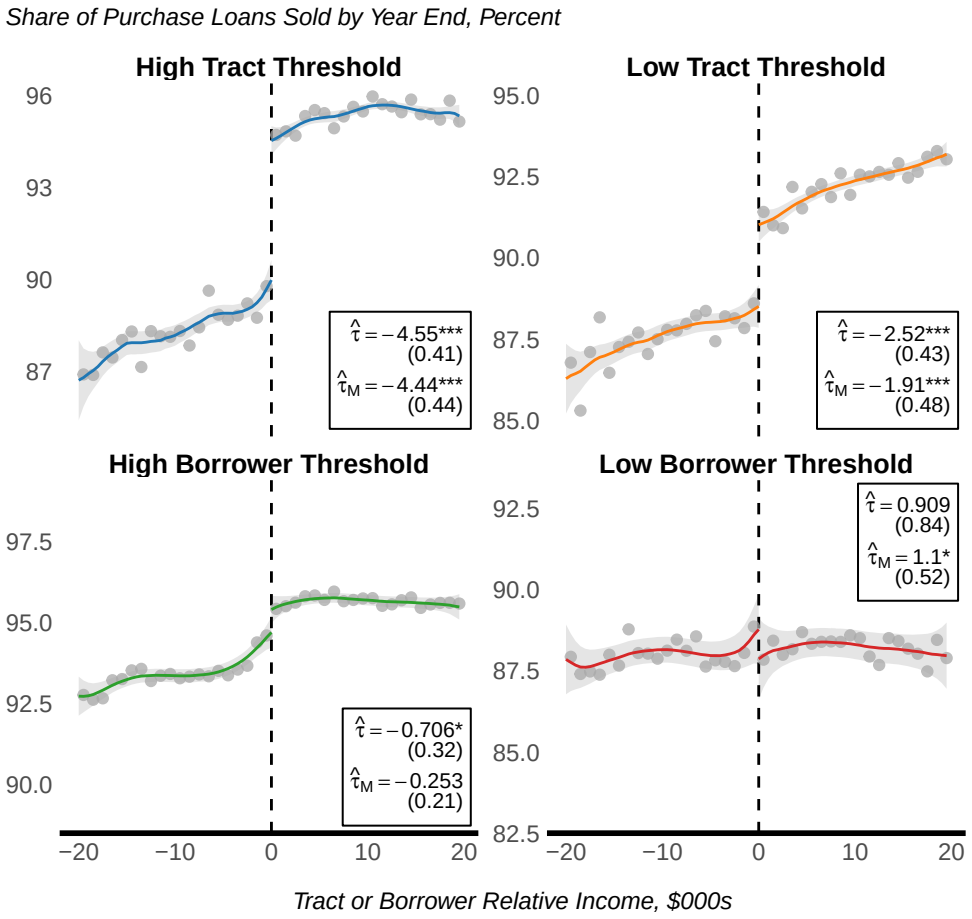


Figure 11: CRA Decreases Indirect GSE Loan Sales

Figure shows the estimation results of the adjusted and unadjusted models using the share of purchased loans that are resold to the GSEs by the end of the year of purchase as the dependent variable. Each panel shows one of the four LMI thresholds. Points show the average of the dependent variable at evenly spaced relative income levels. Solid lines show a local linear approximation of the relationship between the dependent variable and relative income, using a triangular kernel and the optimal bandwidth from the unadjusted model. The local linear approximations are estimated separately for the negative and non-negative relative-income ranges. Estimated parameter $\hat{\tau}$ is the estimated threshold effect from the unadjusted model. Parameter $\hat{\tau_M}$ is the threshold effect from the adjusted model with robust standard errors clustered at the MSA/MD level. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.



significantly (at the 0.1% level) along both tract thresholds (Figure 11). Effects at the borrower thresholds are small and neither is statistically significant at the 1% level, though once again there is a notable inflection point at the high borrower threshold similar to that observed for purchases by banks within their assessment areas.

Together, the data on the sale of originations and purchases suggest that lenders divert sales away from the GSEs because of the CRA. A back-of-the-envelope calculation suggests that these loan diversions are large enough to account for the CRA-induced loan purchases by banks within their assessment areas. For example, applying the estimated increase in purchases at the high tract threshold for banks within their assessment areas from the adjusted model to the number of originations and purchases in tracts with relative incomes no more than $1,000 below the high tract threshold, yields an estimate of 2,816 addition purchases in this narrow income range because of the CRA. Using the same methodology, there are 3,446 diverted GSE sales at the high tract threshold, of which 53 percent are diverted direct-to-GSE loan sales. Aggregating across the four LMI thresholds 1,843 are would-have-been direct GSE sales and 1,603 are would-have-been indirect GSE sales. The threshold effects in loan sales to the GSEs, based on this back-of-the-envelope calculation, are large enough to account for all of the increase in loan purchases by banks within their assessment areas.

Because the HMDA data only report loans sales within the same calendar year as a loan's origination or purchase, they cannot be used to determine where the loans ultimately go. But they are consistent with a lot of diverted loans eventually reaching the GSEs. Most loan purchases in HMDA are resold in the same year and, of those that are resold, over 90% are then sold to the GSEs. However, this cannot rule out the possibility mentioned earlier of loan *churning* where the same loans are repeatedly resold among banks to boost their LMI lending shares.

The National Mortgage Database can shed light on the ultimate disposition of many of these loans. Among the loan-level information contained in the NMDB are each loan's date of origination, an indicator of whether the loan was acquired by Fannie Mae or Freddie Mac,

and, for the loans that were acquired, the acquisition date. I use this information to assess whether the CRA ultimately causes fewer conventional loans to be acquired by Fannie Mae and Freddie Mac. Because similar information is not available for Ginnie Mae (or Farmer Mac), I exclude nonconventional loans from the analysis. Consistent with the HMDA data analyses, I examine the 2013-2016 and 2018-2020 sample period and aggregate the data to the same observation levels.

I estimate versions of the adjusted and unadjusted models on the sample of NMDB data using the share of loans acquired by Fannie Mae or Freddie Mac as the dependent variable (Figure 12). None of the four estimations suggests that the CRA significantly affects the likelihood that a conventional loan is acquired by those two GSEs. This suggests that any loans that were not directly sold to Fannie or Freddie because of the CRA are nonetheless ultimately acquired by them. The loans may just be taking a more circuitous route to their final destination.

If loans are taking a more circuitous route, this might increase the amount of time between a loan's origination and its acquisition by Fannie or Freddie. The NMDB data provide evidence of such a CRA-induced delay. Estimations of the adjusted and unadjusted models using the share of Fannie or Freddie acquisitions that were acquired within 60 days of origination as the dependent variable exhibit a drop in the share of loans acquired in this time frame (Figure 13). At the high-tract threshold, where CRA-induced purchases are largest, the share of loans acquired within 60 days falls by 2 percentage points, which is significant at the 0.1% level. The decline at the high borrower threshold is smaller, but remains about 1 percentage point in size and significant at the 5% level. At the low tract threshold the decline is not statistically significant and at the low borrower threshold, where there is no apparent increase in loan purchases, there is also no evidence of a delay in acquisitions.

Similar estimations using the share of loans acquired within 120 days indicate that, at the tract-based thresholds, the CRA has no effect on the share of loans acquired within this longer time frame (Figure 14). Along the high borrower threshold, the CRA continues to cause statistically significant acquisition delays at the 5% level, though the point estimate

Figure 12: The Share of Conventional Loans that are Acquired by Fannie Mae or Freddie Mac is not Affected by CRA

Figure shows the estimation results of the adjusted and unadjusted models using the share of conventional loans that are acquired by Fannie Mae or Freddie Mac as the dependent variable. Each panel shows one of the four LMI thresholds. Points show the average of the dependent variable at evenly spaced relative income levels. Solid lines show a local linear approximation of the relationship between the dependent variable and relative income, using a triangular kernel and the optimal bandwidth from the unadjusted model. The local linear approximations are estimated separately for the negative and non-negative relative-income ranges. Estimated parameter $\hat{\tau}$ is the estimated threshold effect from the unadjusted model. Parameter $\hat{\tau_M}$ is the threshold effect from the adjusted model with robust standard errors clustered at the MSA/MD level. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.

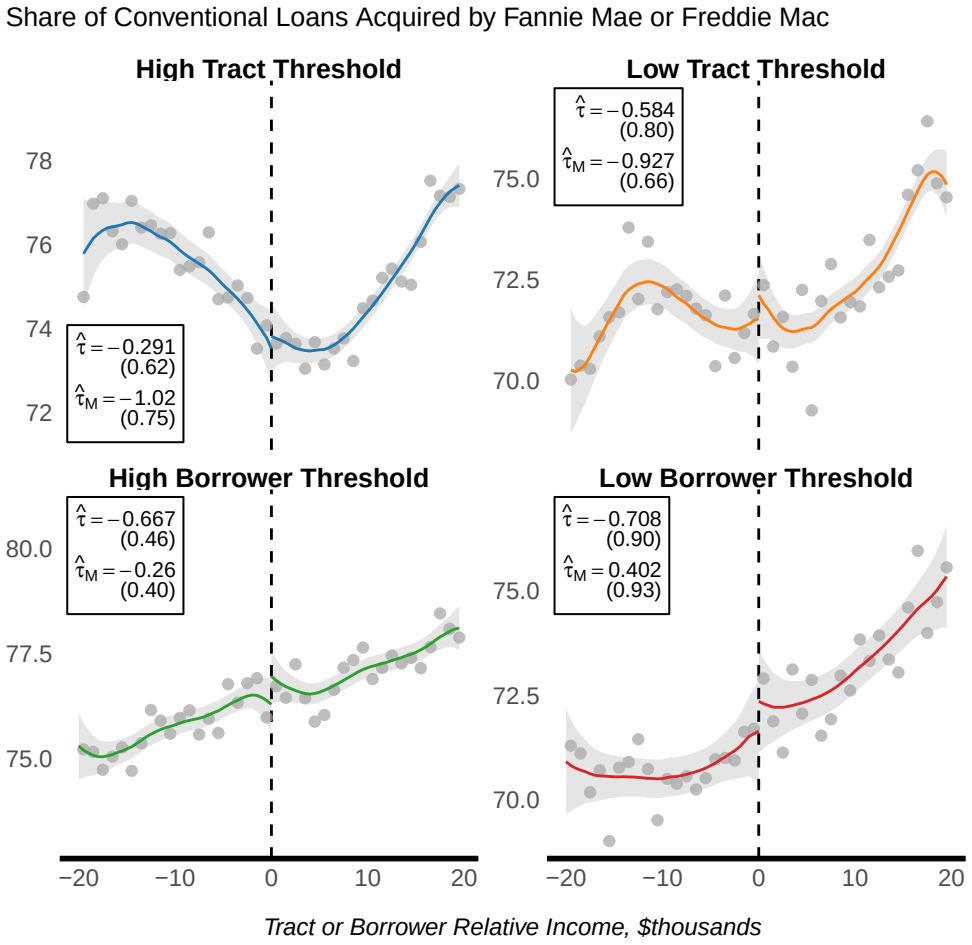


Figure 13: Share of Fannie Mae or Freddie Mac Loans that are Acquired within 60 Days of Origination

Figure shows the estimation results of the adjusted and unadjusted models using the share loans acquired by Fannie Mae or Freddie Mac that were acquired within 60 days of origination as the dependent variable.. Each panel shows one of the four LMI thresholds. Points show the average of the dependent variable at evenly spaced relative income levels. Solid lines show a local linear approximation of the relationship between the dependent variable and relative income, using a triangular kernel and the optimal bandwidth from the unadjusted model. The local linear approximations are estimated separately for the negative and non-negative relative-income ranges. Estimated parameter $\hat{\tau}$ is the estimated threshold effect from the unadjusted model. Parameter $\tau\hat{_M}$ is the threshold effect from the adjusted model with robust standard errors clustered at the MSA/MD level. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.

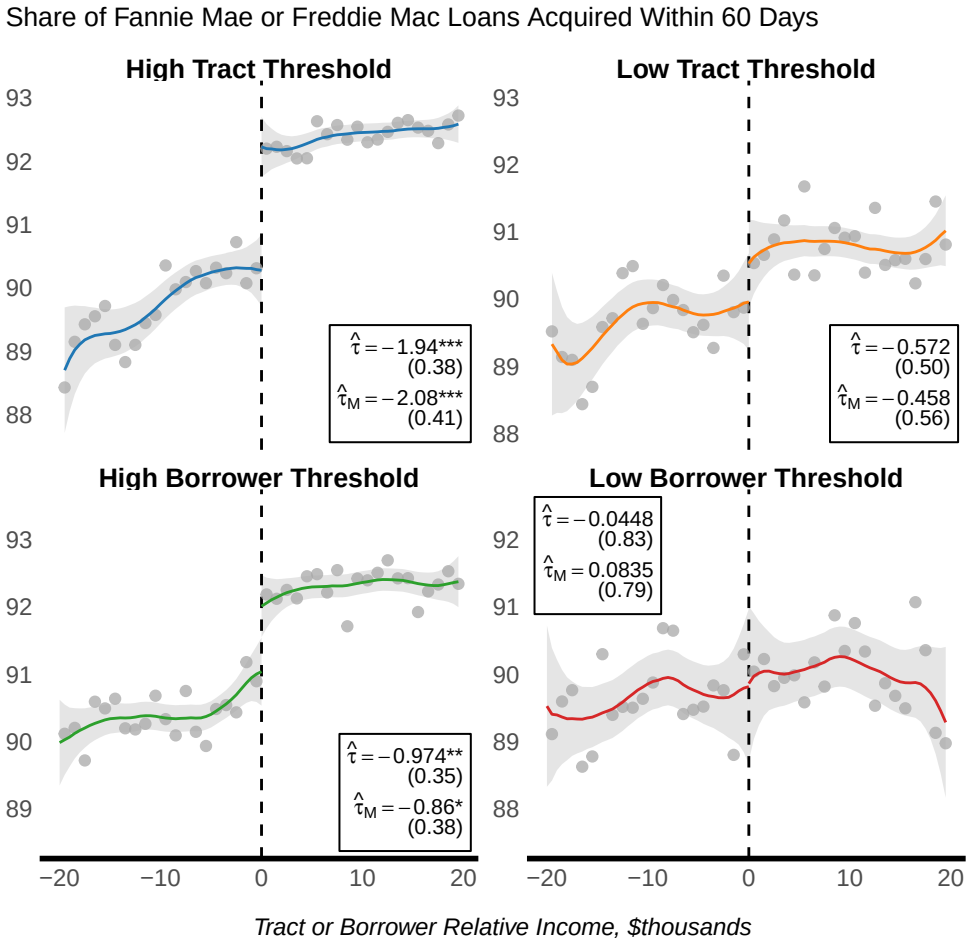
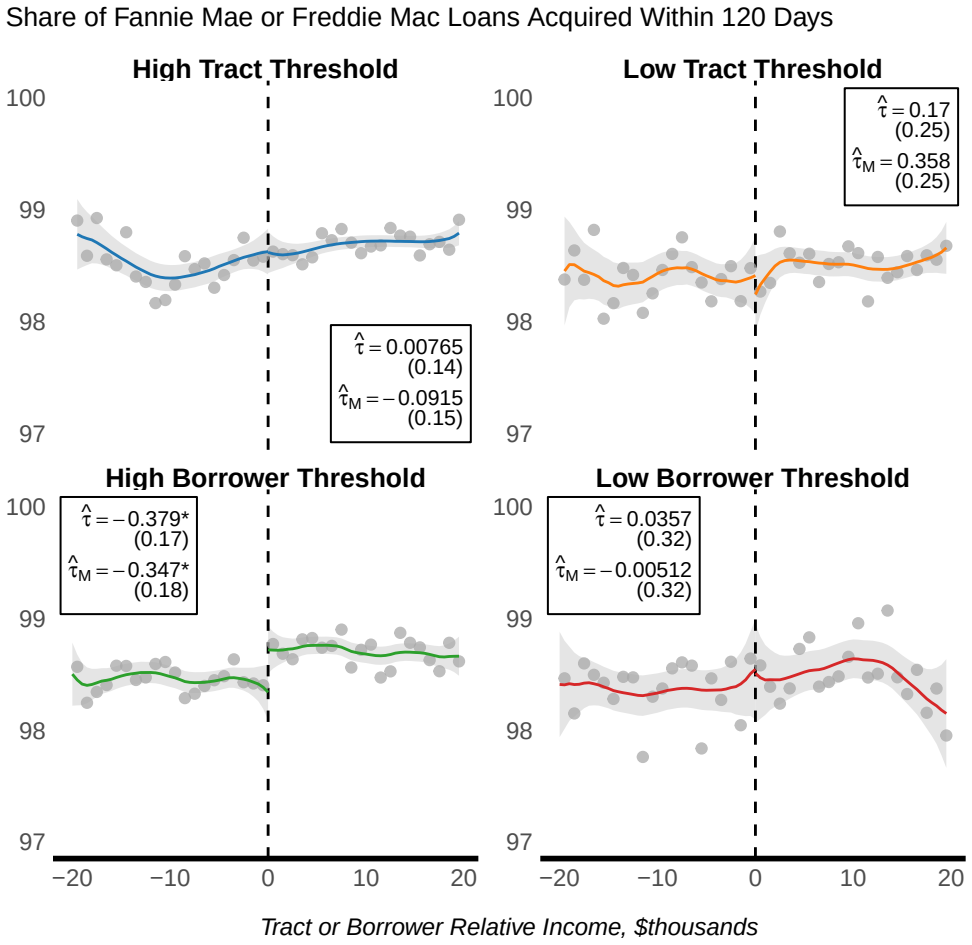


Figure 14: Share of Fannie Mae or Freddie Mac Loans that are Acquired within 120 Days of Origination

Figure shows the estimation results of the adjusted and unadjusted models using the share loans acquired by Fannie Mae or Freddie Mac that were acquired within 120 days of origination as the dependent variable.. Each panel shows one of the four LMI thresholds. Points show the average of the dependent variable at evenly spaced relative income levels. Solid lines show a local linear approximation of the relationship between the dependent variable and relative income, using a triangular kernel and the optimal bandwidth from the unadjusted model. The local linear approximations are estimated separately for the negative and non-negative relative-income ranges. Estimated parameter $\hat{\tau}$ is the estimated threshold effect from the unadjusted model. Parameter $\hat{\tau_M}$ is the threshold effect from the adjusted model with robust standard errors clustered at the MSA/MD level. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.



at 120 days is less than half of the point estimate at 60 days. This suggests that all of the loans at the tract thresholds and most of the loans at the high borrower threshold that would have been acquired by the GSEs within the first 60 days are acquired during the next 60.

This implies that the delays caused by LMI loans taking more circuitous routes to the GSEs are generally short. Unless loan resales occur quickly (which is inconsistent with banks within their assessment areas retaining a larger share of their loans until the end of the year because of CRA), loan churning can account for only a small portion of the purchases that lenders make in response to the CRA. Instead, the evidence suggests that CRA-induced loan purchases are being fueled by a temporary diversion of loans meant for the GSEs that ultimately resolves after a few months.

5.5. Does Credit for Loan Purchases Materially Change LMI Lending Shares?

The analysis documented in this paper shows that banks within their assessment areas increase their loan purchases without an observable effect on lending to LMI communities. These results suggest that the benefits to LMI communities of including loan purchases as part of a bank's lending activity on its CRA exam are minimal. But as long as the inclusion of loan purchases does not materially alter a bank's LMI share there will also be little harm. In this section, I examine what happens to the LMI shares of banks when purchases are incorporated into the calculation at full weight.

For each bank in the sample with an assessment area, I calculate its LMI share two ways. First, I calculate an *all-in LMI share* based on the purchases and originations it reported during the 7 years analyzed in this study. Second, I calculate an *originations-only LMI share* based solely on its originations. Each of share is calculated separately for banks within and outside their assessment areas. Separate shares are also calculated for lending in LMI neighborhoods and lending to LMI borrowers. Since the analysis does not use regression discontinuity to identify threshold effects, I do not distinguish between high and low portions of the LMI thresholds and I use data from all tract or borrower relative income levels, not just those within $20,000 of an LMI threshold.

Table 5: Estimation Results for Regressions of LMI Share Differences

This table shows estimation results from a regression of a bank's originations-only LMI share on the change to its LMI share when calculated based on originations and purchases. Separate estimations were conducted for banks within their assessment ares ('Inside AA') and outside their assessment areas ('Outside AA') at the tract and borrower LMI thresholds. Estimation samples were limited to banks with assessment areas aggregated over the 7 years used in this study (2013-2016 and 2018-2020). Standard errors are shown in parentheses. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.

	Tract Threshold		Borrower Threshold	
	Inside AA	Outside AA	Inside AA	Outside AA
Intercept	0.47***	0.12	0.81***	0.11
	(0.13)	(0.09)	(0.18)	(0.09)
Tract Orig. LMI Share	−0.12***	−0.03**		
	(0.01)	(0.01)		
Borrower Orig. LMI Share			−0.11***	−0.02**
			(0.01)	(0.01)
Num.Obs.	877	853	877	853
R2	0.080	0.011	0.068	0.009
F	75.644	9.673	63.879	7.506

The effect of giving equal treatment for purchases and originations is given by the difference between its all-in and originations-only LMI shares. I regress this difference on the originations-only LMI shares to highlight the relationship between a bank's LMI originations and the extent to which its LMI share changes when purchases are included. The originations-only LMI shares used in the regressions are demeaned, so that the estimated coefficient reflects the LMI share difference at the sample average. The estimations are conducted separately for banks inside and outside of their assessment area and for each LMI threshold.

Two patterns are apparent from the estimation results (shown in Table 5). First, at both the borrower and tract LMI thresholds, the LMI shares of banks within their assessment areas increase on average when purchases are included. These increases, which are reflected by the estimated intercepts, are both significantly different from zero at the 0.1% level. In contrast, the average effects for banks outside of their assessment areas are notably smaller and not significantly different from zero. Second, the slope in the relationship between the

originations-only LMI share and the LMI-share difference is negative for banks within and outside of their assessment areas. This negative relationship means that banks with lower originations-only LMI shares experience larger LMI-share increases when purchases and originations are treated equally. However, the magnitude of the declines is 4 to 5 times larger for banks within their assessment areas than for banks outside of their assessment areas, suggesting that banks with low originations-only LMI shares benefit significantly more from the equal treatment of purchases and originations than banks that originate a larger share of loans in LMI communities.

While the coefficients from these estimations are statistically significant, their sizes are generally small. This reflects the fact that these estimated parameters are conditional averages and purchases at many banks are small relative to their originations. Among banks that engage in large-scale purchases magnitudes can be much larger. Figure 15 shows the underlying data for banks with at least 5,000 originations and 1,000 purchases over the 7 years examined. LMI shares of some banks within their assessment areas increase by 10 percentage points or more when purchases and originations are treated equally. These banks, almost all of whom have originations-only LMI shares that are well below average, appear to benefit disproportionately from equal treatment.

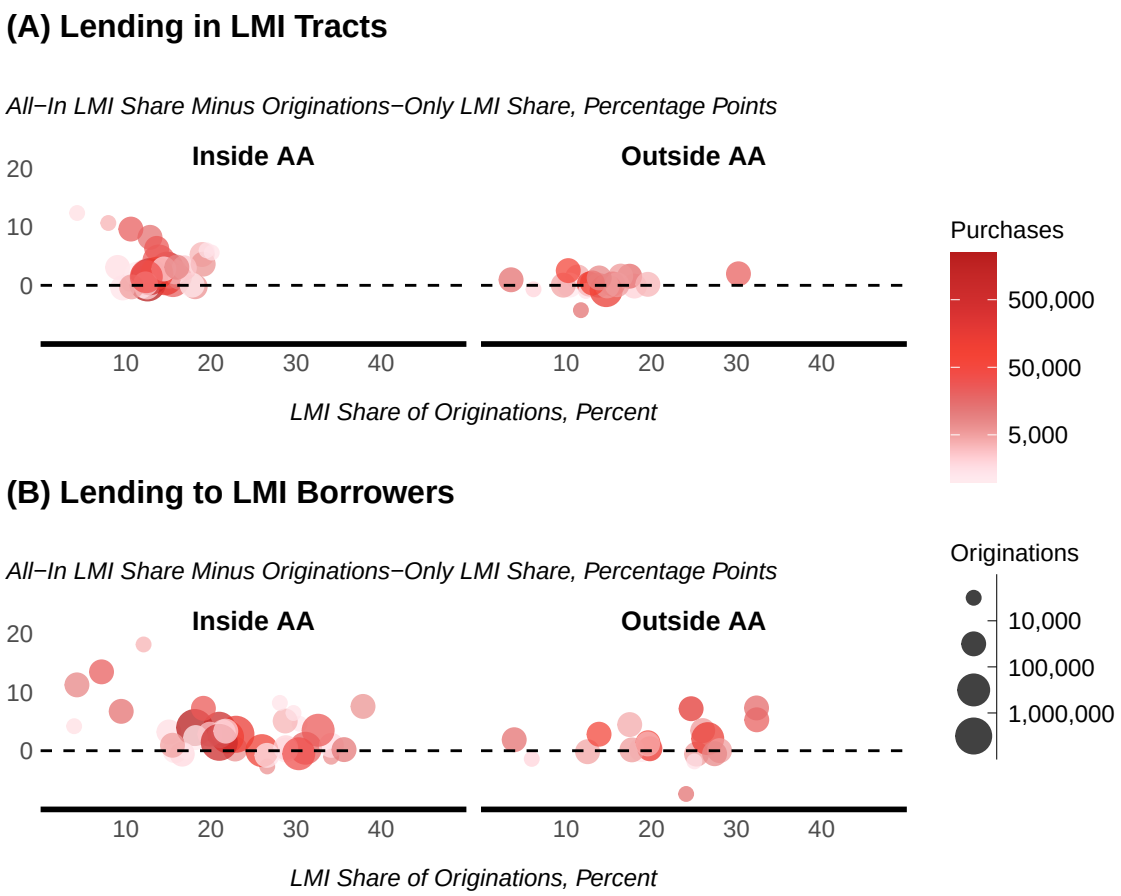
6. Robustness

6.1. Using a Different Sample Period: Results from 2004-2009

The results documented in this analysis show how CRA affected loan purchases in years following the Great Recession, a potentially idiosyncratic period dominated by government-guaranteed lending. In this section, I evaluate the robustness of these results to the mortgage market environment by repeating the analysis using data from an earlier period with a more active private-label securitization market.

Figure 15: The Effect of Including Purchases on LMI Shares

Figure showing each bank's originations-only LMI share (x-axis) against the increase in the LMI share that occurs when originations and purchases are used. Panels (A) and (B) show data on lending in LMI neighborhoods and to LMI borrowers respectively. Within each panel, banks within their assessment areas are shown on the left, banks outside of their assessment areas on the right. Observations are limited to lenders with at least 5,000 originations and 1,000 purchases in total over the years 2013-2016 and 2018-2020. The size of each point is proportional to the log of the number of originations and the color of each point is proportional to the log of the number of purchases.



The analysis covered in this section, uses data from 2004 to 2009. I start the time period at 2004 because it was the first year of an expanded HMDA data collection that added several variables not previously available (Avery et al., 2007).[10] This span covers the high-water marks for the U.S. subprime mortgage market, a period with a very active secondary market for conventional mortgages. This was also a period where the thresholds in place for the GSE goals were set at higher levels (90% of the surrounding area MFI) than those for the CRA, which helps avoid potentially confounding effects between the two programs.

Results from the adjusted model over this earlier period are broadly consistent with the main results of the paper (Table 6). At the high and low tract thresholds, purchase increases are significant at the 0.1% level for banks within their assessment areas but insignificant for other lenders. At these same thresholds, effects on originations are sporadically significant at the 5 percent level, but none is significant at the 1 percent level. Nor is there evidence that lenders retained fewer loans in their portfolios during this period. Instead, CRA-induced purchases again appear to have been fueled by reduced direct and indirect loan sales to the GSEs.

At the high borrower threshold, unlike the earlier results, there is no evidence of an increase in purchases at the threshold, though purchases exhibit the same inflection observed for the later period (Figure 16). Again, this inflection is only observed for banks operating within their assessment area, suggesting that CRA appears to increase purchases of loans to LMI borrowers away from the threshold. But in the absence of an effect on purchases at the threshold, there is little reason to suspect threshold effects for the other measures of lending activity and these are largely insignificant.

6.2. Uncertainty at the Borrower Threshold

Perhaps the most puzzling results in this analysis have been at the high borrower threshold, where discontinuities have been much smaller than at the high tract threshold but with

[10] For example, this study focuses on first-lien mortgages which were not identified in the HMDA data prior to 2004.

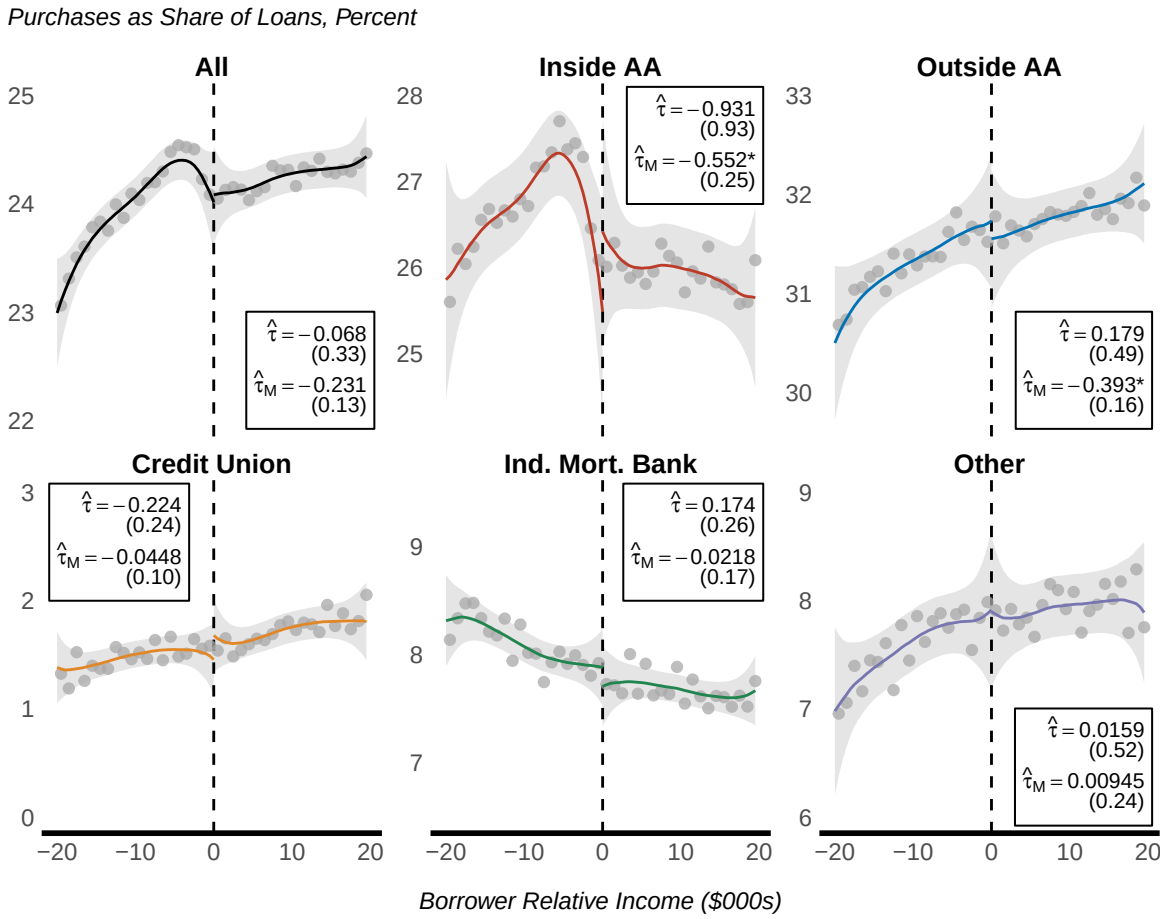
Table 6: Selected Estimation Results for Adjusted Model Using 2004-2009 HMDA Data

Table shows the estimation results of the adjusted model for the listed dependent variables using data for 2004 to 2009. Each column shows estimated threshold effects at each of the four LMI thresholds. Each parameter in the table displays a result from an estimation conducd using the full sample or limited to a specific lender type. All estimations are weighted by the denominator of the dependent variable. Robust standard errors are clustered at the MSA/MD level and are shown in parentheses. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.

	Thresholds			
	Tract		Borrower	
	High	Low	High	Low
Purchases (by select lender type)				
All	0.645*	0.705**	-0.231	-0.048
	(0.26)	(0.22)	(0.13)	(0.19)
Inside AA	1.944***	1.374***	-0.552*	-0.433
	(0.41)	(0.35)	(0.25)	(0.33)
Outside AA	-0.017	0.254	-0.393*	-0.398
	(0.30)	(0.22)	(0.16)	(0.31)
Indep. Mort. Bank	0.168	0.314	-0.022	0.469
	(0.18)	(0.19)	(0.17)	(0.29)
Originations (by select lender type)				
All	4.434	3.515*	1.920	1.586
	(3.13)	(1.79)	(1.97)	(0.88)
Inside AA	0.673	0.633	1.263*	0.331*
	(0.86)	(0.46)	(0.50)	(0.16)
Outside AA	2.724	1.977*	0.837	0.473
	(1.73)	(0.86)	(0.95)	(0.40)
Indep. Mort. Bank	0.580	0.565	-0.575	0.524
	(0.59)	(0.42)	(0.93)	(0.45)
Retained Loans	0.372	-0.165	0.582***	0.384
	(0.27)	(0.38)	(0.16)	(0.22)
Direct GSE Sales	-1.245***	-0.407	0.265	0.050
	(0.32)	(0.38)	(0.22)	(0.38)
Indirect GSE Sales	-1.429***	-1.584***	0.146	-1.398**
	(0.37)	(0.43)	(0.27)	(0.53)

Figure 16: Purchases Around the High Borrower Threshold, 2004-2009

Figure shows the estimation results of the adjusted and unadjusted models using purchases as a share of CRA lending activity (originations plus purchases) as the dependent variable. Each panel shows one of the four LMI thresholds. Points show the average of the dependent variable at evenly spaced relative income levels. Solid lines show a local linear approximation of the relationship between the dependent variable and relative income, using a triangular kernel and the optimal bandwidth from the unadjusted model. The local linear approximations are estimated separately for the negative and non-negative relative-income ranges. Estimated parameter $\hat{\tau}$ is the estimated threshold effect from the unadjusted model. Parameter $\hat{\tau_M}$ is the threshold effect from the adjusted model with robust standard errors clustered at the MSA/MD level. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.



clear inflections. One potential explanation is possibility of uncertainty about how purchases are treated in CRA at the LMI borrower thresholds.

As an example of the source of uncertainty, consider the case of a loan originated in 2019 to a borrower in Washington, DC, whose income was $93,000. Because the borrower LMI threshold that year was $91,760, that loan was to a middle-income borrower and, thus, would not have counted as an LMI origination. However, if that loan was sold the next year, when the borrower LMI threshold increased to $94,960 the status of that loan might be considered ambiguous: Can a loan made to a middle-income borrower at the time of origination count as an LMI purchase in later years?

One might expect that the answer to that question is "no" and that a loan originated to a middle-income borrower would retain its classification in subsequent purchases. However, because the HMDA data do not include origination dates for purchased loans, it has not been possible, without additional information, to classify purchases based on their origination dates.[11] Instead, LMI borrower designations for purchases are based on the year of purchase.[12] As a result, the answer to the question above is "yes" and that $93,000 loan to a middle-income borrower would count as an LMI purchase in 2020.

If banks, anticipating their need for LMI purchases, enter into advance agreements to purchase loans the next year, those agreements might be based on the surrounding area MFIs from the year in which the agreement was reached. Alternatively, banks selling LMI loans on the secondary market may not update borrower LMI statuses and thus sell loans based on the borrower LMI designation at origination. Situations like these, along with the fact that surrounding area MFIs tend to increase each year, could explain the small borrower threshold effects and inflections at the borrower LMI thresholds.

To evaluate this possibility, versions of the adjusted and unadjusted models were estimated using the data constructed in the same way as the other analyses in this paper but using the prior year's surrounding area MFI to calculate the borrower LMI thresholds. The

[11] Since 2018, the HMDA data have included a Uniform Loan Identifier, which should make it easier to determine the year of origination for most loan purchases.

[12] This treatment of purchased loans in CRA exams can be confirmed by reproducing lending tables from the CRA Performance Evaluations published by the federal banking agencies that conduct CRA examinations.

Figure 17: Purchases Around the High Borrower Threshold Based On Lagged 1-Year Lagged MFIs

Figure shows the estimation results of the adjusted and unadjusted models using the purchases as a share of CRA lending activity (purchases plus originations) as the dependent variable. Each panel shows one of the four LMI thresholds. Points show the average of the dependent variable at evenly spaced relative income levels. Solid lines show a local linear approximation of the relationship between the dependent variable and relative income, using a triangular kernel and the optimal bandwidth from the unadjusted model. The local linear approximations are estimated separately for the negative and non-negative relative-income ranges. Estimated parameter $\hat{\tau}$ is the estimated threshold effect from the unadjusted model. Parameter $\hat{\tau_M}$ is the threshold effect from the adjusted model with robust standard errors clustered at the MSA/MD level. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.

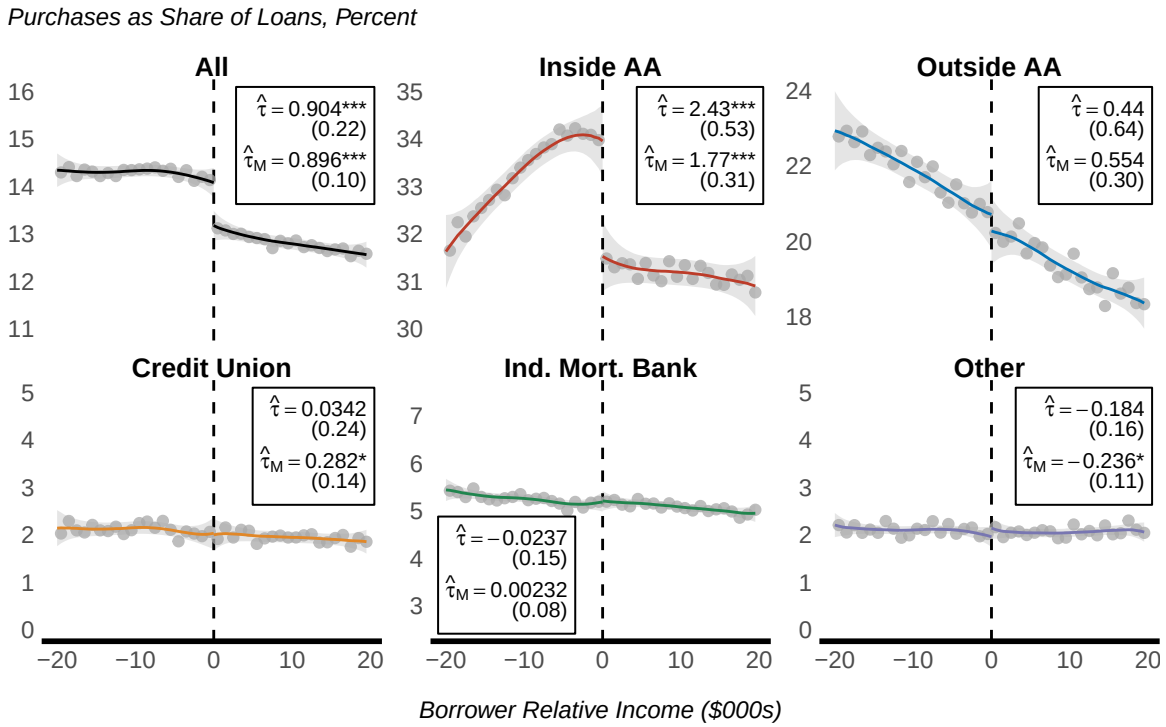
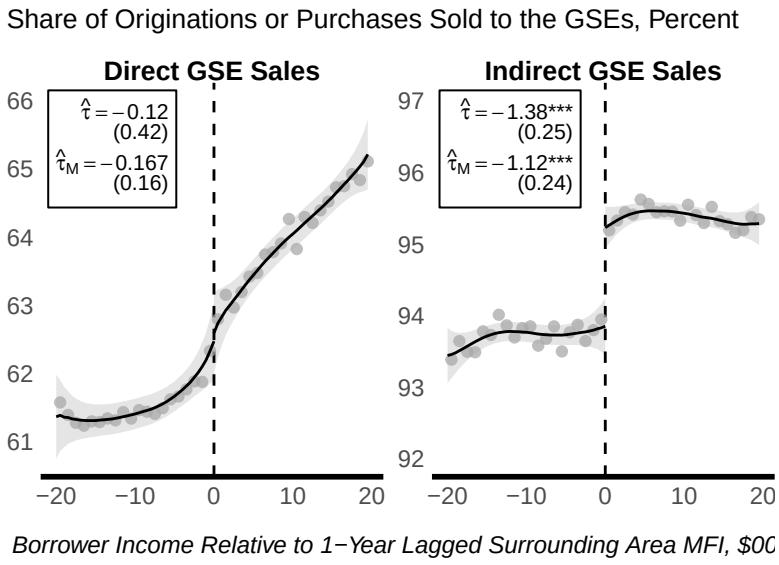


Figure 18: Direct and Indirect GSE Loan Sales Around the High Borrower Threshold Based On Lagged 1-Year Lagged MFIs

Figure shows the estimation results of the adjusted and unadjusted models. The dependent variable for the left panel is the share of loan originations that were sold to the GSEs conditional on having been sold before the end of the calendar year of origination. The dependent variable for the right panel is the share of purchases that are sold to the GSEs conditional on having been resold before the end of the calendar year of purchase. Points show the average of the dependent variable at evenly spaced relative income levels. Solid lines show a local linear approximation of the relationship between the dependent variable and relative income, using a triangular kernel and the optimal bandwidth from the unadjusted model. The local linear approximations are estimated separately for the negative and non-negative relative-income ranges. Estimated parameter $\hat{\tau}$ is the estimated threshold effect from the unadjusted model. Parameter $\hat{\tau_M}$ is the threshold effect from the adjusted model with robust standard errors clustered at the MSA/MD level. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.



results of this analysis, using purchases as a share of CRA lending is shown in Figure 17, which can be compared to the earlier results in Figure 5. The estimated threshold effects for all lenders and for banks within their assessment areas are 2-3 times larger than those estimated using non-lagged surrounding area MFIs and the effects are now significant at the 0.1 percent level for both the adjusted and unadjusted model threshold effects. Additionally, the inflections are not as apparent. For other lenders, the threshold effects are not significant at the 1% level.

Similar to the inflection observed for purchases at the high borrower threshold, inflections were also found earlier in direct and indirect loan sales to the GSEs. The results gen-

erated by re-estimating the adjusted and unadjusted models using lagged LMI borrower thresholds provide mixed evidence of the importance of the previous year's MFI (Figure 18). Like the main results, threshold effects for direct GSE sales are not statistically significant, though the point estimates using lagged MFIs are more negative than using MFIs from purchase years. In contrast, indirect GSE sale at the high borrower threshold show clear evidence of a threshold effect when lagged MFIs are used. Threshold effects from the adjusted and unadjusted models are both significant at the 0.1% level, whereas the main results from neither model had been significant at the 1% level.

Overall, these results support the notion that CRA induces additional loan purchases of banks to LMI borrowers from banks within their assessment areas. There is no reason within the CRA's regulations that I have been able to find that would explain why banks should prefer making purchases based on a prior year's surrounding area MFI. But the results in this section suggest that they might though the exact reasons remain unclear.

6.3. Does CRA Affect Loan or Borrower Characteristics

The analysis in this paper focuses on CRA's effects on mortgage originations and purchases because of the central role they play in CRA evaluations. In addition to potentially increasing the number of originations, enhanced LMI loan liquidity could lower interest rates or reduce underwriting standards. While both of these changes would be expected to increase originations, this section focuses more directly on whether CRA-induced purchases have had these effects at the LMI thresholds.

This analysis uses the NMDB sample of loans. Unlike HMDA, the NMDB contains information on loan interest rates, credit scores, loan-to-value ratios, and other underwriting characteristics for loans originated during our entire sample period.[13]

The results from the estimation of the adjusted model, shown in Figure 7, suggest that the increase in LMI loan liquidity from CRA-induced purchases has no effect on mortgage

[13]The information collected under HMDA was expanded starting in 2018, which would provide most of this information, but for less than half of the sample period examined here.

Table 7: Adjusted Model Estimation Results for Loan Characteristics

Table shows the estimation results of the adjusted model for the listed dependent variables using data from the NMDB for 2013-2016 and 2018-2020. Each column shows estimated threshold effects at one of the four LMI thresholds. Each parameter in the table displays a result from an estimation conducted using the full sample. All estimations are weighted by the denominator of the dependent variable. Robust standard errors are clustered at the MSA/MD level and are shown in parentheses. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.

	Thresholds			
	Tract		Borrower	
	High	Low	High	Low
Interest Rate (%)	-0.002	-0.002	0.004	-0.002
	(0.01)	(0.02)	(0.01)	(0.02)
Credit Score	0.857	-0.817	0.319	-0.817
	(0.82)	(1.24)	(0.66)	(1.24)
Share with Subprime Score (%)	-0.009*	0.006	0.003	0.006
	(0.00)	(0.01)	(0.00)	(0.01)
Debt-to-Income Ratio (%)	-0.101	-0.136	0.126	-0.136
	(0.11)	(0.19)	(0.10)	(0.19)
Combined Loan-to-Value Ratio (%)	-0.326	0.009	0.847***	0.009
	(0.30)	(0.43)	(0.25)	(0.43)

interest rates. The estimated threshold effects for interest rates are well below 1 basis point at each LMI threshold and not statistically significant. Additionally, there is little indication that purchases reduce underwriting standards. None of the threshold effects for average credit scores, the share of loans going to borrowers with subprime credit scores, or average debt-to-income ratios are consistent with reduced underwriting standards at the LMI thresholds. The threshold effect for combined loan-to-value ratios at the high borrower threshold is significant at the 0.1% level; however, the point estimate is modest and there is no evidence of similar effects at the high tract threshold where there are more CRA-induced loan purchases.

6.4. Alternative Kernel Specifications

The estimation results reported in this paper all rely on local-linear approximations of the relationship between tract or borrower relative incomes and the dependent variables. Each of these approximations uses a triangular kernel with the empirically derived bandwidth suggested by Imbens and Kalyanaraman (2012). This section explores whether the results of this paper depend on those choices.

Table 8 shows the main estimation results from the adjusted model when a uniform kernel instead of a triangular kernel. In each of these estimations, optimal bandwidths are recalculated based on the uniform kernel. The results are consistent with main findings of the paper. Loan purchases increase significantly at 3 of the 4 LMI thresholds for banks within their assessment areas, but not for other lenders. There is little evidence that the increase in purchases lead to more originations or fewer loans being retained by lenders in portfolio. Again, there is evidence of reduced direct and indirect GSE loan sales at the high and low tract thresholds.

Figure 9 shows the estimation results using a triangular kernel with a wider bandwidth. Each estimation uses a bandwidth that is double the optimally chosen bandwidth. At the high-borrower threshold, the estimated threshold effect is somewhat lower, but the estimated effects at all but the low borrower threshold remain significant at the 1% level. Some

Table 8: Selected Results from Estimations Using Uniform Kernels

Table shows the estimation results of the adjusted model for the listed dependent variables using HMDA data for 2013-2016 and 2018-2020. Each column shows estimated threshold effects at one of the four LMI thresholds. Parameters in the table display the result from an estimation conducted using all lenders or limited only to the specific lender type listed. All estimations are weighted by the denominator of the dependent variable. Robust standard errors are clustered at the MSA/MD level and are shown in parentheses. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.

	Thresholds			
	Tract		Borrower	
	High	Low	High	Low
Purchases (by select lender type)				
All	1.297***	0.441**	0.238**	0.129
	(0.15)	(0.15)	(0.09)	(0.15)
Inside AA	2.853***	1.687***	0.810***	0.108
	(0.55)	(0.48)	(0.23)	(0.41)
Outside AA	0.299	-0.978	-0.518	-0.333
	(0.48)	(0.68)	(0.32)	(0.52)
Indep. Mort. Bank	0.067	0.090	-0.050	0.030
	(0.13)	(0.15)	(0.06)	(0.14)
Originations (by select lender type)				
All	0.268	0.851	-1.663	-0.677**
	(1.12)	(0.83)	(1.04)	(0.26)
Inside AA	0.414	0.081	0.073	-0.041
	(0.36)	(0.21)	(0.29)	(0.10)
Outside AA	0.111	0.202*	0.110	-0.049
	(0.13)	(0.08)	(0.11)	(0.04)
Indep. Mort. Bank	0.452	0.357	-1.428	-0.263
	(0.78)	(0.57)	(0.81)	(0.22)
Retained Loans	0.091	0.368	0.094	-0.262
	(0.36)	(0.26)	(0.11)	(0.18)
Direct GSE Sales	-0.922***	-0.379	-0.004	-0.293
	(0.25)	(0.30)	(0.17)	(0.31)
Indirect GSE Sales	-3.954***	-1.626***	-0.200	0.277
	(0.43)	(0.42)	(0.20)	(0.43)

Table 9: Selected Estimation Results Using a Wider-than-Optimal Bandwidth

Table shows the estimation results of the adjusted model for the listed dependent variables using HMDA data for 2013-2016 and 2018-2020. Each column shows estimated threshold effects at one of the four LMI thresholds. Parameters in the table display the result from an estimation conducted using all lenders or limited only to the specific lender type listed. All estimations are weighted by the denominator of the dependent variable. Robust standard errors are clustered at the MSA/MD level and are shown in parentheses. Stars denote statistical significance at the 0.1 (***), 1 (**), and 5 (*) percent levels respectively.

	Thresholds			
	Tract		Borrower	
	High	Low	High	Low
Purchases (by select lender type)				
All	1.164***	0.446**	0.224**	0.077
	(0.15)	(0.14)	(0.09)	(0.15)
Inside AA	2.719***	1.528***	0.710**	0.321
	(0.53)	(0.44)	(0.22)	(0.44)
Outside AA	0.487	-1.190*	-0.545	-0.192
	(0.51)	(0.59)	(0.34)	(0.53)
Indep. Mort. Bank	0.014	0.062	-0.163*	0.020
	(0.11)	(0.14)	(0.07)	(0.13)
Originations (by select lender type)				
All	0.162	0.601	-2.143*	-0.794*
	(1.15)	(0.76)	(1.09)	(0.35)
Inside AA	0.358	0.137	0.054	-0.047
	(0.42)	(0.19)	(0.25)	(0.08)
Outside AA	0.018	0.169*	0.064	-0.067
	(0.14)	(0.07)	(0.10)	(0.05)
Indep. Mort. Bank	-0.135	0.125	-2.038*	-0.529
	(0.67)	(0.49)	(0.87)	(0.27)
Retained Loans	0.073	0.299	0.098	-0.340
	(0.40)	(0.23)	(0.10)	(0.19)
Direct GSE Sales	-0.748**	-0.426	0.013	-0.303
	(0.27)	(0.27)	(0.16)	(0.26)
Indirect GSE Sales	-3.874***	-1.857***	-0.130	0.447
	(0.38)	(0.39)	(0.18)	(0.38)

origination results are significant at the 5% level, though these are mostly negative. There continues to be no evidence of threshold effects on the share of loans retained in portfolio, but again direct and indirect loan sales to the GSEs decline at the tract thresholds.

The main results of this paper, therefore, appear to be robust to alternative specifications of the local linear approximations used in the estimations of the adjusted models.

7. Discussion

The policy of allowing banks to meet their CRA retail lending obligations by purchasing loans has been motivated by a belief that purchases increase credit availability in LMI communities by enhancing the liquidity of LMI loans (Community Reinvestment Act Regulations, 2001). The data examined in this paper are consistent with CRA having increased the liquidity of LMI loans but find no evidence that CRA-induced purchases have had any effect on credit availability in LMI communities. Instead, banks within their assessment areas appear to purchase loans that would otherwise be sold to the GSEs and that the GSEs ultimately acquired after a delay of less than 4 months.

While allowing lenders to meet their CRA obligations by purchasing loans appears to confer little benefit to LMI communities, the same cannot be said of banks. LMI shares calculated using purchases are notably higher for banks within their assessment areas than are originations-only shares, with the largest increases at banks whose originations-only LMI shares are lowest. While it is difficult to determine how much these purchases aided banks on their CRA exams, the fact that they chose to make these purchases implies they saw value in them.

While LMI communities appear to experience little in the way of benefits from this policy, assessing the costs to these communities is harder. It is difficult to determine how bank behavior would have changed had purchases not been included or been discounted. That banks would have reduced their loan purchases at the LMI thresholds seems likely. But would they also have increased their efforts to originate loans in LMI communities? That counterfactual is harder to answer.

The possibility exists, however, that the answer is "yes" and that banks are putting less effort into originating loans in LMI communities because of this policy. If banks are being less proactive about making LMI loans, less-competitive mortgage terms, such as higher interest rates, would be expected. Higher interest rates make mortgages more expensive which could have reduced the number of households who were able to move into homeown-

ership and, for those that did, increased the number who defaulted on their less-affordable loans. The costs to these communities of this policy may be substantial.

One caveat that comes with this analysis is that, while regression discontinuity is a robust method of detecting causal effects at thresholds where treatments change, its external validity is limited. That is, regression discontinuity can be ineffective at identifying policy-induced changes that occur away from those thresholds. It is possible that the CRA's equal treatment of purchases and originations may have caused banks to increase purchases at tract- or borrower-relative-income levels lower than 80 percent and, at those lower incomes, increased originations.

While possible, there are reasons to doubt such an outcome. With the affordable housing goals on Fannie Mae and Freddie Mac (as well as their Duty to Serve requirements) there is already a source of secondary market liquidity for loans to sufficiently creditworthy borrowers in LMI communities. It is unclear that CRA-induced purchases add anything more than short-term liquidity for LMI loans below the threshold unless banks are willing to purchase loans that the GSEs are not to satisfy their CRA obligations. There seems little reason to believe that banks would take on such additional risk given the CRA's requirements about safe and sound business practices and the apparent ease with which they can increase their all-in LMI shares by purchasing and reselling GSE-qualifying loans.

Regardless of whether these results are externally valid, however, the evidence in this paper clearly indicate that banks purchase significantly more loans at the CRA's LMI thresholds with little-to-no effect on the volume of mortgage credit flowing to LMI communities.

8. References

Aaronson, Daniel, Jacob Faber, Daniel Hartley, Bhashkar Mazumder, and Patrick Sharkey (2021) "The Long-Run Effects of the 1930s HOLC 'Redlining' Maps on Place-Based Measures of Economic Opportunity and Socioeconomic Success," *Regional Science and Urban Economics*, 86(103622), pp. 1–15.

Agarwal, Sumit, Efraim Benmelech, Kittai Bergman, and Amit Seru (2012) *Did the Community Reinvestment Act (CRA) Lead to Risky Lending?* National Bureau of Economic Research; National Bureau of Economic Research Working Paper No. 18609.

Ambrose, Brent W and Thomas G Thibodeau (2004) "Have the GSE Affordable Housing Goals Increased the Supply of Mortgage Credit?" *Regional Science and Urban Economics*, 34(3), pp. 263–73.

An, Xudong and Raphael W Bostic (2008) "GSE Activity, FHA Feedback, and Implications for the Efficacy of the Affordable Housing Goals," *The Journal of Real Estate Finance and Economics*, 36(2), pp. 207–31.

Avery, Robert B. and Kenneth P. Brevoort (2015) "The Subprime Crisis: Is Government Housing Policy to Blame?" *Review of Economics and Statistics*, 97(2), pp. 352–63.

Avery, Robert B., Kenneth P. Brevoort, and Glenn B. Canner (2007) "Opportunities and Issues in Using HMDA Data," *Journal of Real Estate Research*, 29(4), pp. 351–79.

Avery, Robert B., Tim Critchfield, Davis Craig, Ian H. Keith, Ismail E. Mohamed, Saty Patrabansh, Jay D. Schultz, and Rebecca Sullivan (2021) *National Mortgage Database Technical Documentation*. No. 1. Federal Housing Finance Agency.

Avery, Robert B, Raphael W. Bostic, and Glenn B. Canner (2005) "Assessing the Necessity and Efficiency of the Community Reinvestment Act," *Housing Policy Debate*, 16(1), pp. 143–72.

Barr, Michael S. (2005) "Credit Where It Counts: The Community Reinvestment Act and Its Critics," *New York University Law Review*, 75, pp. 512–745.

Bhutta, Neil (2011) "The Community Reinvestment Act and Mortgage Lending to Lower Income Borrowers and Neighborhoods," *The Journal of Law and Economics*, 54(4), pp. 953–83.

Bhutta, Neil (2012) "GSE Activity and Mortgage Supply in Lower-Income and Minority Neighborhoods: The Effect of the Affordable Housing Goals," *The Journal of Real Estate Finance and Economics*, 45(1), pp. 238–61.

Bhutta, Neil and Glenn B. Canner (2009) "Did the CRA Cause the Mortgage Market Meltdown?" *Community Dividend (Federal Reserve Bank of Minneapolis). Retrieved June*, 14, p. 2010.

Bhutta, Neil and Daniel Ringo (2015) "Assessing the Community Reinvestment Act's Role in the Financial Crisis," *FEDS Notes*, (2015-05), pp. 26–21.

Bierman, Leonard, Donald R. Fraser, and Asghar Zardkoohi (1994) "The Community Reinvestment Act: A Preliminary Empirical Analysis," *Hastings Law Journal*, 45, pp. 383–412.

Bostic, Raphael W and Stuart A Gabriel (2006) "Do the GSEs Matter to Low-Income Housing Markets? An Assessment of the Effects of the GSE Loan Purchase Goals on California Housing Outcomes," *Journal of Urban Economics*, 59(3), pp. 458–75.

Butcher, Kristin F. and Ana Patricia Muñoz (2017) "Using Credit Reporting Agency Data to Assess the Link Between the Community Reinvestment Act and Consumer Credit Outcomes," *Cityscape*, 19(2), pp. 85–108.

Calonico, Sebastian, Matias D. Cattaneo, Max H. Farrell, and Rocío Titiunik (2019) "Regression Discontinuity Designs Using Covariates," *The Review of Economics and Statistics*, 101(3), pp. 442–51.

Calonico, Sebastian, Matias D. Cattaneo, and Rocío Titiunik (2015) "Rdrobust: An R Package for Robust Nonparametric Inference in Regression-Discontinuity Designs," *The R Journal*, 7(1), pp. 38–51.

Canner, Glenn and Joe M. Cleaver (1980) "The Community Reinvestment Act: A Progress Report," *Federal Reserve Bulletin*, 66, pp. 87–96.

Collin, Lindsay J., Anne H. Gaglioti, Kristen M. Beyer, Yuhong Zhou, Miranda A. Moore, Rebecca Nash, Jeffrey M. Switchenko, Jasmine M. Miller-Kleinhenz, Kevin C. Ward, and Lauren E. McCullough (2021) "Neighborhood-Level Redlining and Lending Bias Are Associated with Breast Cancer Mortality in a Large and Diverse Metropolitan Area," *Cancer Epidemiology, Biomarkers & Prevention*, 30(1), pp. 53–60.

Community Reinvestment Act Regulations (2001) "Joint Advance Notice of Proposed Rulemaking," *Federal Register*, 66(139), pp. 37602–8.

Community Reinvestment Act Regulations (2004) "Joint Notice of Proposed Rulemaking," *Federal Register*, 69(25), pp. 5729–47.

Community Reinvestment Act Regulations (1993) "Joint Notice of Proposed Rulemaking," *Federal Register*, 58(243), pp. 67466–508.

Ding, Lei and Leonard Nakamura (2021) "'Don't Know What You Got till It's Gone": The Community Reinvestment Act in a Changing Financial Landscape," *Journal of Real Estate Research*, 43(1), pp. 96–122.

Fishback, Price, Jonathan Rose, Ken Snowden, and Thomas Storrs (Forthcoming) "New Evidence on Redlining by Federal Housing Programs in the 1930s," *Journal of Urban Economics*.

Fishbein, Allen J. (1992) "The Community Reinvestment Act After Fifteen Years: It Works, but Strengthened Federal Enforcement Is Needed," *Fordham Urban Law Journal*, 20, pp. 293–310.

Ghent, Andra C., Rubén Hernández-Murillo, and Michael T. Owyang (2015) "Did Affordable Housing Legislation Contribute to the Subprime Securities Boom?" *Real Estate Economics*, 43(4), pp. 820–54.

Hillier, Amy E. (2003) "Redlining and the Home Owner's Loan Corporation," *Journal of Urban History*, 29(4), pp. 394–420.

Imbens, Guido W. and Joshua D. Angrist (1994) "Identification and Estimation of Local Average Treatment Effects," *Econometrica*, 62(2), pp. 467–75.

Imbens, Guido and Karthik Kalyanaraman (2012) "Optimal Bandwidth Choice for the Regression Discontinuity Estimator," *The Review of Economic Studies*, 79(3), pp. 933–59.

Lee, Hyojung and Raphael W. Bostic (2020) "Bank Adaptation to Neighborhood Change: Mortgage Lending and the Community Reinvestment Act," *Journal of Urban Economics*, 116, p. 103211.

Macey, Jonathan R. and Geoffrey P. Miller (1993) "The Community Reinvestment Act: An Economic Analysis," *Virginia Law Review*, 79, pp. 291–348.

Mitchell, Bruce and Juan Franco (2018) *HOLC 'Redlining' Maps: The Persistent Structure of Segregation and Economic Iquality*. National Community Reinvestment Coalition, pp. 1–29. Available at: https://ncrc.org/download/49454/.

Nardone, Anthony, Joey Chiang, and Jason Corburn (2020) "Historic Redlining and Urban Health Today in U.S. Cities," *Environmental Justice*, 13(4), pp. 109–19.

Nardone, Anthony, Kara E. Rudolph, Rachel Morello-Frosch, and Joan A. Casey (2021) "Redlines and Greenspace: The Relationship Between Historical Redlining and 2010 Greenspace Across the United States," *Environmental Health Perspectives*, 129(17006), pp. 1–9.

Pinto, Edward (2010) "Triggers of the Financial Crisis,"

Reid, Carolina, Ellen Seidman, Mark Willis, Lei Ding, Josh Silver, and Janneke Ratcliffe (2013) *Debunking the CRA Myth – Again*. UNC Center for Community Capital Research Report; UNC Center for Community Capital. Available at: https://communitycapital.unc.edu/wp-content/uploads/sites/340/2013/01/DebunkingCRAMyth.pdf.

Ross, Stephen L. and Geoffrey M. B. Tootell (2004) "Redlining, the Community Reinvestment Act, and Private Mortgage Insurance," *Journal of Urban Economics*, 55(2), pp. 278–97.

Swire, Peter P. (1993) "Safe Harbors and a Proposal to Improve the Community Reinvestment Act," *Virginia Law Review*, 79, pp. 349–82.

Wallison, Peter J. (2011) *Dissent from the Majority Report of the Financial Crisis Inquiry Commission*. American Enterprise Institute Press.

Wilson, Bev (2020) "Urban Heat Management and the Legacy of Redlining," *Journal of the American Planning Association*, 86(4), pp. 443–57.