The Effects of Competition in Consumer Credit Markets*

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Abstract

Using changes in financial regulation that create exogenous entry in some consumer credit markets, we find that increased competition induces banks to become more specialized and efficient, while deposit rates increase and borrowing costs for riskier collateral decline. However, shadow banks change their credit policy when faced with more competition and aggressively expand credit to riskier borrowers at the extensive margin, resulting in higher default rates. These results show how the form of intermediation can shape economic fluctuations. They also suggest that increased competition can lead to large changes in credit policy at institutions outside the traditional supervisory umbrella, possibly creating a less stable financial system.

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I. Introduction

In the past decade, the US financial system has been reshaped by large-scale regulatory changes and continued rapid technological innovation, especially in consumer credit markets. The tumult of the recent past has also led to new theories linking competition in credit markets and the form of intermediation to broader economic fluctuations (Brunnermeier and Sannikov (2014), He and Krishnamurthy (2015), Gertler and Kiyotaki (2010)). Much of this theoretical work is ongoing and the consequences of competition remain ambiguous. Greater competition in credit markets can generate more efficient intermediation, reduce borrowing costs and relax credit constraints for marginalized borrowers.[1] But more competition can also erode the profitability of incumbent financial institutions, leading to riskier lending and unstable banking.[2] In the most extreme case, increased competition can foster an ex-post misallocation of credit to riskier borrowers, producing asset price booms and busts (Mian and Sufi (2009), Favara and Imbs (2015), and Rajan and Ramcharan (2015)). Although these questions have grown in importance in recent years, they have a long history. In the decades after the Great Depression for example, regulatory policy, like Glass-Steagall, explicitly sought to restrain banking competition and create local monopolies across the US in order to contain risk-taking and perceived credit misallocation (Shull and Hanweck (2001)).

Therefore, evidence on the effects of consumer credit market competition can help in evaluating better these new theories linking intermediation to economic fluctuations and inform the ongoing regulatory debates. However, because unobserved factors that determine entry into markets also shape ex-post outcomes—endogenous entry—identifying the effects of financial sector competition remains difficult. To address better this identification challenge, and to provide new evidence on the effects of competition in the modern financial system, where now both depository institutions

[1] Recent academic surveys include Allen and Gale (2004), Beck (2008), and Claessens (2009); Vives (2016) provides a book length treatment of many of the underlying theoretical ideas. Bernanke (2009) and Vickers (2010) discuss some of the policy issues surrounding financial competition within the US and international contexts respectively. Earlier work on the distributional effects of credit access include Aghion and Bolton (1997), Banerjee and Newman (1991), and Galor and Zeira (1993).

[2] Bhattacharya (1982), Keeley (1990), Besanko and Thakor (1993), and Hellmann et al. (2000) are seminal references in the "franchise value" literature: How increased competition reduces bank profits and increases the incentives for greater risk-taking. In contrast, Boyd and Nicoló (2005) show that competition can lower lending rates, inducing firms to choose safer projects and thereby improving bank asset quality and safety. Berger et al. (2009) find that banks with less market power have more overall risk exposure, but at the same time have higher equity capital ratios to partially offset their risk exposure. Martinez-Miera and Repullo (2010) point to the limits of this argument, noting that lower rates also reduce bank revenues, possibly increasing the bank failure rates. A number of papers also emphasize the interaction between information asymmetries, lending standards and competition. See for example Rajan (1994), Petersen and Rajan (1995) and Dell'Ariccia and Marquez (2006).

and shadow banks compete, this paper uses recent changes in federal regulations that allowed some credit unions (CUs) to compete directly with banks and shadow banks–examples of the latter include captive auto lenders and pools of private capital that originate and securitize consumer loans.

CUs are a major source of consumer finance in the US. Individuals with a common bond—such as employees of a university or residents of a town—can establish a credit union to access financial services. The industry serves about 105 million people, has about $1.4 trillion in assets, and originates roughly 28 percent of all new car loans and accounts for over 25 percent of all consumer unsecured lending in the US.[3] The analysis is thus not only of broad economic significance, but the regulatory change that we use is a new and plausibly exogenous source of variation in entry across local credit markets.

CUs are traditionally restricted from intermediation outside of the common bond. But under the "low income" rule, some CUs that serve lower income areas have long been exempted from this competition restriction and can freely lend or accept deposits outside their common bond. Beginning in 2008, the industry's federal regulator changed both the legal eligibility standard for the "low income" rule and eventually the process by which a CU could become eligible. Competition increased sharply thereafter. By 2016, the total assets of "low income" CUs, those now able to compete directly with incumbent institutions, rose to nearly $400 billion—an almost 8 fold increase compared to 2008.

The research design exploits the fact that to reduce the regulatory burden of demonstrating eligibility under the revised legal standard, the federal regulator eventually determined each CU's eligibility for the low income exemption at the time of the supervisory exam. Examination schedules are on a preset cycle. Their timing is not driven by local economic conditions, expectations about future lending opportunities within the local market, beliefs about local demand, or the behavior of local incumbent intermediaries. This link between the timing of "entry"—the lifting of the common bond competition restriction—and the supervisory exam schedule is a potentially exogenous increase in local competition. The regulator also issued a notification letter to potentially elegible CUs. The narrative evidence around this letter also weighs against strategic entry: Once notified

[3]See Experian's 2007 report on http://www.experian.com/assets/automotive/quarterly-webinars/2017-q3-safm-recording.pdf.

of their LICU-eligibility, over 90 percent of these institutions take-up the program within a year, in order to benefit from diversifying their lending outside the common bond constraint, and gain access to federal grants.

The statisical evidence comports with this narrative. In each of the four quarters before a CU becomes designated as a low income credit union (LICU), there is no change in lending or any other balance sheet observable. But once designated, there is an immediate surge in marketing expenses followed by a significant balance sheet expansion. Likewise, past lending growth at nearby banks–those within a five mile radius of a CU–does not predict whether a CU becomes a LICU, suggesting that CUs do not select into LICU status when loan demand at nearby banks is high.

The form of intermediation might matter and we study the impact of this increased competition on both incumbent banks, as well as on shadow or non-banks. Among banks, there is a mirror decline in lending and deposit growth when the number of nearby LICUs increases—those within a five-mile radius of the bank's headquarters. Because many banks set their loan and deposit pricing at the branch level, we also study the effects of competition using bank branch-level data on pricing. The evidence shows that deposit interest rates increase and lending rates decline sharply, especially for riskier collateral (Goldstein and Pauzner (2005)). For example, the rate on used car loans declines by about 10 basis points one year after a standard deviation increase in the number of low-income CUs within a 5-mile radius of the bank's branch. The fine level of disaggregation in the data allows us to establish robustness using parametric controls, such as zip-code level house prices changes and non-parametric controls such as census tract fixed effects as well as county by year-quarter fixed effects.

There is also evidence that increased competition drives selective survivorship and improves efficiency. LICU entry is associated with more bank failures, especially among the smaller, less well capitalized banks. Banks also respond to increased LICU competition by becoming more specialized.[4] CUs traditionally lend to consumers and we find that banks tend to accommodate LICU entry by shifting their loan portfolio towards commercial and industrial loans. After a one standard deviation increase in LICU competition, the growth in commercial and industrial loans increases by about 0.14 percentage point. This shift in the loan product mix reduces the

[4]This result is related to a rich and large literature on competition and specialization more generally–see for example (Aghion and Howitt (1992), Boot and Thakor (2000), and Melitz (2003)).

substitutability between the two types of institutions and is associated with improved profitability at surviving banks when LICU competition increases.

Shadow banks respond very differently to increased competition. These institutions, like captive auto-finance lenders and private funding pools, are thinly capitalized, highly specialized, unregulated institutions that mainly use short-term credit markets to fund arms-length consumer loans, which are then securitized (Benmelech et al. (2017)). Also, non-banks usually have little alternative to lending in their primary market and make riskier loans, since they face fewer regulatory constraints and can in principle diversify risks through securitization (Gennaioli and Shleifer (2010)). And unlike local banks, the funding costs of shadow banks remain unchanged when local competition increases, allowing them to defend market share more aggressively. To understand the effects of increased competition at the extensive margin across different types of lenders, we use individual-level data that identify the Equifax Risk Score, zip-code and importantly whether the lender in each car loan is a bank, CU or a non-bank.

The data show that competition affects an expansion in automobile lending at the extensive margin as well as a dramatic reallocation of credit towards subprime borrowers—a "race to the bottom". Much of this shift in credit policy appears to be driven by non-bank lenders. At the extensive margin, the estimates show that a one standard deviation increase in the number of LICUs is associated with a 0.7 percent increase in the number of newly originated car loans inside a zip code over the next twelve months. Of which, the number of newly originated loans increase by about 0.5 and 1.2 percent, respectively for CUs and non-banks. In keeping with the balance sheet evidence indicating that banks tended to accommodate entry by shifting towards business lending, the impact of increased competition on car loan origination is insignificant among banks.

Information on borrower Equifax Risk Scores helps us measure the extent of the credit policy shift. We find that both CUs and non-banks expand credit at the extensive margin sharply towards borrowers in the bottom quartile of the credit risk distribution. For this riskiest sample of borrowers, a one standard deviation increase in competition is associated with a 1.2 percent increase in newly originated car loans by CUs and a nearly 2.2 percent increase by non-bank lenders. The effects are economically and statistically insignificant for safer borrowers. Notwithstanding the exogeneity in the timing of LICU designations, a concern is that aggregate regulatory and funding shocks might have allowed non-banks to expand credit into riskier areas during this period, helping to explain

the simultaneous LICU and non-bank credit expansion. We show however that these results are robust to most parametric and non-parametric controls, including zip-code specific time trends. We also find evidence that this reallocation in automotive credit to riskier borrowers on account of increased competition is also associated with a significant increase in non-performing loans.

Taken together, these results show that increased competition can significantly reduce the cost of credit and discipline inefficient banks. Also, once competition increases, previously marginalized borrowers gain improved access to credit. But consistent with theories of competition and credit misallocation, the evidence unambiguously shows that increased competition can lead to a significant reallocation of credit towards riskier borrowers. This appears especially true when incumbent lenders can easily securitize loans, have few other lending opportunities, and are lightly regulated—shadow banks. That competition is also associated with rising delinquencies and leverage suggests that some of the credit expansion might be socially inefficient.

We cannot measure the net present value of the loans at the time of origination, but increased competition from the regulated financial system that induces the shadow banking system to originate and distribute a greater volume of riskier loans can lead to greater fragility, especially if "neglected risks" materialize (Gennaioli et al. (2015)). This evidence on a competition induced increase in risk-taking by the unregulated non-bank sector also weighs against the common policy view that enhanced supervision of the traditional banking sector allows economies to reap the benefits of increased competition while mitigating socially harmful risk-taking.[5]

This is the first paper to use the relaxation in lending and deposit-taking restrictions at CUs to study the effects of competition on both banks and shadow banks. We however build on enormously influential literatures that have used various deregulation waves across US states beginning in the 1970s or the variation in cross-state regulatory environments in the period before the Great Depression to tackle the identification problem inherent when studying the effects of entry (Black and Strahan (2002), Jayaratne and Strahan (1998) and Carlson and Mitchener (2006)).[6] The most common interpretation of this literature is that increased competition in the financial sector leads

[5]See the discussion in the Economist at https://www.economist.com/finance-and-economics/2009/06/25/deliver-us-from-competition.

[6]There is also a sizable literature that uses cross-country variation in financial regulation to understand the effects of competition–see for example Barth et al. (2013) and Demirguc-Kunt et al. (2004). Unobserved heterogeneity remains a key challenge in that setting. Braggion et al. (2017) use historical micro data from the UK to overcome some of these identification challenges, while Carlson et al. (2018) use population changes as exogenous variation during the National Banking Era in the US for identification.

to greater efficiency and faster economic growth.

But evidence drawn in this literature largely from only two sources of variation and built upon mostly aggregate data—state or county level data—makes it difficult to identify the mechanism through which competition affects broader outcomes, including whether competition leads to the possible misallocation of credit. Notably, while aggregate outcomes, such as state-level economic growth or new business incorporations might improve after increased competition, only disaggregated data on credit standards can reveal how competition affects credit access at the extensive margin. Also, some theories predict that the impact of competition can differ between consumer and corporate credit markets. Unlike business lending, consumer lending contracts–a mortgage or an automobile loan–are more homogeneous across the country and the underlying collateral, especially in the case of automobiles, require little specialized knowledge to value. Lenders also tend to operate with more information in consumer credit markets (Pagano and Jappelli (1993)). Thus, while increased competition could lead to more efficient business lending, it could also produce an increased volume of lower quality loans in consumer credit markets, as lenders cut rates and possibly overestimate the credit quality of their clientele (Broecker (1990)).

Also, the modern financial system differs considerably from previous empirical settings. Today both the highly regulated depository institutions and the shadow banking system now compete directly in consumer credit markets. Yet little is known about how the unregulated "system" might respond to increased competition from the regulated "system". For example, the deregulatory waves of the 1970s led to increased competition on both sides of the balance sheet for depository institutions at a time when many of these institutions retained loans on balance sheet. But today non-bank lenders operate an originate-to-distribute volume business and their funding costs remain unchanged when local competition increases. This can allow non-banks to mount a more aggressive defense of market share in the information-rich consumer lending market relative to local depository institutions when local competition increases.[7]

[7]The United States has had significant experience with competition between dual banking systems. In the decades prior to the Great Depression, there was an explosion of banks, as both state and national bank regulators competed by issuing new bank charters and making credit more easily available. Observers at the time noted that this competition led to rampant over-banking and greater instability: "One of the major causes of lax-chartering policies was competition between the national and state banking systems. Unfortunately, this competition was not always in the field of the banking virtues–not always intent on winning the distinction of having the best banks and the most able bankers–but rather it appeared at times controlled by the ambition to have the most banks in the greatest number of places"–page 12, the Economic Policy Commission, 1935.

II. Research Design

To understand the effects of competition in credit markets, we use changes in federal regulations that relaxed restrictions on some credit unions' ability to compete directly with banks and non-bank financial institutions for loans and deposits in local markets. This subsection offers narrative and statistical evidence on why this regulatory change is a conditionally exogenous source of variation in entry into local credit markets across the US that can help identify the effects of competition on both banks and non-banks.

A. The Narrative Evidence

Credit unions (CU) are not-for-profit tax-exempt financial institutions that operate in the model of traditional relationship-based financial intermediation. Employees of a specific corporation—fraternal bonds—or residents that live within a particular radius of a town—geographic bond—might for example form a CU in order to use relationship-based financial services. They fund themselves primarily through membership deposits and do not usually raise outside equity or use subordinated debt. CUs also make loans to geographically proximate consumers and small business within the same narrow field of membership or bond. The National Credit Union Administration (NCUA) is the industry's federal regulator.

In exchange for CUs' tax-exempt status, federal regulations and the courts have traditionally restricted CUs' ability to compete with banks. To be sure, the boundaries of competition between banks and CUs remain highly contested and continue to be shaped by ongoing legal and political pressure.[8] But generally, on the liability side of the balance sheet, CUs are not allowed to compete with banks for deposits and can only accept deposits from members within their chartered field of membership. Lending is also similarly restricted to members within the same field of membership. These regulations further restrain the scope for competition in commercial lending, capping a credit

[8]Competitive pressures between banks and CUs have long led to legal and legislative battles. Beginning in the mid 1970s, the American Bankers Association (ABA) sued to stop CUs from offering interest bearing checking accounts; Congress eventually sided with the CU industry. In the 1990s, the ABA sued to stop the formation of CUs based on multiple common bonds. The Supreme Court sided with the ABA, but Congress quickly allowed multiple common bonds, in exchange for restrictions on CU business lending. More recently, community bankers sued the NCUA in 2016 to stop CUs from purchasing commercial loans and loan participation originated by other institutions without counting these loans against their restrictions on business lending—the courts sided with the NCUA. The ABA also filed suit against the NCUA in 2016 because of a loosening of field of membership restrictions for community-chartered CUs that allowed these institutions to serve large geographic areas; this case remains in litigation. See the surveys in https://www.americanbanker.com/news/credit-unions-vs-banks-how-we-got-here.

union's member business lending—commercial and industrial loans—to either 1.75 times the net worth of a well-capitalized credit union or 12.25 percent of total assets.[9]

However, the Federal Credit Union Act of 1972 authorizes the NCUA to designate a credit union as "low income", allowing the designated CU to operate outside of its field of membership and compete directly with banks and non-banks for deposits and lending opportunities. In 1993, the NCUA specified that a federal credit union qualified for "low-income" designation if more than 50 percent of its membership was low income. Under the 1993 rule, to be "low income", a member's household income needed to be less than or equal to 80 percent of the national median household income. These regulations also provided an adjustment for higher cost areas derived from data from the Employment and Training Administration of the Department of Labor.

In 2006, a NCUA task force found the "low-income" regulation outdated and impractical. The task force noted that the use of the "household income" standard in the 1993 rule was inconsistent with the subsequent adoption of the family income standard by other federal agencies when defining economically undeserved areas.[10] The task force also noted that the Department of Labor based adjustment for high cost areas was outdated and geographically incomplete. In response to these findings, in 2008 the NCUA revised the 1993 low-income rule and adopted the family income standard for 2009. Figure 1 summarizes the key institutional changes in this rule.[11]

The 2009 rule change had little impact on the number of LICUs (Figures 2 and 3). Many credit unions were unaware of the rule change or were baffled by the difficult application process and the new family income standard.[12] Many CUs had little current data from their membership on either members' individual or especially family income. And for those with individual membership income data, it was unclear whether these data could be legally benchmarked against the family income standard. The NCUA thus issued a revised low-income rule in 2010 that clarified the income

[9] See the Credit Union Membership Access Act (CUMAA) (P.L.105-219) passed in 1998.

[10] Notably, the US Treasury provides support for financial institutions—the Community Development Banking and Financial Institutions Act of 1994—that operate in the undeserved areas; these areas are in part legally identified using the 80 percent family income standard for the census tract.

[11] See for example page 9 of https://www.ncua.gov/services/Pages/small-credit-union-initiatives/Documents/Maximizing-Low-Income-Designation.pdf. Also see the following links for more information:
https://www.ncua.gov/Legal/Documents/LowIncomeDesignationFactSheet.pdf
https://www.ncua.gov/services/Pages/resources-expansion/fom-expansion/low-income.aspx

[12] Consider the following quote from Joseph Thomas Jr., the CEO of Fairfax County Federal Credit Union, on his CU's LI eligibility: "We were very surprised to find that we were eligible". This CU has about 14,500 members, mostly active or retired Fairfax county government employees, and is located just 25 miles from the NCUA. https://www.bizjournals.com/washington/blog/2014/08/credit-unions-designated-to-serve-low-income.html

standard: Individual income data would be benchmarked against median individual income data from the 2010 US Census, while family income data would be benchmarked against median family income from the census.

Central to our identification strategy, the 2010 revision also linked low-income designations to the timing of the supervisory bank exam:

> "NCUA will make the determination of whether a majority of a FCU's members are low-income based on data it obtains during the examination process. This will involve linking member address information to publicly available information from the U.S. Census Bureau to estimate member earnings. Using automated, geo-coding software, NCUA will use member street addresses collected during FCU examinations to determine the geographic area and metropolitan area for each member account. NCUA will then use income information for the geographic area from the Census Bureau and assign estimated earnings to each member."[13]

Under this 2010 revision then, CUs earliest on the examination schedule would be notified sooner of their LI eligibility; those eligible for designation quickly selected into low-income status. The key facts are that the timing of these supervisory examination schedules are pre-specified and are not driven by local economic conditions, expectations about future lending opportunities within the local market, beliefs about local demand, or the behavior of local banks—banks are regulated and examined independently by the Federal Reserve and state banking authorities. Thus, this linking of entry into LI status with the timing of the supervisory exam is a potentially exogenous redefinition of the extent of the market for designated low-income credit unions (LICUs), allowing them to compete directly with local financial institutions on both sides of the balance sheet.

A notification letter sent in the second quarter of 2012 to 1,003 potentially eligible CUs accompanied the implementation of this revised eligibility process. Within a year of the letter, over 900 of these institutions selected into low-income status.[14] Because the letter was sent to eligible institutions, of which the overwhelming majority selected into the program, there is again little concern that beliefs about local demand likely played a role in driving the timing of selection into low income status. These institutions are non-profits, but the very large take-up rate, once they

[13] NCUA 12 CFR Part 701, published in the Federal Register Vol.75, No. 150, 8/05/2010.
[14] See for example https://www.ncua.gov/newsroom/Pages/NW20131219LowIncomeCUs.aspx.

learn of the program, reflect the opportunity to diversify their business outside of the common bond constraint as well as the increased availability of federal grants and outside capital injections. The small number that delayed entry are the very tiny institutions with limited organizational capacity; some 14 small CUs still manually filed Call Reports and received computers from the NCUA to help modernize their operations.[15] Figures 2 and 3 show the effects of the letter and the subsequent automation of eligibility linked to supervisory exams. The fraction of CUs designated as LICUs rose from its steady-state level of around 12 percent in 2009 to 36 percent by the end of 2015.

Stepping back from the details, even the overall timing of the LI rule overhaul appears exogenous with respect to broader economic conditions. Recall that the motivation for the revision to the original 1993 rule was begun in 2006, at the peak of the business cycle and did not anticipate the imminent economic collapse and subsequent concerns about local credit supply or demand. Also, the subsequent timing of the rule's finalization and implementation over the sample period was significantly shaped by the interplay between data constraints on membership income and the need to clarify the family income regulatory standard.

B. The Statistical Evidence

There are possible reasons to be skeptical of the argument that the linking of selection into the LI program to the supervisory exam date provides a conditionally exogenous source of variation in local credit market competition. Weaker financial institutions are examined over an abbreviated exam cycle–6 months versus the standard 18 month cycle–and it is possible that weaker institutions could enter into low-income status earlier than eligible but stronger credit unions that are examined less frequently. It is also possible that eligible credit unions that face declining local lending opportunities or worsening profitability might select earlier into low-income status conditional on eligibility—the standard Ashenfelter dip. At the same time, incumbent banks operating in these local markets might also face a similar decline in lending and profitability. These forces can then lead to a spurious association between more low-income CUs—greater competition in an area—and worse outcomes at incumbent financial institutions. Of course, as Table 1 shows, the median LICU and non-LICU are very similar on observables, suggesting that they are unlikely to be subject to

[15] See https://www.ncua.gov/Legal/Documents/Reports/AR2012.pdf and the discussion on capacity building at small CUs (page 38).

dissimilar shocks.[16]

Nevertheless, this narrative evidence is convincing up to a point, and we next turn to statistical evidence on the behavior of credit unions in the period around designation in order to investigate whether balance sheet trends at the CU-level might systematically precede selection into low income CU status. These tests also measure the impact of low income status on subsequent balance sheet and income outcomes, helping to reveal the potential competitive impact of these regulatory changes.

The basic specification uses an indicator variable that equals 1 in the quarter a credit union selects into low-income status and 0 otherwise. To detect pre-existing balance sheet or profitability trends in the quarters before selection into low-income status, the baseline specification also includes four leads of this variable. We also include four lags of this indicator variable, as well as a post-low-income indicator variable that equals one in the years following low income status. To absorb non-parametrically pre-existing factors, like the relative income of a credit union field of membership that might determine eligibility, all specifications include credit union fixed effects; we also include the county of headquarters-by-year-quarter fixed effects to absorb local economic conditions; standard errors are clustered at the credit union level.

We report the results from these specifications in Table 2, which uses the full sample of available credit unions. There is no evidence that the timing of selection into low income status is driven by pre-existing trends in balance sheet outcomes or profitability. Instead, entry into low income status leads to a sizable increase in local credit market competition, as LICUs significantly expand their marketing and advertising to reach new customers after LI designation. There is a concomitant increase in lending growth, especially in the case of car loans, as well as deposit growth after low income designation.

The dependent variable in column 1 is loan growth, defined as the quarter on quarter change in lending, scaled by assets in the previous quarter. In the four quarters before designation, lending growth is not significantly different relative to other periods and institutions. But the effects of low income status appear almost immediately. In the quarter of low income designation, the coefficient doubles and becomes statistically significant one quarter after designation. The impact of designation on lending growth peaks about 2 quarters afterwards, and lending growth is about

[16] Table IA.1 provides a list of variable items from the Call Report data.

0.27 percentage point or 0.11 standard deviation higher than otherwise in that quarter. The long-run effect is also significant: average lending growth one year and beyond after designation is about 0.1 percentage point higher than otherwise. Figure 4 depicts the findings in column 1 of Table 2, plotting the coefficients in the four quarters before and after designation, and one year after designation.

During the sample period, the NCUA increasingly allowed CUs to broaden the boundaries of competition with other financial institutions using multiple common bonds. A credit union could for example apply to both serve the teachers of Boston—its traditional field of membership—and also residents of Massachusetts. This is of course distinct from the LI rule with its exogenous timing, but it could also affect inference. As a robustness check, Table IA.2 in the internet appendix shows that the impact of LI designation on lending growth among CUs with a single bond as well among those that serve multiple bonds is similar.

The CU call report disaggregates lending into broad consumer categories, and columns 2 and 3 of Table 2 suggest that automobile loans accounted for much of the increase in loan growth after low income designation. From column 2, the point estimate in the quarter of designation becomes statistically significant and is about 100 times larger than the previous quarter. At its peak, about two quarters after low-income designation, the growth in car loans is about 0.16 percentage point or 0.1 standard deviation higher than otherwise.

In contrast, there is no significant evidence of any change in real estate lending around the low-income designation period. Column 4, using the loan to assets ratio, suggests that low-income CUs rebalanced their assets towards loans after designation, as the ratio of loans to assets increases by about 1.3 percentage points in the years after designation. However, there is also evidence of an expansion at the extensive margin, as asset growth itself is significantly higher after designation (column 5).

Columns 6 and 7 show that this balance sheet expansion was largely financed by faster deposit growth after low-income designation. After the lifting of the restrictions on deposit taking, the growth in deposits significantly increases in the subsequent quarter. Deposit growth in the years after designation is about 0.18 percentage point or 0.05 standard deviation higher than otherwise. There is also evidence that after low-income designation, earnings, rather than being retained and added to net worth, are increasingly lent out, with net worth – the ratio of total equity, which

includes retained earnings, to assets – declining by 0.4 percentage point.

A large and immediate increase in marketing and promotional expenses after LI designation appears to help facilitate this balance sheet expansion. The dependent variable in column 8 is the log of "educational and promotional expenses", which captures expenditures on advertising and marketing. In the quarter of designation, these expenses jump by about 3 percent, gradually rising thereafter. One year and beyond after designation, marketing expenses are about 6 percent higher than otherwise. The impact of designation on the log number of members is less rapid, since new customers need not become members immediately, but one year out, membership is about 1.4 percent higher than otherwise (column 9).

Finally, despite the increase in marketing costs to attract new customers, the average return on equity is significantly higher one year after low-income designation (column 10), and there is no evidence of any trend in earnings in the quarters before low-income designation. Across these specifications there is virtually no significant evidence of any trend in lending, deposit-taking, net-worth profitability or even advertising expenses in the quarters before entry into low-income status. Only one out of the 40 coefficients in the pre-low-income quarters is significant (at the 10 percent level)—car loans growth (column 2).

That said, the internet appendix considers a variety of robustness checks to help gauge the sensitivity of these results to the choice of control group. In particular, eligibility for low-income designation is restricted to CUs in lower income areas, but Table 2, which uses the full sample of about 6,000 CUs, includes credit unions in the control group that are ineligible for designation on account of their membership's relative income. It also includes LICUs designated under the previous regulatory regime. In both instances, these institutions could in turn differ in important ways from eligible CUs, resulting in misleading inference.

Table IA.3 excludes the previously designated LICUs; the results remain unchanged. Table IA.4 restricts the sample only to those CUs headquartered in counties that had at least one low income CU designation over the 2009-2016 sample period. This sample of geographically proximate CUs are likely subject to similar shocks, and the undesignated CU-quarter observations are arguably a more realistic control group. The main results are little changed.

The county might however be too spatially aggregated given the geographic proximity of most CU lending. Table IA.5 re-runs the estimation in Table 2 but restricts the sample to CUs located in

census tracts with median income below the national median. These CUs collectively serve economically similar members and are significantly more likely to be eligible for low-income designation. The main results remain unchanged.

Tables IA.6 and IA.7 focus on the cross-section and use propensity score matching based on the pre-existing balance sheet and census tract income of a CU's headquarters to identify the "nearest neighbor" to a LICU (Table IA.7). These "nearest neighbor" CUs are the set of non-LICUs that are most similar to the set of LICUs, as determined by their pre-2009 balance sheet and the potential income of their membership. Even within this relatively homogeneous cross-section, there is evidence that lending growth is significantly higher during the quarters a CU becomes LI relative to its nearest "untreated" or undesignated neighbor.

This statistical evidence indicates that lifting regulatory restrictions on lending and deposit-taking—low income status—led to a significant increase in intermediation, allowing designated low-income credit unions to compete directly with local banks and other financial institutions on both sides of the balance sheet. And consistent with the previous documentary evidence that the overwhelming majority of LI eligible CUs take-up LI status once made aware of their eligibility, this statistical evidence strongly suggests that the timing of designations across CUs is not driven by pre-existing balance sheet factors or trends in intermediation at CUs.

But the variation in the potential rents from the ex-ante industrial organization of the local banking markets might still influence the LI take-up decision. LI-eligible CUs could systematically select into LI status in areas with more limited banking competition and greater potential rents from operating outside the common bond constraint. If this pattern of entry is systematic in the data, then it can skew the geographic variation in LICUs in the sample towards less competitive areas, possibly leading to biased inference when studying the impact of LICU entry on bank outcomes. To understand then the spatial variation in LI adoption, we compute the ratio of LICUs to all CUs in 2015 Q4 for each county.

Table IA.8 then regresses this measure of LICU adoption on various measures of ex-ante banking sector competition at the county level in 2008 along with the initial ratio of LICUs to all CUs in 2008. Column 1 uses the Herfindal Index of bank deposit shares from the FDIC's survey of deposits–higher values of this index suggest greater concentration. Column 2 uses the log number of bank branches in the county, while column 3 uses the log number of banks. All regressions

include state fixed effects and standard errors are clustered at the state-level. There is no evidence that the ex-ante industrial organization of the local banking market mattered for the subsequent spatial variation in LI adoption.

A related concern centers on the fact that LI-eligible CUs might systematically select into LI status in response to lending growth at nearby banks, contaminating the research design. Suppose that loan demand among a CU's common bond clientele is uncorrelated with loan demand in the local population. Then if loan demand at nearby banks is high, then a LI-eligible CUs might select earlier into LI status in order to compete for these additional lending opportunities. In this way faster lending growth at nearby banks would precede entry into LI status among CUs. To be clear, if loan demand among a CU's common bond clientele is correlated with loan demand among the local population, this endogenous selection mechanism would appear as an increase in CU lending before LI take-up–a prediction already rejected by the data.

Nevertheless, foreshadowing the analysis on the impact of LICU designation on incumbent banks, we use a simple difference-in-difference specification to assess whether faster lending growth at nearby banks precede entry into LI status among CUs. Geography defines the extent of the market for community banks and credit unions, and this specification creates a circle of radius 5 miles around the headquarters of each community bank in the sample. We then create an indicator variable that equal one beginning in the quarter when a CU within the 5 mile radius first converts to a LICU, and 0 if no CUs within the 5 mile radius change status. In this setting, the treated bank-quarter observations are those in which a community bank is exposed to competition from at least one LICU. The control group comprise the set of banks in the county never exposed to a nearby LICU and the bank-quarter observations before a CU converts to a LICU.

To detect pre-trends in bank lending growth, this indicator variable also enters with four leads. If rapid lending growth at a neighborhood bank precipitates "LI entry", then these lead variables should be positive and significant: banks with faster lending growth endogenously become exposed to competition from CUs converting to LI status to meet loan demand outside the common bond. The difference-in-difference specification also includes four lags of this indicator variable in order to provide preliminary evidence on the impact of LICUs on subsequent bank lending. The specification also includes bank-by-year fixed effects, county fixed effects and year-by-quarter fixed effects; standard errors are clustered at the county.

From Table IA.9, the four lead variables are individually and jointly insignificant; if anything, the sum of the four lead coefficients is negative: -0.002 (p-value=0.36). Future selection into LICU status among CUs is unrelated to previous loan growth among nearby banks. In contrast, in the five quarters after LICU entry, average lending growth is about -0.005 percentage points lower (p-value=0.03), suggesting that exposure to LICUs might reduce community bank lending. The next subsection studies the impact of LICU entry on bank outcomes in greater detail.

III. The Effects of Credit Market Competition: Banks

A. Basic Results

This subsection examines the impact of LICU competition on banks. Credit unions and local community banks are close substitutes, and the baseline empirical specification restricts the sample to banks that meet the FDIC's definition of community banks–see Table 1 for a comparison between CUs, community banks and large multi-market banks. The FDIC's definition is based in part on a bank's size, its liabilities and asset composition, and the geographic range of the bank's operations.[17] As before, we build on the fact that geography helps define the extent of the market for most community banks and credit unions and the baseline specification creates a circle of radius 5 miles around the headquarters of each community bank in the sample. However, to understand better the intensity of LICU exposure on bank outcomes, we measure LICU exposure based on the log number of low-income CUs within this 5-mile radius. The sample period itself extends from 2008 Q1 through 2015 Q4.

Credit unions expanded deposits and lending with some lag after low-income status, and banks are also likely to respond gradually to increased competition. To model these lags, the baseline specification uses a distributed lag model. Let lic_{jt} denote the log number of low-income CUs located within a 5 mile radius of bank j's headquarters in the current quarter t. And let y_{jit} measure outcomes, such as lending growth, at bank j located in market i—county or census tract—in period t. The estimating equation is thus:

[17] The details can be found here: https://www.fdic.gov/regulations/resources/cbi/study.html.

$$y_{jit} = \sum_{k=0}^{k=4} \beta_{t-k} lic_{jt-k} + b_j + c_t + v_i + e_{jit} \quad (1)$$

The parameters b_j, c_t and v_i are bank, year-by-quarter and local market—county or census tract—fixed effects. In some specifications, we also consider local market by year-quarter fixed effects to non-parametrically absorb time varying local economic conditions that might jointly determine bank outcomes and the pattern of entry into low-income CU status.

Conversion to low-income status is generally permanent. Even if a CU becomes ineligible for LI status at a subsequent supervisory exam, it can still retain its LI status for 5 more years; thus far, no CU has exited LI status in our sample period. We are therefore interested in the effect of a permanent increase in competition on bank outcomes over the estimation horizons. The main tables report the sum of the coefficients $\{\beta_{t-k}\}_{k=0}^{k=4}$ at each horizon along with its corresponding p-value. For example, the impact of a permanent 10 percent increase in the number of low-income CUs within 5 miles of bank j's headquarters on bank's lending growth over the next 4 quarters equals: $(\beta_t + \beta_{t-1} + \beta_{t-2} + \beta_{t-3} + \beta_{t-4}) \times 10\%$. The underlying coefficients and their standard errors are in the internet appendix.

The dependent variable in Table 3 is the quarter on quarter change in loans divided by total assets in the previous quarter: $((loans_{jt} - loans_{jt-1})/assets_{jt-1})$. Column 1 uses the sample of all community banks, as designated by the FDIC. The point estimates suggest that after a one standard deviation permanent increase in the number of low-income CUs within a bank's neighborhood—the 5 mile radius of the bank's headquarters—the incumbent bank's lending growth declines by about 0.20 percentage point in the current quarter. This immediate response mirrors the results in column 1 of Table 2 which show that low-income designation among CUs is associated with an almost immediate expansion in lending growth and increased marketing expenses. Over the one-year estimation horizon, the cumulative or "long-run" impact of a one standard deviation permanent increase in the number of low-income CUs is a 0.2 percentage point decline in lending growth (p-value=0.00); this decline is about 28 percent relative to the mean lending growth in the sample period.

The community banking business is local, and unobserved local shocks remain a potential source of bias. Notably, CUs eligible for low-income designation are more likely to be located in poorer

neighborhoods. And the demand for financial services could have been more depressed in these areas, helping to explain the negative association between an increase in low-income designation and bank lending growth. The evidence in the previous section, which shows that CU lending actually increased after low-income designation, clearly contradicts this weak demand interpretation: These results more likely reflect the effects of competition, as new CU entrants attract business away from local banks.

But the local variation in house price movements provides a direct and simple way to gauge the potential effects of latent demand. There is by now an enormous literature showing both that house price movements varied sharply across the country during the 2008-2015 sample period and that this variation was a key driver of local economic activity and demand. Column 2 includes the current and four lags of changes in Zillow's zip code level single family house price index. The zip code is matched to the headquarters of the bank. The sample drops sharply since this index is not available for all zip codes, but the main results remain unchanged.

Community banks sometimes operate branches beyond the zip code of their headquarters, and column 3 uses county-by-year-quarter fixed effects to non-parametrically absorb all time-varying economic shocks in the local market. We lose some observations in this specification, but the negative impact of increased competition on bank lending after about a year remains unchanged. Latent relevant economic shocks might be present at a finer level of geography than the county. To address this concern, column 4 uses census tract fixed effects to absorb differences in relative income and local socioeconomic factors that might determine LI eligibility and the subsequent evolution of low-income CUs, along with latent credit demand.

The long-run effect of competition is, if anything, about 33 percent larger when controlling for census tract fixed effects. Also, we have used the log number of low-income CUs within a 5 mile radius to measure competition, but this variable might well be proxying for the overall number of CUs in the area. Column 5 excludes this possibility by directly controlling for the log number of CUs within the same 5 mile radius. The result is identical to the baseline specification.

Also, while the timing of each CU's supervisory exam is orthogonal to economic conditions, the timing of the regulatory letter in 2012 that led to the jump in LICUs in the middle of that year could have been driven by broader economic factors. These factors could in turn shape entry into the LI program and also subsequent bank lending decisions. Column 6 therefore drops 2012 from

the sample. The results remain unchanged. All this suggests that local economic conditions do not explain these results.

This was a period of large scale changes in banking regulation, mainly aimed at the larger banks. And since smaller banks rely on these bigger institutions for liquidity and other services, the sample period's spate of regulatory changes aimed at the large banks could still affect our results.[18] Dodd-Frank and Basel increased capital and liquidity standards, mainly for banks with assets in excess of $50 billion. Also, the Durbin Amendment imposed a cap on interchange fees, though banks below $10 billion in assets were exempted. Many of these regulations were announced and phased in at different times during the sample period. Liquidity regulations were for example first finalized in early 2013 (the liquidity coverage ratio) and in 2014 (the net stable funding ratio)–though implementation was gradual thereafter– the Durbin Amendment was included in the 2010 Dodd-Frank bill but only fully implemented in 2014 after legal challenges.[19]

To gauge the impact of these regulatory shocks then, we re-estimate the baseline specification (column 1 of Table 3) but sequentially drop each year from the sample period, beginning with 2009. For concision, Figure 5 reports the cumulative sum of the coefficients on the log number of LICUs after four quarters for each of the seven regressions. Despite the significant variation in regulatory shocks over the sample period, the effects of a permanent increase in LICU entry on bank lending growth is unchanged regardless of which year is dropped from the sample. This stability suggests that these results cannot be easily explained by the announcement or implementation of these various regulatory changes.

The variation in bank size provides another means of gauging the effects of regulation on these results. Specifically, if these results conflate the possible adverse effects of bank regulatory changes on bank lending with the variation in LI status across the CU industry, our findings should be weaker for the very small banks; these smaller banks were mostly exempted from much of the regulatory reform. To be sure, the "qualified mortgage rule" could disproportionately affect smaller banks, but as we have already seen, CUs themselves were not major players in this market and were also equally affected by this rule.

In contrast, because most credit unions and smaller banks operate in the same geographic

[18] See the survey in Disalvo and Johnston (2017).
[19] See https://www.gpo.gov/fdsys/pkg/FR-2014-10-10/pdf/2014-22520.pdf.

markets and compete for similar customers–the two industries are close substitutes, the competition hypothesis would predict that LICUs will likely have bigger impacts on geographically proximate smaller banks. The remaining columns of Table 3 investigate this hypothesis. Column 7 restricts the sample to those banks below $1 billion in assets—these are considered "level 1" banks and are regulated more similarly to CUs, with less frequent examination cycles and lower capital and other regulatory requirements.

Consistent with the idea that the effects of competition depend on the substitutability between banks and CUs, for the sub sample of banks with assets below $1 billion, the impact of low-income CU competition on lending growth is larger. A one standard deviation permanent increase in the log number of low income credit unions is associated with a cumulative 0.23 percentage point decline in lending growth over the subsequent year. Column 8 uses the $100 million dollar threshold—the banks with asset size around that of the median CU. For this sub sample, a one standard deviation permanent increase in low-income competition is associated with a 0.28 percentage point drop in lending over the long-run—an impact over 50 percent larger than the full sample. The Federal Reserve defines community banks as those banks owned by banking organizations with assets below $10 billion in the previous calendar year.[20] And rather than the FDIC's definition, column 9 uses the $10 billion threshold. The results are identical to that obtained in column 1.

Finally, under the competition hypothesis, the impact of an increase in LICUs is unlikely to affect balance sheet aggregates at the larger banks–the non-community banks. These institutions have a substantial lending presence outside of the consumer segment and operate across a much larger geography than community banks. These factors suggest that local entry by LICUs will likely have little impact on loan quantities at the bank-level–the call report data do not disaggregate lending at the branch level. Also, because large banks tend to securitize much of their consumer lending, such as automobile and home loans, regulatory balance sheet data on loans cannot easily measure any changes in lending at the extensive margin in response to competition. From column 10, among the sample of non-community banks, the effect of LICU competition is insignificant.

These results suggests that bank size in conjunction with geography help define the extent of the market for low-income CU competition. Table 4 makes this point more clearly. Rather than

[20] See https://www.federalreserve.gov/supervisionreg/topics/community_banking.htm. For more on the characteristics of smaller banks, see https://www.fdic.gov/regulations/resources/cbi/report/cbi-full.pdf. The results are similar if we use the $10 billion cutoff instead.

defining a radius of 5 miles around each bank, this table uses the baseline specification but gradually expands the radius, using radii of 10, 20, 30, 40, and 50 miles. For reference, the benchmark 5 mile specification is also included. The cumulative impact of an increase in low-income CU competition at the one-year horizon is largest within the 5 mile window. The point estimate declines as the radii increase, becoming statistically insignificant at the 50 mile window and beyond.

Using the baseline specification, Table 5 focuses on other dimensions of the balance sheet. Low-income CUs compete on the liabilities side of the balance sheet as well, and the dependent variable in column 1 is the growth in deposits, defined similarly to lending growth. There is significant evidence that deposit growth among incumbent banks declines when competition increases. After 4 quarters, a one standard deviation permanent increase in competition is associated with a 0.2 percentage point decrease in deposit growth—an impact that is about 18 percent relative to the mean deposit growth rate in the sample. The decline in asset growth (column 2) is also a similar order of magnitude.

We next study how banks adjust their asset composition in response to increased competition. Column 3 uses the loans to asset ratio as the dependent variable. After a one standard deviation increase in competition, this ratio increases by about 0.5 percentage point, suggesting that banks shift their asset composition away from cash and securities towards possibly higher yielding and less liquid loans. Models of competition also predict that incumbents might alter their product mix to reduce substitutability when faced with increased competition. CUs mainly lend to consumers, and column 4 shows that in response to increased competition in the consumer market, banks increase their commercial and industrial (C&I) lending. A one standard deviation increase in competition is associated with a 0.01 percentage point increase in C&I loan growth.

Some models of banking also predict that competition can affect a bank's capital structure, and column 5 hints at a moderate decline in the ratio of tier 1 to risk weighted assets when LICUs increase. Columns 6 and 7 report a concomitant increase in profitability in response to competition, as both the return to equity and the return to assets increase (columns 6 and 7). From column 6 for example, a one standard deviation increase in competition is associated with a 0.2 percentage point—or a 5 percent standard deviation—increase in the return to equity.

Table 6 uses RateWatch data on deposit and lending rates observed at the bank branch-level to study the effects of competition on pricing. RateWatch provides weekly information on deposit

rates at various maturities for certificates of deposits and annual data on the offered interest rate at the branch for loans on new and used automobile loans as well as on various mortgage products. For those banks with rate-setting branches, we use the latitude and longitude of the branch to compute the number of low-income credit unions within a five-mile radius of the rate-setting branch. Alternatively, if the bank sets interest rates at the headquarters, then we compute the number of low-income credit unions within a five-mile radius of the bank's headquarters. The results using the branch-level interest rate data are strikingly consistent with those obtained using balance sheet aggregates: Deposit rates increase and loan rates decline when banks face more competition.

Panel (a) of Table 6, using the baseline model from column 1 of Table 3, focuses on deposit rates. It shows that the largest impact is concentrated among longer term CDs with bigger minimums, suggesting that greater competition may have increased the demand for longer duration sources of financing among financial institutions. From column 1 of panel (a), a one standard deviation permanent increase in competition from low-income CUs is associated with a cumulative 0.4 percentage point increase in the 6-month CD rate for $100,000 or higher deposits. This effect increases as the maturity of CDs lengthens and is about 60 percent larger at the 36 month term relative to the 6 month outcome (column 3). A similar pattern emerges when using CDs with a minimum maturity of $250,000 and $500,000. But at the $10,000 minimum, increased competition is not associated with any significant impact on deposit rates. The economic effects of these estimates are also sizable. For a $100,000 deposit compounded monthly, this impact suggests an additional $2,400 over a 3 year term.

Panel (b) of Table 6 examines the impact of competition on a variety of automobile and other loan products. Columns 1-4 focus on new car loans at various terms, while columns 5-7 use data on the pricing of used car loans. The remaining columns examine mortgage pricing using rates offered on 30 year and 15 year fixed rate mortgages and home equity lines of credit (HELOCs). We have already seen balance sheet-level evidence that CUs significantly expanded automobile lending after LI designation and the lifting of the common bond competition restrictions, and the branch-level pricing data corroborate this balance sheet-level evidence.

An increase in the number of LICUs is associated with a significant drop in the interest rate on bank automobile loans. This effect is especially large for riskier collateral, as the rates on longer duration used car loans fall significantly in response to increased LICU competition. The

coefficients on the new car rates are negative but insignificant. But in the case of used cars, a one standard deviation increase in competition is associated with a 10 basis point drop in the 36 month used car rate. Credit unions did not expand into mortgage lending once designated as low-income, and if anything, the evidence in columns 7 and 8 suggest that bank mortgage rates actually rose in response to increased low-income credit union competition that may have focused mainly on automobile loans.

B. Selection Pressure and Failures

Having established the basic effects of competition on balance sheet quantities as well as on loan and deposit pricing, this subsection examines the impact of competition on bank failures. Economic theory observes that an increase in competition from low-income CUs and the narrowing of interest rate margins—the gap between lending and deposit rates—could help drive out inefficient or less profitable banks from the sample through failures or mergers. This can make the effects of competition on bank outcomes heterogeneous. While failing or weak banks might experience a sharp drop in lending in the face of low-income CU competition or a loss of deposits, this selection mechanism could in turn leave behind survivors that lend more aggressively or shift into loan markets that face less competition from LICUs in order to boost profitability and efficiency. Given that the number of banks declined by about 1,400 over the sample period; of which, some 475 failed outright, selection pressures could feature in the data, inducing very different responses to competition among incumbent survivors.

To understand then the effects of competition on failures, Table 7 uses an indicator variable that equals 1 in the quarter that a bank fails and exits the panel, and 0 otherwise. The failures data are obtained from the FDIC's list of failed banks.[21] The specification is the same as the baseline case (column 1 of Table 3) and the independent variable of interest remains the log number of low-income CUs within 5 miles of the bank's headquarters, along with four lags. Note that the mean probability of observing a failure in the panel is 0.2 percent.

From column 1, which uses the full sample of banks, a one standard deviation increase in the log number of low-income CUs within 5 miles of a bank's headquarters is associated with a cumulative 0.06 percent increase in the probability of failure over the next four quarters. This impact is about

[21] https://www.fdic.gov/bank/individual/failed/banklist.html.

a third of the mean failure rate in the sample. But this result likely masks significant heterogeneity across banks, as a bank's propensity to fail in response to increased competition might depend on its pre-existing regulatory capital and efficiency, as well as its size, which can proxy for the bank's diversity of lending opportunities.

The remaining columns of Table 7 examines the impact of increased CU competition on the probability of failure using the cross-sectional variation in these variables, observed between 2006 and 2007. Columns 2 and 3 restrict the sample to those banks with below median (column 2) and above median (column 3) ratios of tier 1 capital to risk weighted assets, averaged over the pre-sample period, 2006-2007. There is evidence that more thinly capitalized banks are more likely to fail in the face of increased competition. From column 2, a one standard deviation increase in the log number of low-income CUs is associated with a 0.07 percentage point increase in the probability of failure among this below median tier 1 ratio (p-value=0.02). The implied effect in column 3 is smaller and not statistically significant (p-value=0.39).

Columns 4 and 5 repeat this exercise for banks with below median return on assets (column 4) and above median return on assets (column 5); columns 6 and 7 consider differences in size, with column 6 restricting the sample to below median assets, and column 7 focusing on above median assets. In all cases, these variables are averaged over 2006-2007. Consistent with theory, there is some evidence that less efficient and smaller banks are more likely to fail and exit the panel in response to increased competition.

Finally, CUs are exempt from federal and state taxes. And under the competition hypothesis, when CUs are able to compete directly with banks, a CU's relative cost advantage will be larger in states where banks face higher corporate taxes. This cost differential should then amplify the effects of competition in driving out weaker banks. Columns 8 and 9 re-estimate the base model for those banks in the top quartile tax states (column 8) and for banks in states with tax rates in the bottom quartile of the national distribution (column 9). The effects of competition on failures are concentrated in the top quartile states. From column 8, the point estimate is significant and about 8 times larger than in column 9, where the cumulative effects of competition is not itself not significant.

IV. Credit Policy, Non-Banks and the Extensive Margin

Greater competition is associated with increased failures by less efficient and less well capitalized banks, and there is also evidence that loan pricing declines, especially for riskier collateral. However, regulatory balance sheet data are too aggregated to measure whether competition expands credit at the extensive margin. These data also make it difficult to measure the extent to which competition can increase risk-taking. Also, non-bank financial institutions, such as captives and other finance companies, are major suppliers of consumer credit and go unmeasured in most regulatory data. At best then, the results thus far provide an incomplete understanding of the effects of competition.

Therefore, this subsection provides more direct tests of the effects of competition using detailed micro-data on automobile lending—one of the key areas of lending expansion after low-income CU designation. In particular, we use the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP) to compute the sum of car purchases that are financed through auto loans in each zip code from the first half of 2009 through the second half of 2017–the data are observed at the 6 month frequency. While the CCP does not identify the lender, in this new version of the data set[22], it does identify whether the lender was a bank, a CU, or a non-bank lender such as a car manufacturer's financing arm or a private pool of capital. The CCP data also contain information on a borrower's Equifax Risk Score, a major credit score created by Equifax and used by lenders to evaluate potential default risk of borrowers.

We can thus measure whether increased competition is associated with a reallocation of consumer credit to riskier borrowers—such as those with lower Equifax Risk Scores. We can also measure the response of non-banks and other lenders. And since the CCP is representative of the credit using population, it can also help us to determine whether increased competition leads to an aggregate expansion in automotive credit at the extensive margin or results in substitution away from incumbents towards the new low-income CU entrants. To construct these tests, we compute the log number of newly financed cars at the zip code level in half-year intervals. We use county by time fixed effects to absorb all demand shocks to the county within each half-year interval. The independent variable of interest is the log number of LICUs in the zip code; this variable enters contemporaneously and up to two lags. The baseline also includes the log number of CUs itself in

[22]This is the new auto trade line data set of the CCP, which covers all the auto loans at the account level.

each zip code.

Column 1 of Panel A in Table 8 shows that increased competition is associated with an expansion in automobile lending at the extensive margin. A one standard deviation increase in the number of LICUs is associated with a 0.7 percent increase in the number of originated cars inside the zip code over the next twelve months. The remaining columns disaggregate originated loans by CUs, banks and non-banks. In keeping with the previous balance sheet evidence, an increase in the number of LICUs is clearly associated with an increase in car loan origination by CUs; in this case, a one standard deviation increase in the number of LICUs suggests a 0.5 percent increase in the number of newly originated car loans by CUs.

We also saw previously that when faced with increased LICU competition, banks accommodated entry by contracting lending in the consumer segment, shifting instead towards commercial and industrial loans. Consistent with this pattern in the balance sheet data, column 3 shows that among banks the impact of increased competition on car origination is insignificant. Instead, non-banks, with few alternative lending markets, appear to respond to increased LICU competition by aggressively fighting for market share. From column 4, a one standard deviation increase in LICUs is associated with a 1.2 percent increase in newly originated car loans over the next 12 months. A concern here is that aggregate shocks, such as regulatory changes, funding shocks or low interest rates, and a search for yield might explain the penetration in non-bank automotive credit across zip codes. In results available upon request, we allow for zip code specific time trends; the results remain unchanged.

Panels B-E of Table 8 use the information on borrower Equifax Risk Scores to understand how increased competition might have affected credit policy at the extensive margin. The CCP data contain information on a borrower's Equifax Risk Score, where a lower score indicates higher default risk. To this end, Panel A restricts the sample to borrowers in the bottom Equifax Risk Score quartile, while Panel B uses those in the 25th to 50th Equifax Risk Score percentile; Panel C uses the 50th to 75th percentile; and Panel D restricts the sample to the top quartile or safest borrowers. There is unequivocal evidence that increased competition from LICUs engendered a sizable shift in credit policy: Both CUs and non-banks expanded credit at the extensive margin towards riskier borrowers. In fact, the effects of competition on lending is mostly concentrated among the bottom Equifax Risk Score quartile.

From Panel B, across all institutions, a one standard deviation increase in competition is associated with a 1.8 percent increase in newly originated car loans for the riskiest class of borrowers. When disaggregated by institution type, among CUs (column 2), a similar increase in competition suggests a 1.2 percent increase in new loans; for non-banks, the effect is nearly twice as large, as these institutions fought entry mainly by making credit available to the riskiest borrowers. As before, banks appear to cede this market to the new entrants. From Panels D and E—the less risky borrowers—the effect of competition drops by half. Indeed, among the safest borrowers (Panel D), competition has no significant effect on new lending.

Table 9 illustrates more clearly how competition induces credit-risk reallocation. For each type of lender, we compute the ratio of newly made auto loans extended to borrowers with below median Equifax Risk Scores to the total number of newly made auto loans by the same type of lender in each zip code-6 month cell. Column 1 uses loans made by all kinds of lenders, while the remaining columns disaggregate by CUs, banks and non-banks. The results show that an increase in competition–the number of LICUs in the zip code–is associated with a significant increase in the fraction of loans made to lower credit quality borrowers at the extensive margin over twelve months. As before, much of this decline in credit quality emanates from CUs and non-banks. Among CUs, a one standard deviation increase in the number of LICUs is associated with a 0.4 percentage point increase in the ratio of below median loans; in the case of non-banks, a similar increase in competition is associated with a 0.2 percentage point increase in this ratio.

Table 10 shows that this reallocation in automotive credit to riskier borrowers on account of increased competition is also associated with a significant increase in non-performing loans. We use 2017 Q2 as the end point and compute the log of the total number of non-performing auto-loans from the CCP data within the zip code. Note that a non-performing auto loan is defined as one more than 30 days overdue. Other county-level controls, such as demographics and economic indicators, are included in the regressions. From column 1, a one standard deviation increase in the change in number of LICUs over this period is associated with a 11 percent rise in the number of delinquent car loans, regardless of origination source. Not surprisingly, columns 2 and 3 show that the effects are largest among loans made by CUs and non-banks. The impact on banks is significant but economically smaller—about half that of non-banks. Table 10 (columns 5 – 8) also measures non-performing loans in terms of the share of total loans–the results are similar.

Table 11 disaggregates the impact of competition on non-performing loans by Equifax Risk Score. The evidence shows that the effects are clearly concentrated among borrowers with worse Equifax Risk Scores. The coefficient estimates are mostly statistically significant for the first and second quartiles or Equifax Risk Scores. A 10 percent increase in the change in number of LICUs between 2010 and 2013 is associated with a 12 percent higher number of delinquent car loans in 2017 for all types of institutions among loans with the lowest Equifax Risk Scores. In contrast, a 10 percent increase in the number of LICUs over the same period is associated with only a 4-5 percent higher number of delinquent car loans by all institutions in 2017 for the two middle quartiles of the Equifax Risk Scores. The coefficient estimates are not statistically significant for the safest borrowers, and as before, the impacts are largest among the non-bank lenders.

V. Conclusion

This paper has studied the effects of financial sector competition using regulatory changes that allowed some credit unions to directly compete with banks. The evidence shows that in response to increased competition, nearby banks became more efficient, profitable and more leveraged. The cost of borrowing, mainly riskier automotive credit, fell, while deposit rates rose sharply when competition increased. We provide evidence that these results stem from increased selection pressures, as competition increased the failure rate of less efficient, smaller and less well-capitalized banks.

But there is also powerful evidence that competition is associated with a sizable reallocation of automotive credit towards riskier borrowers. This reallocation is especially large among non-bank lenders such as captive finance companies and private pools of capital. There is also evidence that increased competition is associated with higher subsequent delinquencies. Taken together, these results point to the benefits of increased competition in relaxing financing constraints for marginalized borrowers. But consistent with models of competition and fragility, these results also show that increased competition can potentially lead to a sizable misallocation of credit to riskier borrowers. Because much of this shift in credit policy is concentrated in the unregulated sector, increased supervision of depository institutions are unlikely to mitigate fully the risks associated with greater competition.

There are a number of limitations with our approach. Most conspicuously, while non-banks

dramatically change their credit policy relative to banks, this paper does not identify why this difference emerges. And we leave it to future work to understand better whether this shift in credit policy reflects agency problems at non-bank institutions that is amplified by securitization; whether it stems from the fact that funding costs at shadow banks are not affected by local competition; or whether supervisory oversight prevent banks from pursuing a similar shift in credit policy in response to increased competition. Also, comparing results derived from Call Report data–which cannot identify the extensive margin–with those from Equifax is difficult. Another limitation stems from the fact that while Equifax data is a major step forward in measuring risk at the extensive margin, we cannot observe the specific lender, and tests that differentiate between the response of big and small banks await even better data.

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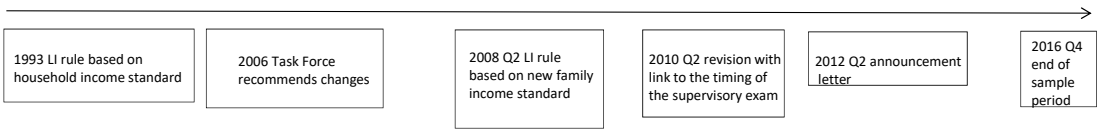
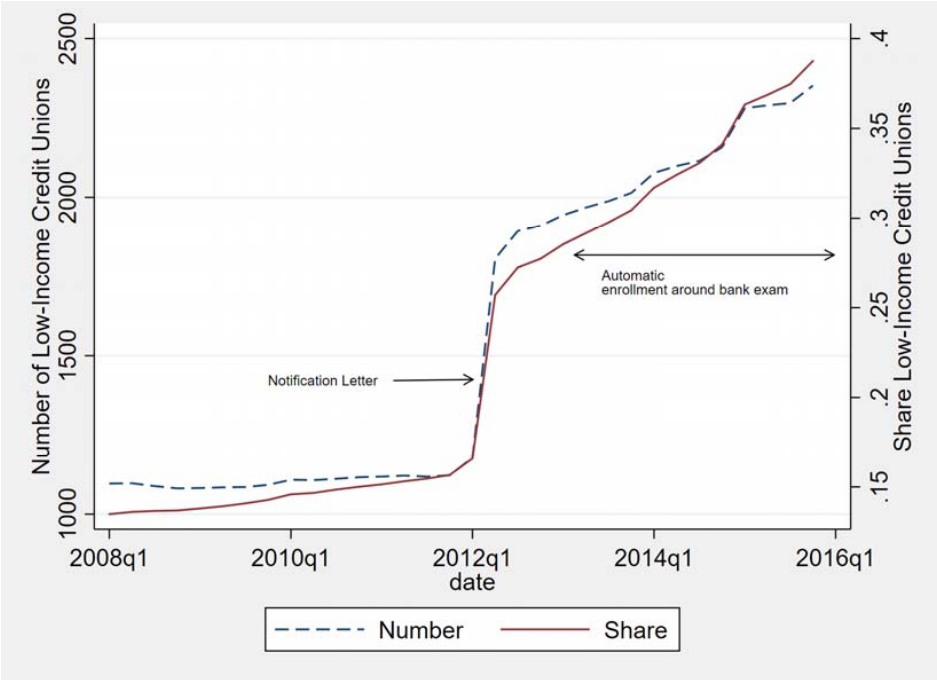
Figures and Tables

Figure 1: Regulation Changes



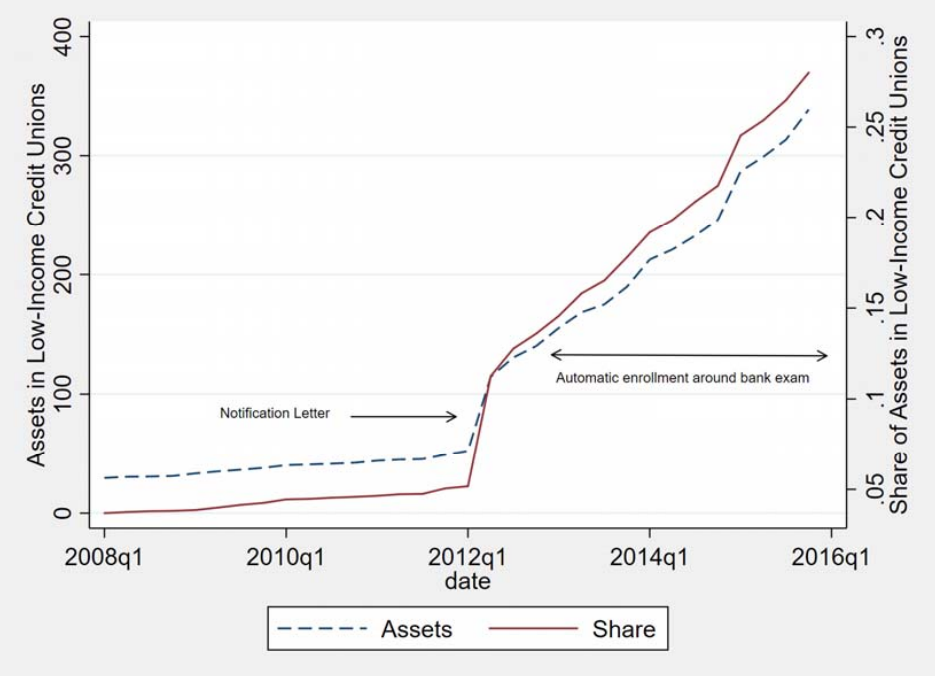
Note: This figure shows the timeline of the regulatory changes surrounding the low income credit union rule.

Figure 2: Low-Income Designated Credit Unions, by Number



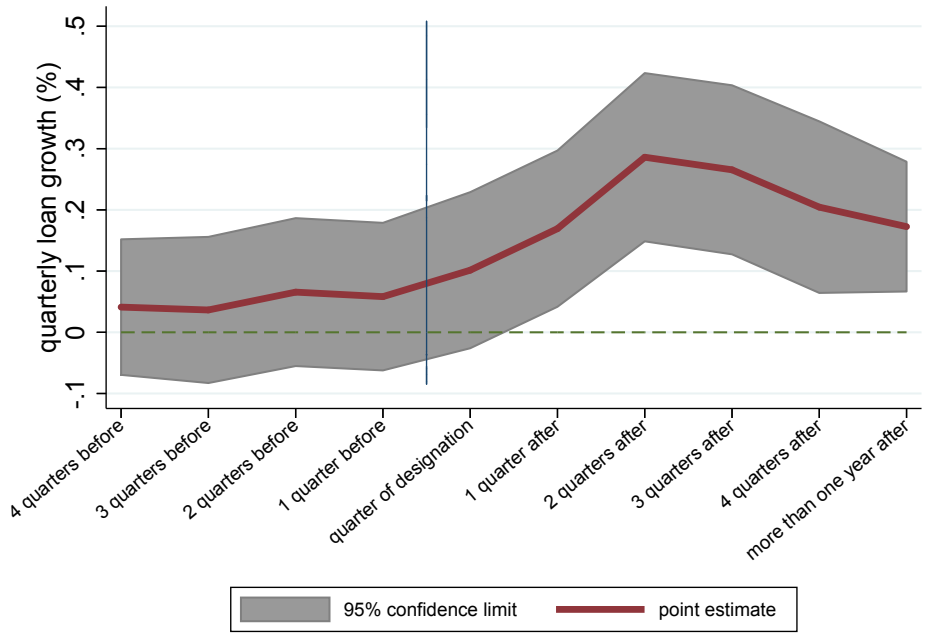
Note: This figure plots the number of credit unions designated as low-income credit unions between 2006 and 2016 as well as the ratio of low-income credit unions to the total number of credit unions. The letter notifying credit unions of their low-income eligibility was sent in the second quarter of 2012. Using geocoding software to determine eligibility, credit unions were thereafter enrolled into the program at the time of the bank exam.

Figure 3: Low Income Designated Credit Unions, by Assets



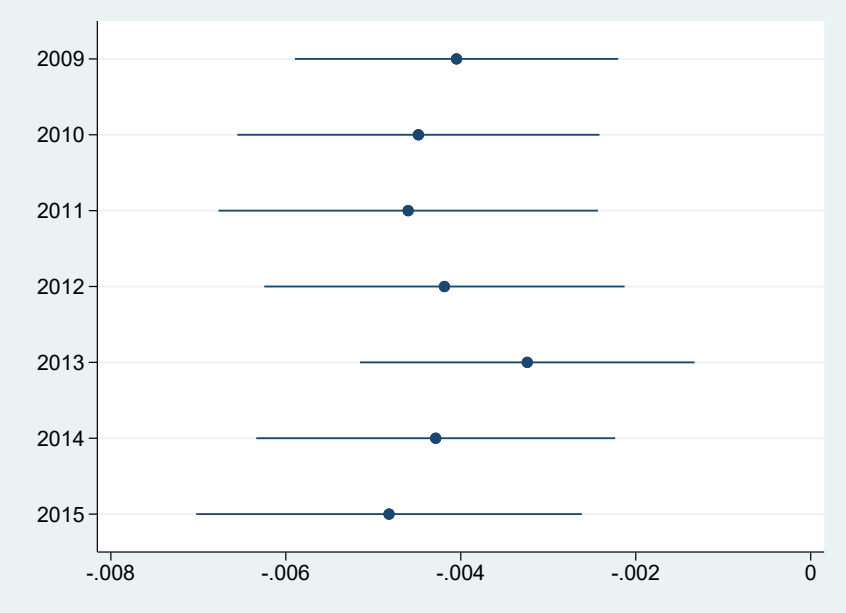
Note: This figure plots total assets of credit unions designated as low-income credit unions between 2006 and 2016 as well as the ratio of low-income credit unions to the total number of credit unions. The letter notifying credit unions of their low-income eligibility was sent in the second quarter of 2012. Using geocoding software to determine eligibility, credit unions were thereafter enrolled into the program at the time of the bank exam.

Figure 4: Impact of Low Income Designations on Credit Unions' Loan Growth



Note: This figure plots the impact of low income designation on the loan growth of credit unions. The bold solid line plots the coefficient estimates report in column (1) of Table 2. The shaded area indicates the 95% confidence interval. The vertical line indicates the timing of the the low income designation.

Figure 5: The Impact of LICU Competition on Bank Lending Growth, Over Time



Note: Using the baseline specification from column 1 of Table 3, this figure plots the cumulative impact of an increase in the log number of LICUs within a 5 mile window after four quarters; the estimation sequentially drops each year from the sample. The label "2009" thus estimates the baseline specification after excluding 2009. The point estimate is the dot, and the line represents the 95 percent confidence band.

Table 1: Summary Statistics

	Panel A. Low-Income Designated Credit Unions			
	Total Assets (thousands)	Loans/Assets	Deposits/Assets	Total Equity/Assets
Mean	144,036	0.54	0.86	0.13
Median	23,828	0.55	0.88	0.11
25th percentile	6,403	0.41	0.84	0.09
75th percentile	89,932	0.69	0.9	0.14
Standard deviation	431,055	0.19	0.06	0.06
Observations	2,352	2352	2352	2349
	Panel B. Non Low-Income Credit Unions			
	Total Assets (thousands)	Loans/Assets	Deposits/Assets	Total Equity/Assets
Mean	234,259	0.52	0.86	0.13
Median	29,434	0.53	0.87	0.12
25th percentile	8,405	0.38	0.83	0.09
75th percentile	112,354	0.67	0.9	0.15
Standard deviation	1,511,000	0.19	0.07	0.07
Observations	3,717	3717	3717	3711
	Panel C. Community Banks			
	Total Assets (thousands)	Loans/Assets	Deposits/Assets	Total Equity/Assets
Mean	369,613	0.62	0.84	0.11
Median	176,085	0.65	0.85	0.1
25th percentile	88,529	0.52	0.81	0.09
75th percentile	370,062	0.75	0.88	0.12
Standard deviation	807,640	0.16	0.06	0.04
Observations	5,735	5722	5735	5722
	Panel D. Non-Community Banks			
	Total Assets (thousands)	Loans/Assets	Deposits/Assets	Total Equity/Assets
Mean	7,788,366	0.62	0.8	0.1
Median	2,718,986	0.68	0.82	0.1
25th percentile	1,051,542	0.56	0.76	0.09
75th percentile	7,672,005	0.75	0.85	0.11
Standard deviation	16,016,691	0.21	0.1	0.02
Observations	330	330	330	330

Note: This table provides summary statistics for low-income credit unions, all other credit unions, community banks and non-community banks. Community banks are defined based on the FDIC's definition. The data are observed at the end of 2015. All data are from banks' and credit unions' quarterly filings of their Call Reports.

Table 2: The Impact of Low Income Designations on Credit Unions' Outcomes

	(1) Loans	(2) Auto	(3) Real Estate	(4) Loans/Assets	(5) Assets	(6) Deposits	(7) Net worth	(8) Marketing	(9) Log(Members)	(10) ROE	(11) ROA
4 quarters before designation	0.000412	0.000780*	-6.53E-05	0.00244	6.69E-05	-0.000209	0.000194	0.00279	-0.00321	0.0013	0.000240**
	(0.00057)	(0.00040)	(0.00024)	(0.00190)	(0.00079)	(0.00077)	(0.00053)	(0.01210)	(0.00667)	(0.00124)	(0.00010)
3 quarters before designation	0.000365	0.000493	-0.000138	0.00219	0.00142*	0.00098	0.000256	-0.00413	0.00566	0.000702	0.000124
	(0.00061)	(0.00042)	(0.00025)	(0.00207)	(0.00081)	(0.00079)	(0.00059)	(0.01290)	(0.00420)	(0.00219)	(0.00017)
2 quarters before designation	0.000656	0.000604	-0.000296	0.00262	0.00115	0.00084	0.000108	0.0179	0.00641	0.00202	0.000159
	(0.00062)	(0.00044)	(0.00025)	(0.00224)	(0.00082)	(0.00079)	(0.00060)	(0.01310)	(0.00446)	(0.00157)	(0.00011)
1 quarter before designation	0.000583	0.000553	0.000125	0.00317	0.00122	0.0011	-0.000294	0.00912	0.00332	0.00182	9.05E-05
	(0.00062)	(0.00045)	(0.00026)	(0.00239)	(0.00084)	(0.00082)	(0.00064)	(0.01400)	(0.00484)	(0.00185)	(0.00013)
Quarter of designation	0.00101	0.000442	0.00029	0.00376	0.000473	0.000417	-9.83E-05	0.0286*	-0.00103	-0.000391	7.88E-05
	(0.00065)	(0.00045)	(0.00027)	(0.00256)	(0.00082)	(0.00080)	(0.00065)	(0.01470)	(0.00600)	(0.00145)	(0.00011)
1 quarter after designation	0.00169***	0.00124***	-7.49E-05	0.00514*	0.00106	0.00102	-0.000493	0.0204	0.00257	0.00126	0.000146
	(0.00065)	(0.00045)	(0.00026)	(0.00269)	(0.00082)	(0.00080)	(0.00063)	(0.01560)	(0.00539)	(0.00090)	(0.00023)
2 quarters after designation	0.00286***	0.00152***	0.000544*	0.00693**	0.00273***	0.00189**	-0.000811	0.0400**	0.00242	0.00174	0.000154
	(0.00070)	(0.00048)	(0.00028)	(0.00288)	(0.00086)	(0.00083)	(0.00064)	(0.01670)	(0.00571)	(0.00138)	(0.00015)
3 quarters after designation	0.00265***	0.00144***	0.000308	0.00738**	0.00328***	0.00279***	-0.00119*	0.0414**	0.0017	-5.02E-05	-4.91E-05
	(0.00070)	(0.00051)	(0.00029)	(0.00302)	(0.00093)	(0.00091)	(0.00070)	(0.01730)	(0.00609)	(0.00127)	(0.00018)
4 quarters after designation	0.00204***	0.00179***	-0.000126	0.00862***	0.00174*	0.00114	-0.00141*	0.0508***	0.00562	0.00244*	0.000433**
	(0.00072)	(0.00051)	(0.00028)	(0.00319)	(0.00093)	(0.00091)	(0.00076)	(0.01770)	(0.00641)	(0.00136)	(0.00022)
More than one year after designation	0.00173***	0.000800**	0.000346	0.0149***	0.00196***	0.00149***	-0.00246***	0.0564***	0.0141*	0.00304**	0.000234**
	(0.00054)	(0.00038)	(0.00023)	(0.00369)	(0.00056)	(0.00053)	(0.00091)	(0.01840)	(0.00798)	(0.00150)	(0.00009)
Observations	192,455	192,332	192,455	192,455	192,455	192,455	171,599	192,097	192,455	171,657	192,453
R-squared	0.325	0.279	0.297	0.915	0.372	0.385	0.956	0.969	0.992	0.107	0.1

Note: This table examines the impact of low income designation on several balance sheet and income outcomes for the full panel of credit unions (CUs). The main independent variable is a dummy variable that is 1 in the quarter a CU becomes designated as low income and 0 otherwise. All regressions include 4 leads and 4 lags of this dummy variable. The variable "more than one year after designation" is a dummy that is 1 in the quarters one year ago after low-income designation and 0 otherwise. Dependent variables are: loan growth (column 1), auto loan growth (column 2), real estate loan growth (column 3), loans to assets ratio (column 4), asset growth (column 5), deposit growth (column 6), net worth ratio (column 7), the log of marketing expenses (column 8), the log of credit union members (column 9), return on equity (column 10), and return on assets (column 11). All growth variables are defined as the quarter on quarter change in the variable divided by total assets in the previous quarter. All regressions include CU fixed effects and year-quarter-county fixed effects. Standard errors are clustered at the CU level.

Table 3: The Impact of Low Income Designation on Bank Loan Growth, 5 mile radius

	(1) Baseline	(2) Control for zip code level house prices	(3) County-year-quarter fixed effects	(4) Census tract fixed effects	(5) Control for total number of credit unions	(6) Exclude year 2012	(7) Banks smaller than $1 billion	(8) Banks smaller than $100 million	(9) Banks smaller than $10 billion	(10) Big banks
Current quarter	-0.00441***	-0.00173	-2.16E-03	-0.00436***	-0.00418***	-0.00279	-0.00455***	-0.00660**	-0.00335***	-0.0000962
	(0.0012)	(0.0014)	(0.0016)	(0.0012)	(0.0012)	(0.0019)	(0.0013)	(0.0026)	(0.0011)	(0.0027)
One quarter	-0.00279**	-0.000618	-0.00047	-0.00272*	-0.00250*	-0.00226	-0.00364***	-0.00324	-0.00207	-0.000704
	(0.0013)	(0.0017)	(0.0017)	(0.0014)	(0.0013)	(0.0019)	(0.0013)	(0.0033)	(0.0013)	(0.0027)
Two quarters	-0.00122	-0.00314*	-0.00234	-0.00157	-0.000894	-0.00115	-0.0014	-0.00306	-0.00098	0.000222
	(0.0013)	(0.0018)	(0.0017)	(0.0015)	(0.0013)	(0.0014)	(0.0015)	(0.0029)	(0.0013)	(0.0027)
Three quarters	-0.00446***	-0.00384**	-0.00496***	-0.00515***	-0.00417***	-0.00440***	-0.00487***	-0.00794***	-0.00419***	0.000119
	(0.0012)	(0.0016)	(0.0017)	(0.0014)	(0.0012)	(0.0013)	(0.0014)	(0.0026)	(0.0013)	(0.0030)
Four quarters	-0.00378***	-0.00391**	-0.00332**	-0.00475***	-0.00360***	-0.00419***	-0.00482***	-0.00652***	-0.00378***	0.000811
	(0.0010)	(0.0015)	(0.0013)	(0.0012)	(0.0010)	(0.0011)	(0.0012)	(0.0020)	(0.0011)	(0.0026)
Observations	203,542	69,748	176,207	180,209	203,542	177,575	181,599	76,793	194,965	15,745

Note: This table examines the impact of a bank's exposure to the log number of low income credit unions (LICUs) within a 5 mile radius of the bank's headquarters. In all cases, the dependent variable is the quarter-on-quarter change in total loans divided by the previous quarter's assets. The independent variable of interest is the log number of LICUs within a 5 mile radius of the bank's headquarters. For this variable, the table reports the cumulative sum of the coefficients up to four quarters later. For example, from column 1, a 10 percent permanent increase in the number of LICUs is associated with a 0.038 percentage point drop in bank lending growth after four quarters. Regression coefficient estimates are reported in Table IA.10 in the Internet Appendix. The corresponding standard errors (in parentheses) are clustered at the county level. The results remain robust if errors are clustered both by county and year-by-quarter. All specifications control for bank, county fixed effects and year-by-quarter fixed effects. Column 2 includes the change in Zillow's zip code level house price index contemporaneously and up to three lags. Column 3 includes county-by-year-by quarter fixed effects. Column 4 includes census tract fixed effects based on the location of the bank's headquarters. Column 5 controls for the log number of CUs within a 5 mile radius of the bank. Column 6 drops observations in the year 2012; Column 7 restricts the sample to banks with $1billion or less in assets; column 8 restricts the sample to banks with $100 million in assets, while column 9 includes only banks with $10 billion or less in assets. Column 10 uses the sample of large and mid-sized banks–those that do not meet the FDIC's community bank definition. Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: The Impact of Low Income Designation on Bank Loan Growth by Different Radius

	(1) 5miles	(2) 10miles	(3) 20miles	(4) 30miles	(5) 40miles	(6) 50miles
four quarters	-0.0038***	-0.0026***	-0.0016***	-0.0013***	-0.0014***	-0.0014***
	(0.0010)	(0.0008)	(0.0006)	(0.0005)	(0.0004)	(0.0004)
Observations	203542	203542	203542	203542	203542	203542
BankFE	Yes	Yes	Yes	Yes	Yes	Yes
CountyFE	Yes	Yes	Yes	Yes	Yes	Yes
QuarterFE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table examines the impact of a bank's exposure to the log number of low income credit unions (LICUs) computed at various radii from the bank's headquarters. In all cases, the dependent variable is the quarter-on-quarter change in total loans divided by the previous quarter's assets. All specifications control for bank, county and year-quarter fixed effects–the baseline specification in column 1 of Table 3. The independent variable of interest is the log number of LICUs within a particular radius. Column 1 computes this variable using a 5 mile radius around the bank's headquarters. Columns 2-6 recomputes this variable using the 10 through 50 mile radii around the headquarters. As before, the table reports the cumulative sum of the coefficients after four quarters later. For example, from column 1, a 10 percent permanent increase in the number of LICUs is associated with a 0.038 percentage point drop in bank lending growth after four quarters. Regression coefficient estimates are reported in Table IA.11 in the Internet Appendix. The corresponding standard errors (in parentheses) are clustered at the county level (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table 5: The impact of low income designation on banks' balance sheets, 5 miles

	(1) Deposit Growth	(2) Asset Growth	(3) Loans/Assets	(4) Commercial and Industrial Loan Growth	(5) Tier 1 capital/Assets	(6) ROA	(7) ROE
Four quarters	-0.00449***	-0.00428***	0.00999**	0.000350***	-0.503***	0.000715***	0.00680*
	(0.0013)	(0.0013)	(0.0045)	(0.000103)	(0.159)	(0.0001)	(0.0039)
Observations	204,081	204,081	204,239	204,081	204,239	204,649	204,115

Note: This table examines the impact of the log number of low income credit unions within a 5 mile radius around a bank's headquarters on a range of bank balance sheet aggregates. It uses the full sample of community banks and the baseline specification (column 1 of Table 3). All specifications control for county, bank and year-quarter fixed effects. We report the cumulative impact of a permanent increase in the number of low-income credit unions located within 5 miles of a bank's headquarters after four quarters. Regression coefficient estimates are reported in Table IA.12 in the Internet Appendix. The standard errors (in parentheses) are clustered at the county level. The dependent variables are deposit growth (column 1), asset growth (column 2), the loans-to-assets ratio (column 3), commercial and industrial loan growth (column 4), the Tier 1 capital to assets ratio (column 5), return on assets (column 6), return on equity (column 7). Standard errors are reported in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$) and are clustered at the county level.

Table 6: The Impact of Low-Income Credit Union Entry on Bank Branch Interest Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$100,000 CD			$250,000 CD			$500,000 CD			$10,000 CD		
	6 months	12 months	36 months	6 months	12 months	36 months	6 months	12 months	36 months	6 months	12 months	36 months
Four quarters	0.0169**	0.0192**	0.0270***	0.0110**	0.0130**	0.0232**	0.0110**	0.0129**	0.0233**	0.00635	0.00998	0.0157*
	(0.0067)	(0.0075)	(0.0093)	(0.0047)	(0.0058)	(0.0090)	(0.0047)	(0.0059)	(0.0091)	(0.0072)	(0.0077)	(0.0091)
Observations	133,564	134,432	114,850	95,371	95,853	86,411	95,085	95,610	86,122	165,900	166,546	149,634

(a) Deposit Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	New car loans				Used car loans			Mortgages		
	36 months	48 months	60 months	72 months	36 months	48 months	60 months	30 years	15 years	HELOC
Four quarters	-0.0846	-0.0956	-0.0939	-0.133	-0.134	-0.157*	-0.198*	0.0133	0.129*	-0.0538
	(0.0693)	(0.0667)	(0.0671)	(0.0911)	(0.0823)	(0.0824)	(0.1170)	(0.0459)	(0.0673)	(0.0625)
Observations	13,907	13,921	13,876	6,665	12,064	9,960	4,895	4,812	5,771	9,321

(b) Lending Rates

Note: Panel (a) examines the impact of the log number of low-income credit unions (LICUs) within a 5 mile radius of a bank's branch on the offered interest rate for certificates of deposit (CDs) of different minimum sizes and at different maturities: 6, 12 and 36 months. We report the cumulative impact of a permanent increase in the number of LICUs after four quarters. All specifications include bank, county and year-by-quarter fixed effects. Standard errors in parentheses are clustered at the bank level. Panel (b) of this table examines the impact of the log number of low-income credit unions (LICUs) within a 5 mile radius of a bank's branch on the offered interest rate for various new and used car loan products, and the 30 and 15 year advertised conforming mortgage rate and the rate on home equity lines of credit (HELOC). We report the cumulative impact of a permanent increase in the number of LICUs after four quarters. All specifications include bank, county and year-by-quarter fixed effects. Standard errors in parentheses are clustered at the bank level (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Regression coefficient estimates are reported in Table IA.13 in the Internet Appendix.

Table 7: The Impact of Credit Union Low Income Designation on the Probability of Bank Failure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Tier 1 capital/Assets		ROA		Assets		State tax rate	
	Full sample	below median	above median	below median	above median	below median	above median	top quartile	bottom quartile
Four quarters	0.00124	0.00164**	0.000939	0.00187	0.000293	0.00270*	0.000422	0.00442**	0.000641
	(0.00094)	(0.00074)	(0.00112)	(0.00131)	(0.00067)	(0.00152)	(0.00076)	(0.00191)	(0.00095)
Observations	204,360	92,138	112,222	94,880	109,480	113,851	90,509	70,565	64,792

Note: This table reports the cumulative impact of a permanent increase in "the log number of low-income credit unions within a 5 mile radius of a bank" after four quarters on the probability that a bank fails over the sample period. The dependent variable equals 1 if a bank fails in a quarter and 0 otherwise. Column 1 reports results for the full sample of banks. Column 2 uses the subset of banks whose average tier 1 equity to assets in 2006-2007 was below the sample median; column 3 uses the above median sample. Columns 4 and 5 split the sample by the average return on assets in 2006-2007; and columns 6 and 7 split the sample by average assets in 2006-2007. Columns 8 and 9 restrict the sample to banks located in states that are in the top quartile corporate tax rate (column 8) and the bottom quartile (column 9). The standard errors are clustered at the county level (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$) and all specifications include bank, county and year-by-quarter fixed effects–the baseline from column 1 of Table 3. Regression coefficient estimates are reported in Table IA.14 in the Internet Appendix.

Table 8: Low Income Designation and Number of New Auto Loans

Panel A: all				
	(1) all institutions	(2) credit unions	(3) banks	(4) non-banks
Four quarters	0.027***	0.019**	0.0070	0.042***
	(0.0052)	(0.0093)	(0.0094)	(0.0061)
Observations	557828	557828	557828	557828
Panel B: 1st quartile in Equifax Risk Score				
	(1) all institutions	(2) credit unions	(3) banks	(4) non-banks
Four quarters	0.067***	0.044***	0.021	0.081***
	(0.0082)	(0.014)	(0.015)	(0.0088)
Observations	557828	557828	557828	557828
Panel C: 2nd quartile in Equifax Risk Score				
	(1) all institutions	(2) credit unions	(3) banks	(4) non-banks
Four quarters	0.035***	0.062***	0.0096	0.047***
	(0.0085)	(0.013)	(0.014)	(0.010)
Observations	557828	557828	557828	557828
Panel D: 3rd quartile in Equifax Risk Score				
	(1) all institutions	(2) credit unions	(3) banks	(4) non-banks
Four quarters	0.030***	0.011	0.018	0.058***
	(0.0082)	(0.013)	(0.012)	(0.011)
	557828	557828	557828	557828
Panel E: 4th quartile in Equifax Risk Score				
	(1) all institutions	(2) credit unions	(3) banks	(4) non-banks
Four quarters	-0.0011	-0.0028	-0.0051	0.016
	(0.0084)	(0.013)	(0.013)	(0.011)
Observations	557828	557828	557828	557828

Note: This table examines the impact of low income designation of credit unions on the number of new auto loans at the zip code level. The unit of observation is zip code by half-years. The dependent variable is the log number of auto loans plus one. The table reports the 4-quarter cumulative effect of the log number of low income credit unions on auto loan issuance. All regressions control for the total number of credit unions in a zip code, zip code fixed effects, and county by time fixed effects. Standard errors are clustered at the zip code level and are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The full table with all coefficient estimates is shown in the Internet Appendix. Panel A reports the regression results for all new auto loans and by institution types. Panels B-E report the regression results for new auto loans by different quartiles of Equifax Risk Scores of the borrower. The full table with all coefficient estimates is shown in Tables IA.15 and IA.16 in the Internet Appendix. The source of the auto loan data is the NY Fed CCP/Equifax database.

Table 9: Low Income Designation and Auto Loan Portfolio Risk

	(1) all institutions	(2) credit unions	(3) banks	(4) non-banks
Four quarters	0.0085***	0.013***	0.0019	0.0076***
	(0.0019)	(0.0047)	(0.0040)	(0.0023)
Observations	557828	391283	429458	473350
Zip code fixed effects	Yes	Yes	Yes	Yes
County by time fixed effects	Yes	Yes	Yes	Yes

Note: This table examines the impact of the log number of low income designation of credit unions on the share of riskier loans at the zip code level. The unit of observation is zip code by half-years. The dependent variable is the share of new loans with below median Equifax Risk Scores within each institution type: the ratio of new loans made by lender type to people with below median Equifax Risk Scores to the total number of new loans by the same lender type. Median Equifax Risk Scores is computed at the national level at half-year intervals. Column 1 uses all lenders. All regressions control for the total number of credit unions in a zip code, zip code fixed effects, and county by time fixed effects. Standard errors are clustered at the zip code level and are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The full table with all coefficient estimates is shown in Table IA.17 in the Internet Appendix. The source of the auto loan data is the NY Fed CCP/Equifax database.

Table 10: Low Income Designation and Non-performing Auto Loans

	log number of non-performing auto loans in 2017				log non-performing auto loan rate in 2017			
	(1) all institutions	(2) credit unions	(3) banks	(4) non-banks	(5) all institutions	(6) credit unions	(7) banks	(8) non-banks
Change in number of designated credit unions (2010 - 2013)	1.18***	0.71***	0.56***	1.13***	0.011***	0.0086***	0.0067**	0.015***
	(0.12)	(0.074)	(0.074)	(0.12)	(0.0036)	(0.0031)	(0.0027)	(0.0045)
Observations	23346	23346	23346	23346	23346	20270	21344	22262
R-squared	0.181	0.108	0.111	0.197	0.076	0.010	0.026	0.053

Note: This table examines the impact of the change in the number of low income designation of credit unions between 2010 and 2013 on the number of non-performing auto loans in 2017 at the zi pcode level. The dependent variable for columns (1)–(4) is the log number of auto loans that are 30+ days past due by institution type in the second half of 2007. The dependent variable for columns (5)–(8) is the fraction of auto loans that are 30+ days past due divided by the total number of auto loans in a zip code, by institution types in the second half of 2007. All regressions control for the change in number of credit unions between 2010 and 2013 in a zip code and county demographics in 2013. Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The full table with all coefficient estimates is shown in Table IA.18 in the Internet Appendix. The source of the auto loan data is the NY Fed CCP/Equifax database.

Table 11: Low Income Designation and Non-performing Auto Loans, by Equifax Risk Score Quartiles

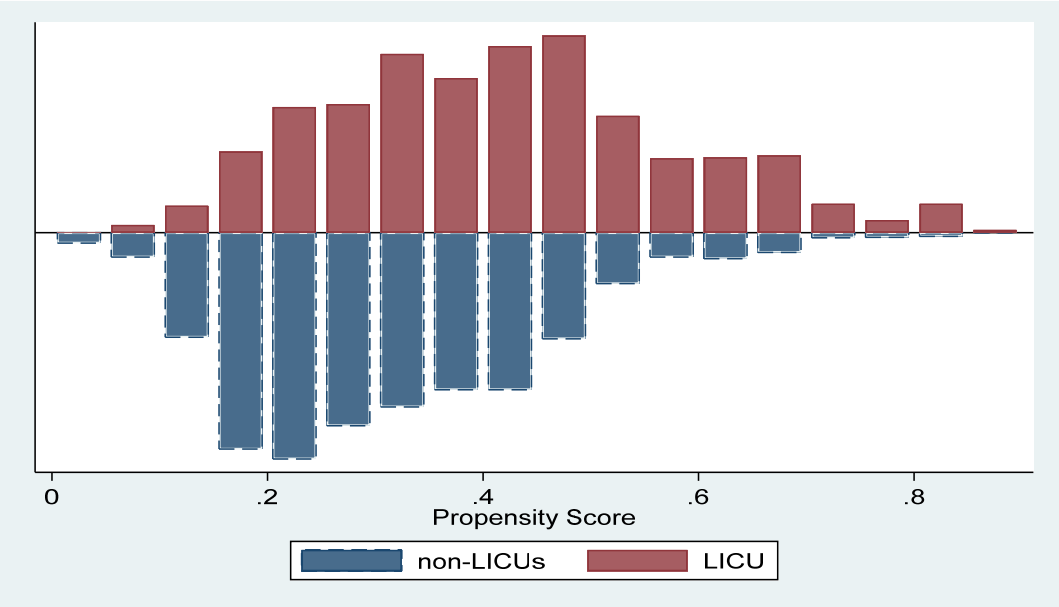
	log number of non-performing auto loans in 2017							
	1st quartile in Equifax Risk Score				2nd quartile in Equifax Risk Score			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	all institutions	credit unions	banks	non-banks	all institutions	credit unions	banks	non-banks
Change in number of designated credit unions (2010 - 2013)	1.19***	0.71***	0.54***	1.13***	0.38***	0.100***	0.10***	0.28***
	(0.12)	(0.073)	(0.071)	(0.12)	(0.058)	(0.023)	(0.030)	(0.054)
Observations	23346	23346	23346	23346	23346	23346	23346	23346
R-squared	0.180	0.104	0.103	0.195	0.145	0.038	0.047	0.144

	3rd quartile in Equifax Risk Score				4th quartile in Equifax Risk Score			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	all institutions	credit unions	banks	non-banks	all institutions	credit unions	banks	non-banks
Change in number of designated credit unions (2010 - 2013)	0.048**	0.0074	0.014	0.031*	0.0079	0.00079	-0.0012	0.0086
	(0.018)	(0.0070)	(0.0091)	(0.016)	(0.0068)	(0.0021)	(0.0011)	(0.0068)
Observations	23346	23346	23346	23346	23346	23346	23346	23346
R-squared	0.064	0.008	0.013	0.058	0.013	0.002	0.004	0.010

Note: This table examines the impact of the change in the number of low income designation of credit unions between 2010 and 2013 on the number of non-performing auto loans in 2017 at the zip code level by Equifax Risk Score Quartiles. The dependent variable is the log number of auto loans that are 30+ days over due by institution types in the second half of 2007. Similar to Table 10, all regressions control for the change in number of credit unions between 2010 and 2013 in a zip code and county demographics in 2013. Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The source of the auto loan data is the NY Fed CCP/Equifax database.

Internet Appendix

Figure IA.1: Propensity Score Matching Overlap



Note: This figure is based on column 4 of Table IA.6. To compute the propensity to become a LICU during the sample period, we use the predicted probabilities from column 4 of Table IA.6. This figure shows the support of these predicted probabilities for both LICUs and the nearest-neighbor non-LICUs.

Table IA.1: Call Report Data Item List

Variable	Source	Detail
Credit Unions		
Total assets	NCUA Form 5300	CUSA010
Deposits	NCUA Form 5300	CUSA018
Loans	NCUA Form 5300	CUSA025B
Equity	NCUA Form 5300	CUSA940+ CUSA 931+ CUSA 668+ CUSA 658+ CUSA 602
Auto loans	NCUA Form 5300	CUSA385+CUSA370
Real estate loans	NCUA Form 5300	CUSA703A
Net worth	NCUA Form 5300	Equity / Total Assets
Marketing expenses	NCUA Form 5300	CUSA270
Members	NCUA Form 5300	CUSA6091
Net income	NCUA Form 5300	CUSA602
ROE	NCUA Form 5300	Net income / Equity
ROA	NCUA Form 5300	Net income / Total assets
Field of membership	NCUA Form 5300	CUSA469
Banks		
Total assets	FFIEC Form 031/ Form 041[1]	RCON2170[2]
Deposits	FFIEC Form 031/ Form 041	RCON2200
Loans	FFIEC Form 031/ Form 041	RCON2122
Equity	FFIEC Form 031/ Form 041	RCON3210
C&I loans	FFIEC Form 031/ Form 041	RCON1763+RCON1764
Tier 1 capital	FFIEC Form 031/ Form 041	RCOA8274
Tier 1 leverage ratio	FFIEC Form 031/ Form 041	RCOA7206
Risk weighted assets	FFIEC Form 031/ Form 041	RCONG641
Net income	FFIEC Form 031/ Form 041	RCON4340
ROA	FFIEC Form 031/ Form 041	Equity / Total assets
ROE	FFIEC Form 031/ Form 041	Equity / Net income
Deposit rates	Ratewatch	
Lending rates	Ratewatch	
Bank failures	FDIC	
Auto loans	Equifax	

Note: This table lists the data items used from the Call Report in this paper.
1. Form 031 is for banks and bank holding companies with offices in the U.S. and other countries, Form 041 is for banks with U.S. offices only.
2. These variable codes reflect the variables reported in Form 041. For banks filing Form 031, the variable code will start with "RCFD" instead of "RCON".

Table IA.2: Single Bond v.s. Multiple Bonds Credit Unions

	(1) Single bond CUs	(2) Multiple bonds CUs
quarter of designation	0.0003	0.0012
	(0.0013)	(0.0008)
1 quarter after designation	0.0008	0.0025***
	(0.0014)	(0.0008)
2 quarters after designation	0.0007	0.0033***
	(0.0015)	(0.0008)
3 quarters after designation	0.0033**	0.0028***
	(0.0015)	(0.0009)
4 quarters after designation	-0.0002	0.0028***
	(0.0014)	(0.0009)
1 quarter before designation	-0.0020*	0.0014*
	(0.0012)	(0.0008)
2 quarters before designation	-0.0007	0.0011
	(0.0012)	(0.0008)
3 quarters before designation	0.0006	0.0001
	(0.0013)	(0.0007)
4 quarters before designation	-0.0001	0.0009
	(0.0012)	(0.0007)
>1 year after designation	0.0020*	0.0015**
	(0.0010)	(0.0007)
Observations	57278	122970

Note: This table uses the same specification from column 1 of Table 2. But column 1 restricts the sample to those credit unions with a single, mostly fraternal bond in membership, while column 2 uses the sample of credit unions with multiple common bonds in membership. There are some differences in the timing of the impact of LI designation on lending growth. But one year and beyond after designation, lending growth is about 0.19 percentage point faster in the "single bond" sample and 0.15 percentage point faster among the "multiple bonds" sample. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

Table IA.3: The Impact of Low Income Designations on Credit Unions Outcomes, Robustness 1

	(1) Loans	(2) Auto	(3) Real Estate	(4) Loans/Assets	(5) Assets	(6) Deposits	(7) Equity	(8) cusa4143	(9) cusa6091	(10) ROE	(11) ROA
quarter of designation	0.0011	0.0003	0.0004	0.0050*	0.0005	0.0006	-0.0003	0.0283*	-0.0018	-0.0002	0.0001
	(0.0007)	(0.0004)	(0.0003)	(0.0026)	(0.0008)	(0.0009)	(0.0007)	(0.0149)	(0.0062)	(0.0014)	(0.0001)
1 quarter after designation	0.0016**	0.0011**	-0.0001	0.0065**	0.0013	0.0014	-0.0006	0.0177	0.0016	0.0011	0.0001
	(0.0007)	(0.0005)	(0.0003)	(0.0027)	(0.0008)	(0.0009)	(0.0006)	(0.0158)	(0.0056)	(0.0009)	(0.0002)
2 quarters after designation	0.0027***	0.0014***	0.0006**	0.0082***	0.0025***	0.0023**	-0.0009	0.0376**	0.0012	0.0014	0.0001
	(0.0007)	(0.0005)	(0.0003)	(0.0029)	(0.0009)	(0.0010)	(0.0006)	(0.0170)	(0.0059)	(0.0013)	(0.0001)
3 quarters after designation	0.0024***	0.0012**	0.0003	0.0083***	0.0034***	0.0032***	-0.0013*	0.0451**	0.0013	-0.0003	-0.0001
	(0.0007)	(0.0005)	(0.0003)	(0.0031)	(0.0009)	(0.0010)	(0.0007)	(0.0176)	(0.0062)	(0.0011)	(0.0002)
4 quarters after designation	0.0019***	0.0017***	-0.0001	0.0094***	0.0018*	0.0015	-0.0015**	0.0485***	0.0047	0.0017	0.0004*
	(0.0007)	(0.0005)	(0.0003)	(0.0033)	(0.0009)	(0.0011)	(0.0008)	(0.0180)	(0.0066)	(0.0012)	(0.0002)
1 quarter before designation	0.0004	0.0004	0.0002	0.0041*	0.0015*	0.0015	-0.0005	0.0106	0.0026	0.0004	0.0001
	(0.0006)	(0.0005)	(0.0003)	(0.0024)	(0.0008)	(0.0009)	(0.0006)	(0.0142)	(0.0050)	(0.0012)	(0.0001)
2 quarters before designation	0.0006	0.0005	-0.0002	0.0038*	0.0011	0.0011	-0.0000	0.0147	0.0059	0.0014	0.0002
	(0.0006)	(0.0004)	(0.0003)	(0.0023)	(0.0008)	(0.0009)	(0.0006)	(0.0133)	(0.0046)	(0.0010)	(0.0001)
3 quarters before designation	0.0003	0.0003	-0.0001	0.0031	0.0017**	0.0015	0.0001	-0.0057	0.0049	0.0019	0.0001
	(0.0006)	(0.0004)	(0.0003)	(0.0021)	(0.0008)	(0.0009)	(0.0006)	(0.0131)	(0.0042)	(0.0011)	(0.0002)
4 quarters before designation	0.0002	0.0007*	-0.0000	0.0034*	0.0001	-0.0001	0.0000	0.0041	-0.0039	0.0014	0.0002**
	(0.0006)	(0.0004)	(0.0002)	(0.0019)	(0.0008)	(0.0009)	(0.0005)	(0.0123)	(0.0068)	(0.0010)	(0.0001)
>1 year after designation	0.0014**	0.0005	0.0003	0.0148***	0.0023***	0.0022***	-0.0029***	0.0516***	0.0121	0.0021**	0.0002**
	(0.0006)	(0.0004)	(0.0002)	(0.0038)	(0.0006)	(0.0006)	(0.0009)	(0.0192)	(0.0083)	(0.0009)	(0.0001)
Observations	167039	166957	167039	167039	167039	167039	149887	166758	167039	149937	167037

Note: This table uses the same specifications as in Table 2, but excludes credit unions that were designated as low income before 2008. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

Table IA.4: The Impact of Low Income Designations on Credit Unions Outcomes, Robustness 2

	(1) Loans	(2) Auto	(3) Real Estate	(4) Loans/Assets	(5) Assets	(6) Deposits	(7) Equity	(8) cusa4143	(9) cusa6091	(10) ROE	(11) ROA
quarter of designation	0.001	0.000	0.000	0.004	0.000	0.001	-0.000	0.029**	-0.001	-0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.003)	(0.001)	(0.001)	(0.001)	(0.015)	(0.006)	(0.001)	(0.000)
1 quarter after designation	0.002***	0.001***	-0.000	0.005*	0.001	0.001	-0.001	0.021	0.002	0.001	0.000
	(0.001)	(0.000)	(0.000)	(0.003)	(0.001)	(0.001)	(0.001)	(0.015)	(0.005)	(0.001)	(0.000)
2 quarters after designation	0.003***	0.002***	0.001*	0.007**	0.003***	0.002**	-0.001	0.040**	0.002	0.002	0.000
	(0.001)	(0.000)	(0.000)	(0.003)	(0.001)	(0.001)	(0.001)	(0.017)	(0.006)	(0.001)	(0.000)
3 quarters after designation	0.003***	0.001***	0.000	0.007**	0.003***	0.003***	-0.001*	0.042**	0.002	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.003)	(0.001)	(0.001)	(0.001)	(0.017)	(0.006)	(0.001)	(0.000)
4 quarters after designation	0.002***	0.002***	-0.000	0.009***	0.002*	0.001	-0.001*	0.051***	0.005	0.002*	0.000**
	(0.001)	(0.001)	(0.000)	(0.003)	(0.001)	(0.001)	(0.001)	(0.018)	(0.006)	(0.001)	(0.000)
1 quarter before designation	0.001	0.001	0.000	0.003	0.001	0.001	-0.000	0.009	0.003	0.002	0.000
	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.014)	(0.005)	(0.002)	(0.000)
2 quarters before designation	0.001	0.001	-0.000	0.003	0.001	0.001	0.000	0.018	0.006	0.002	0.000
	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.013)	(0.004)	(0.002)	(0.000)
3 quarters before designation	0.000	0.000	-0.000	0.002	0.001*	0.001	0.000	-0.004	0.006	0.001	0.000
	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.013)	(0.004)	(0.002)	(0.000)
4 quarters before designation	0.000	0.001**	-0.000	0.002	0.000	-0.000	0.000	0.003	-0.003	0.001	0.000**
	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.012)	(0.007)	(0.001)	(0.000)
>1 year after designation	0.002***	0.001**	0.000	0.015***	0.002***	0.002***	-0.002***	0.057***	0.014*	0.003**	0.000**
	(0.001)	(0.000)	(0.000)	(0.004)	(0.001)	(0.001)	(0.001)	(0.018)	(0.008)	(0.001)	(0.000)
Observations	173952	173843	173952	173952	173952	173952	154705	173616	173952	154759	173950

Note: This table examines the impact of low income designation on several balance sheet and income outcomes for the sample of credit unions (CUs) located in counties with at least one low-income CU. The main independent variable is a dummy variable that is 1 in the quarter a CU gets a low income designation and 0 otherwise. All regressions include 4 leads and 4 lags of this dummy variable. The variable "more than one year after designation" is a dummy that is 1 if a CU was designated more than one year ago and 0 otherwise. All regressions include CU fixed effects, and year-quarter-county fixed effects. Standard errors are clustered at the CU level (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). All "growth" variables are defined as the quarter on quarter change in the variable divided by total assets in the previous quarter.

Table IA.5: The Impact of Low Income Designations on Credit Unions Outcomes, Robustness 3

	(1) Loans	(2) Auto	(3) Real Estate	(4) Loans/Assets	(5) Assets	(6) Deposits	(7) Equity	(8) cusa4143	(9) cusa6091	(10) ROE	(11) ROA
quarter of designation	0.001	0.000	0.000	0.004	-0.000	-0.000	0.000	0.031*	-0.003	0.001	0.000
	(0.001)	(0.001)	(0.000)	(0.003)	(0.001)	(0.001)	(0.001)	(0.017)	(0.007)	(0.002)	(0.000)
1 quarter after designation	0.001*	0.002***	-0.000	0.005	0.000	0.000	0.000	0.021	-0.002	0.001	0.000
	(0.001)	(0.001)	(0.000)	(0.003)	(0.001)	(0.001)	(0.001)	(0.018)	(0.006)	(0.001)	(0.000)
2 quarters after designation	0.003***	0.001**	0.001**	0.007*	0.003***	0.002*	-0.001	0.048**	-0.001	0.002	0.000
	(0.001)	(0.001)	(0.000)	(0.003)	(0.001)	(0.001)	(0.001)	(0.020)	(0.006)	(0.001)	(0.000)
3 quarters after designation	0.003***	0.002**	0.000	0.007**	0.002**	0.002	-0.001	0.035*	-0.005	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.004)	(0.001)	(0.001)	(0.001)	(0.020)	(0.007)	(0.002)	(0.000)
4 quarters after designation	0.003***	0.002***	0.000	0.009**	0.001	0.001	-0.001	0.051**	-0.001	0.003*	0.001**
	(0.001)	(0.001)	(0.000)	(0.004)	(0.001)	(0.001)	(0.001)	(0.020)	(0.007)	(0.002)	(0.000)
1 quarter before designation	0.001	0.001	0.000	0.003	0.001	0.000	-0.000	0.007	0.000	0.001	0.000
	(0.001)	(0.001)	(0.000)	(0.003)	(0.001)	(0.001)	(0.001)	(0.016)	(0.005)	(0.002)	(0.000)
2 quarters before designation	0.001	0.000	-0.000	0.002	0.001	0.002	0.000	0.024	0.005	0.001	0.000
	(0.001)	(0.001)	(0.000)	(0.003)	(0.001)	(0.001)	(0.001)	(0.015)	(0.005)	(0.001)	(0.000)
3 quarters before designation	0.000	0.001*	-0.000	0.002	0.000	-0.000	0.001	-0.006	0.004	0.002	0.000
	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.015)	(0.005)	(0.001)	(0.000)
4 quarters before designation	0.001	0.001*	0.000	0.002	-0.001	-0.001	0.000	-0.001	-0.007	0.002	0.000
	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.014)	(0.008)	(0.001)	(0.000)
>1 year after designation	0.002***	0.001*	0.000	0.016***	0.001**	0.001*	-0.003**	0.067***	0.011	0.003*	0.000*
	(0.001)	(0.000)	(0.000)	(0.004)	(0.001)	(0.001)	(0.001)	(0.021)	(0.009)	(0.002)	(0.000)
Observations	134825	134723	134825	134825	134825	134825	120183	134553	134825	120228	134823

Note: This table examines the impact of low income designation on several balance sheet and income outcomes for the sample of credit unions (CUs) located in census tracts with median income below the national median. All regressions include CU fixed effects, and year-quarter-county fixed effects. Standard errors are clustered at the CU level (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). All "growth" variables are defined as the quarter on quarter change in the variable divided by total assets in the previous quarter.

Table IA.6: Propensity Score Selection

	(1)	(2)	(3)	(4)
median income of census tract, log, 2010	-0.566***	-0.320***	-0.359***	-0.375***
	(0.109)	(0.116)	(0.121)	(0.127)
1 if tract income>national median income		-0.386***	-0.445***	-0.448***
		(0.132)	(0.128)	(0.122)
1 if tract income>CBSA median income			0.126	0.123
			(0.143)	(0.145)
total equity/assets, 2008-2007				-2.558***
				(0.939)
average assets, 2008-2007, log				-0.006
				(0.030)
average ROA, 2008-2007				-0.774
				(1.082)
average loans/assets, 2007-2008				0.306
				(0.273)
(mean) nmlb_bal_out_asst_2008				-93.588
				(71.421)
Observations	4450	4450	4450	4450

Note: Among the sample of CUs not yet designated as LI in 2008, this table uses a logit model to predict the probability that a CU becomes a LICU over the subsequent sample period 2009-2016. Specifically, the dependent variable equals 1 if a credit union is designated as "low-income" over the sample period, 2009Q1-2016 Q4, and 0 otherwise. All specifications include state-fixed effects and standard errors are clustered at the state-level (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). All balance sheet variables are averaged immediately before the rule change, 2007-2008. The sample consists of the cross-section of credit unions in 2009 Q1 that are not yet designated.

Table IA.7: Propensity Score Matching

	LICUs	"Nearest Neighbor" Non-LICUs	t-test	p-value
Tract Median Income, log	10.528	10.518	0.55	0.581
Indicator that equals 1 if tract median income>national median income	0.224	0.229	-0.38	0.7
Indicator that equals 1 if tract median income>MSA median income	0.239	0.241	-0.29	0.77
Equity/Assets	0.142	0.141	0.4	0.69
Assets, log	10.228	10.161	1.04	0.297
Return on Assets	0.001	0.001	-1.31	0.192

Note: This table compares the mean of the covariates used to predict the propensity of LI designation for those institutions that become LICUs and their nearest neighbor counterparts that did not become LICUs during the sample period. In all cases, the t-tests (and p-values) show that the means from the two distributions are statistically identical. The average treatment effect on the treated is 0.004 with a robust standard error of (0.0004). That is, average lending growth is about 0.4 percentage point higher during the period in which a CU is designated as LI compared to average growth rate among matched undesignated CUs.

Table IA.8: Bank Market Structure

VARIABLES	(1) HHI	(2) branches	(3) banks
ratio of LICU/CUs, 2008	0.679***	0.686***	0.675***
	(0.0346)	(0.0357)	(0.0362)
Herfindahl Deposit Index, 2008	-0.0334		
	(0.0805)		
Bank branches in county, logs, 2008		0.0101	
		(0.00903)	
Banks in county, logs, 2008			-0.00135
			(0.0150)
Observations	1,272	1,272	1,272
R-squared	0.466	0.467	0.466

Note: This table examines the impact of bank market structure in 2008 at the county-level on the 2015 Q4 ratio of low-income credit unions to all credit unions in the county. All regressions include state fixed effects and standard errors are clustered at the state-level.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table IA.9: Difference-in-difference Regression

VARIABLES	(1) loan growth
4 quarters before exposure to LICU	-0.000873
	(0.00129)
3 quarters before exposure to LICU	0.00112
	(0.00170)
2 quarters before exposure to LICU	-0.000653
	(0.00190)
1 quarter before exposure to LICU	-0.00192
	(0.00157)
exposure to LICU	-0.00107
	(0.00119)
1 quarter after exposure to LICU	0.00281**
	(0.00129)
2 quarters after exposure to LICU	-0.00199
	(0.00174)
3 quarters after exposure to LICU	-0.00390**
	(0.00156)
4 quarters after exposure to LICU	-0.000698
	(0.00132)
Observations	174,831
R-squared	0.470
Sum of coefficients:	
before exposure to LICUs -0.0023 (p-value=0.36)	
after to exposure to LICUs -0.0048 (p-value=0.04)	

Note: This table examines the impact of exposure to LICUs on a bank's loan growth. The variable "exposure to LICU" equals 1 in the quarters in which a bank faces competition from at least one newly converted LICU and 0 otherwise. The regression includes bank-by-year fixed effects; county fixed effects and year-by-quarter fixed effects. Standard errors are clustered at county-level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table IA.10: The Impact of Low Income Designation on Bank Loan Growth, 5 mile radius

	(1) Baseline	(2) Control for zip code level house prices	(3) County-year-quarter fixed effects	(4) Census tract fixed effects	(5) Control for total number of credit unions	(6) Exclude year 2012	(7) Banks smaller than $1 billion	(8) Banks smaller than $100 million	(9) Banks smaller than $10 billion	(10) Big banks
Log Number of LICUs, current quarter	-0.00441***	-0.00173	-0.00216	-0.00436***	-0.00418***	-0.00279	-9.62e-05	-0.00455***	-0.00660**	-0.00335***
	(0.00120)	(0.00140)	(0.00160)	(0.00123)	(0.00121)	(0.00194)	(0.00266)	(0.00125)	(0.00260)	(0.00112)
Log Number of LICUs, one quarter lag	0.00162	0.00111	0.00168	0.00165	0.00168	0.000525	-0.000608	0.000905	0.00336	0.00129
	(0.00130)	(0.00172)	(0.00190)	(0.00143)	(0.00131)	(0.00206)	(0.00345)	(0.00141)	(0.00311)	(0.00131)
Log Number of LICUs, two quarters lag	0.00156	-0.00252	-0.00187	0.00114	0.00161	0.00112	0.000925	0.00224	0.000175	0.00109
	(0.00136)	(0.00175)	(0.00181)	(0.00158)	(0.00136)	(0.00179)	(0.00404)	(0.00149)	(0.00316)	(0.00142)
Log Number of LICUs, three quarters lag	-0.00323**	-0.000706	-0.00262	-0.00358**	-0.00328***	-0.00325**	-0.000103	-0.00347**	-0.00488*	-0.00321**
	(0.00126)	(0.00150)	(0.00161)	(0.00140)	(0.00127)	(0.00129)	(0.00386)	(0.00149)	(0.00291)	(0.00128)
Log Number of LICUs, four quarters lag	0.000675	-6.12e-05	0.00164	0.000396	0.000578	0.000210	0.000691	5.05e-05	0.00142	0.000410
	(0.00108)	(0.00141)	(0.00161)	(0.00125)	(0.00108)	(0.00112)	(0.00335)	(0.00136)	(0.00268)	(0.00120)
Observations	203,542	69,748	176,207	180,209	203,542	177,575	15,745	181,599	76,793	194,965
R-squared	0.251	0.358	0.498	0.275	0.252	0.261	0.256	0.274	0.330	0.270

Note: This is the full table corresponding to Table 3 in the main text. This table examines the impact of a bank's exposure to the log number of low income credit unions (LICUs) within a 5 mile radius of the bank's headquarters. In all cases, the dependent variable is the quarter-on-quarter change in total loans divided by previous quarter's assets. The independent variable of interest is the log number of LICUs within a 5 mile radius of the bank's headquarters. This table reports the coefficient estimates for the log number of LICUs at various lags. The corresponding standard errors (in parentheses) are clustered at the county-level. The results remain robust if errors are clustered both by county and year-by-quarter. All specifications control for bank, county fixed effects and year-by-quarter fixed effects. Column 2 includes the change in Zillow's zip code level house price index contemporaneously and up to three lags. Column 3 includes county-by-year-by quarter fixed effects. Column 4 includes census tract fixed effects based on the location of the bank's headquarters. Column 5 controls for the log number of CUs within a 5 mile radius of the bank. Column 6 drops observations in the year 2012; Column 7 restricts the sample to banks with $1billion or less in assets; column 8 restricts the sample to banks with $100 million in assets, while column 9 includes only banks with $10 billion or less in assets. Column 10 uses the sample of large and mid-sized banks–those that do not meet the FDIC's community bank definition. Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table IA.11: The Impact of Low Income Designation on Bank Loan Growth by Different Radius

	(1) 5 miles	(2) 10 miles	(3) 20 miles	(4) 30 miles	(5) 40 miles	(6) 50 miles
Log Number of LICUs, current quarter	-0.00441***	-0.00493***	-0.00314***	-0.00366***	-0.00320***	-0.00304***
	(0.00120)	(0.00110)	(0.000953)	(0.000755)	(0.000683)	(0.000629)
Log Number of LICUs, one quarter lag	0.00162	0.00247**	0.00154*	0.000482	-0.000325	-0.000371
	(0.00130)	(0.00108)	(0.000913)	(0.000839)	(0.000796)	(0.000845)
Log Number of LICUs, two quarters lag	0.00156	0.00211*	0.00291***	0.00467***	0.00494***	0.00511***
	(0.00136)	(0.00117)	(0.000959)	(0.000907)	(0.000857)	(0.000908)
Log Number of LICUs, three quarters lag	-0.00323**	-0.00282**	-0.00333***	-0.00433***	-0.00409***	-0.00445***
	(0.00126)	(0.00119)	(0.000942)	(0.000771)	(0.000765)	(0.000823)
Log Number of LICUs, four quarters lag	0.000675	0.000547	0.000399	0.00155**	0.00128*	0.00133**
	(0.00108)	(0.00114)	(0.000933)	(0.000734)	(0.000677)	(0.000672)
Observations	203,542	203,542	203,542	203,542	203,542	203,542
R-squared	0.251	0.251	0.251	0.251	0.251	0.251

Note: This is the full table corresponding to Table 4 in the main text. This table examines the impact of a bank's exposure to the log number of low income credit unions (LICUs) computed at various radii from the bank's headquarters. In all cases, the dependent variable is the quarter-on-quarter change in total loans divided by the previous quarter's assets. All specifications control for bank, county and year-quarter fixed effects–the baseline specification in column 1 of Table IA.10. The independent variable of interest is the log number of LICUs within a particular radius. The table reports the coefficient estimates for the log number of LICUs at various lags. Column 1 computes this variable using a 5 mile radius around the bank's headquarters. Columns 2-6 recompute this variable using the 10 through 50 mile radii around the headquarters. The corresponding standard errors (in parentheses) are clustered at the county level. Standard errors in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$) are clustered at the county level.

Table IA.12: The impact of low income designation on banks' balance sheets, 5 miles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Deposit Growth	Asset Growth	Loans/Assets	Commercial and Industrial Loan Growth	Tier 1 capital/Assets	ROA	ROE
Log Number of LICUs, current quarter	-0.00286	-0.00308	0.00765**	0.000152	-0.649***	0.000711***	0.00535
	(0.00186)	(0.00196)	(0.00313)	(0.000196)	(0.181)	(0.000175)	(0.00390)
Log Number of LICUs, one quarter lag	-0.00360	-0.00412	0.00180	0.000282	0.149***	0.000145	0.00137
	(0.00280)	(0.00260)	(0.00136)	(0.000270)	(0.0567)	(0.000179)	(0.00649)
Log Number of LICUs, two quarters lag	-0.00354	-0.000794	0.00516***	1.37e-05	0.0538	-8.53e-05	-0.00312
	(0.00249)	(0.00240)	(0.00129)	(0.000256)	(0.127)	(0.000141)	(0.00688)
Log Number of LICUs, three quarters lag	0.00747***	0.00651***	-0.00221	-0.000325	0.0527	-8.65e-06	0.0261
	(0.00244)	(0.00250)	(0.00160)	(0.000272)	(0.120)	(0.000168)	(0.0194)
Log Number of LICUs, four quarters lag	-0.00197	-0.00280	-0.00242	0.000227	-0.110	-4.66e-05	-0.0229
	(0.00195)	(0.00191)	(0.00282)	(0.000213)	(0.151)	(0.000145)	(0.0167)
Observations	204,081	204,081	204,239	204,081	204,239	204,649	204,115
R-squared	0.149	0.162	0.860	0.106	0.613	0.699	0.138

Note: This is the full table corresponding to Table 5 in the main text. This table examines the impact of the log number of low income credit unions within a 5 mile radius around a bank's headquarters on a range of bank balance sheet aggregates. It uses the full sample of community banks and the baseline specification (column 1 of Table 3). All specifications control for county, bank and year-quarter fixed effects. The table reports the coefficient estimates for the log number of LICUs at various lags. The standard errors (in parentheses) are clustered at the county-level (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). The dependent variables are deposit growth (column 1), asset growth (column 2), loans-to-assets ratio (column 3), commercial and industrial loan growth (column 4), the Tier 1 capital to assets ratio (column 5), and return on assets (column 6), return on equity (column 7).

Table IA.13: The Impact of Low-Income Credit Union Entry on Bank Branch Interest Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$100,000 CD			$250,000 CD			$500,000 CD			$10,000 CD		
	6 months	12 months	36 months	6 months	12 months	36 months	6 months	12 months	36 months	6 months	12 months	36 months
Log Number of LICUs, current quarter	0.00837	0.00597	0.00792	0.0105***	0.00818**	0.00963	0.0101***	0.00796*	0.00926	-0.000927	-0.00173	0.000721
	(0.00584)	(0.00643)	(0.00712)	(0.00325)	(0.00407)	(0.00588)	(0.00326)	(0.00410)	(0.00593)	(0.00660)	(0.00706)	(0.00817)
Log Number of LICUs, one quarter lag	0.00179	-0.00102	0.00595	-0.00257	-0.00263	0.000802	-0.00220	-0.00233	0.00141	-0.000371	-0.000172	0.00311
	(0.00318)	(0.00331)	(0.00364)	(0.00195)	(0.00227)	(0.00344)	(0.00195)	(0.00227)	(0.00349)	(0.00398)	(0.00410)	(0.00486)
Log Number of LICUs, two quarters lag	0.000214	0.00233	0.00832**	0.00246	0.00563**	0.0117***	0.00217	0.00539**	0.0116***	0.00336	0.00338	0.00704
	(0.00274)	(0.00319)	(0.00418)	(0.00185)	(0.00240)	(0.00410)	(0.00186)	(0.00241)	(0.00412)	(0.00366)	(0.00374)	(0.00456)
Log Number of LICUs, three quarters lag	-0.000190	0.00132	0.00184	0.00129	0.000760	0.00190	0.00170	0.00136	0.00213	-0.000485	-0.00250	-0.00121
	(0.00308)	(0.00340)	(0.00454)	(0.00183)	(0.00238)	(0.00398)	(0.00186)	(0.00241)	(0.00400)	(0.00342)	(0.00360)	(0.00468)
Log Number of LICUs, four quarters lag	0.00672	0.0106**	0.00302	-0.000616	0.00106	-0.000823	-0.000736	0.000517	-0.00113	0.00478	0.0110**	0.00600
	(0.00460)	(0.00495)	(0.00615)	(0.00261)	(0.00330)	(0.00562)	(0.00263)	(0.00332)	(0.00565)	(0.00532)	(0.00554)	(0.00682)
Observations	133,564	134,432	114,850	95,371	95,853	86,411	95,085	95,610	86,122	165,900	166,546	149,634
R-squared	0.930	0.940	0.923	0.866	0.884	0.873	0.870	0.887	0.873	0.945	0.951	0.941

(a) Deposit Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	New car loans				Used car loans			Mortgages		
	36 months	48 months	60 months	72 months	36 months	48 months	60 months	30 years	15 years	HELOC
Log Number of LICUs, current quarter	-0.104	-0.121	-0.124	-0.0791	-0.130	-0.0266	-0.138	-0.0133	0.109	-0.0683
	(0.111)	(0.101)	(0.102)	(0.138)	(0.130)	(0.139)	(0.192)	(0.0652)	(0.0907)	(0.107)
Log Number of LICUs, one quarter lag	-0.0290	-0.0143	-0.000350	-0.136	0.0563	-0.0896	-0.00979	-0.0397	-0.0512	-0.00818
	(0.146)	(0.136)	(0.135)	(0.180)	(0.167)	(0.191)	(0.262)	(0.0917)	(0.125)	(0.158)
Log Number of LICUs, two quarters lag	0.0163	0.0231	0.0273	0.0753	-0.0326	0.0234	-0.000899	0.103	-0.0492	-0.0192
	(0.114)	(0.110)	(0.108)	(0.144)	(0.132)	(0.141)	(0.225)	(0.0857)	(0.118)	(0.138)
Log Number of LICUs, three quarters lag	0.100	0.0973	0.0763	0.00481	0.240	0.0651	0.149	0.110	0.241	0.00593
	(0.126)	(0.123)	(0.125)	(0.158)	(0.149)	(0.152)	(0.239)	(0.0851)	(0.160)	(0.138)
Log Number of LICUs, four quarters lag	-0.0687	-0.0809	-0.0733	0.00198	-0.267**	-0.129	-0.198	-0.146*	-0.121	0.0360
	(0.119)	(0.117)	(0.119)	(0.159)	(0.131)	(0.135)	(0.224)	(0.0754)	(0.166)	(0.120)
Observations	13,907	13,921	13,876	6,665	12,064	9,960	4,895	4,812	5,771	9,321
R-squared	0.821	0.825	0.827	0.842	0.810	0.812	0.854	0.890	0.875	0.789

(b) Lending Rates

Note: This is the full table corresponding to Table 6 in the main text. Panel (a) examines the impact of the log number of low-income credit unions (LICUs) within a 5 mile radius of a bank's branch on the offered interest rate for certificates of deposit (CDs) of different minimum sizes and at different maturities: 6, 12 and 36 months. The table reports the coefficient estimates for the log number of LICUs at various lags. Panel (b) of this table examines the impact of the log number of low-income credit unions (LICUs) within a 5 mile radius of a bank's branch on the offered interest rate for various new and used car loan products: the 30 and 15 year advertised conforming mortgage rate and the rate on home equity lines of credit (HELOC). We report the coefficient estimates for the log number of LICUs at various lags. All specifications include bank, county and year-by-quarter fixed effects. Standard errors in parentheses are clustered at the bank level (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table IA.14: The Impact of Credit Union Low Income Designation on the Probability of Bank Failure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Tier 1 capital/Assets		ROA		Assets		State tax rate	
	Full sample	below median	above median	below median	above median	below median	above median	top quartile	bottom quartile
Log Number of LICUs, current quarter	-0.000537	-0.000172	-0.000849	8.14e-05	-0.00135*	-0.000153	-0.000717	0.000718	-0.000427
	(0.00111)	(0.00155)	(0.00182)	(0.00220)	(0.000809)	(0.00332)	(0.000904)	(0.00225)	(0.00328)
Log Number of LICUs, one quarter lag	0.00237	0.00520	0.000495	0.00302	0.00166	0.00178	0.00271	0.00676	-0.000188
	(0.00192)	(0.00442)	(0.00209)	(0.00379)	(0.00160)	(0.00439)	(0.00218)	(0.00512)	(0.00385)
Log Number of LICUs, two quarters lag	-0.000641	-0.00179	0.000145	-0.00293	0.00163	0.00218	-0.00222	-0.00145	-0.00159
	(0.00177)	(0.00472)	(0.00153)	(0.00317)	(0.00173)	(0.00391)	(0.00176)	(0.00517)	(0.00219)
Log Number of LICUs, three quarters lag	-0.000285	-0.00483	0.00257	0.000679	-0.00122	-0.00339	0.00148	-0.00333	0.00249
	(0.00179)	(0.00388)	(0.00177)	(0.00321)	(0.00170)	(0.00501)	(0.000912)	(0.00414)	(0.00288)
Log Number of LICUs, four quarters lag	0.000213	0.00309	-0.00153	0.000864	-0.000511	0.00208	-0.000907	0.00131	0.000286
	(0.00130)	(0.00199)	(0.00157)	(0.00271)	(0.000576)	(0.00336)	(0.000794)	(0.00186)	(0.00250)
Observations	204,770	92,358	112,412	95,148	109,622	114,061	90,709	70,663	65,008
R-squared	0.122	0.118	0.128	0.118	0.130	0.109	0.137	0.134	0.126

Note: This is the full table corresponding to Table 7 in the main text. This table reports the cumulative impact of a permanent increase in "the log number of low-income credit unions within a 5 mile radius of a bank" after four quarters on the probability that a bank fails over the sample period. The dependent variable equals 1 if a bank fails in a quarter and 0 otherwise. We report the coefficient estimates for the log number of LICUs at various lags. Column 1 reports results for the full sample of banks. Column 2 uses the subset of banks whose average tier 1 equity to assets in 2006-2007 was below the sample median; column 3 uses the above median sample. Columns 4 and 5 split the sample by the average return on assets in 2006-2007; and columns 6 and 7 split the sample by average assets in 2006-2007. Columns 8 and 9 restrict the sample to banks located in states that are in the top quartile corporate tax rate (column 8), and the bottom quartile (column 9). The standard errors are clustered at the county level (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$) and all specifications include bank, county and year-by-quarter fixed effects–the baseline from column 1 of Table IA.10.

Table IA.15: Low Income Designation and Number of New Auto Loans

		Panel A: all			
		(1)	(2)	(3)	(4)
Log number of new car loans		all institutions	credit unions	banks	non-banks
Log number of designated credit unions		0.017***	0.010	0.0072	0.027***
		(0.0065)	(0.014)	(0.013)	(0.0088)
Log number of designated credit unions (lag 1)		-0.00022	-0.0070	0.0054	-0.0035
		(0.0081)	(0.018)	(0.017)	(0.011)
Log number of designated credit unions (lag 2)		0.010	0.016	-0.0056	0.018**
		(0.0068)	(0.015)	(0.014)	(0.0088)
Log number of credit unions		-0.011***	-0.014*	0.00043	-0.012***
		(0.0037)	(0.0071)	(0.0064)	(0.0045)
Observations		557828	557828	557828	557828
R-squared		0.97	0.91	0.88	0.95
Zip Code fixed effects		Yes	Yes	Yes	Yes
County by time fixed effects		Yes	Yes	Yes	Yes
Cumulative effect:					
Contemporaneous + lag 1	coefficient	0.017***	0.0034	0.013	0.024***
	p-value	0.0087	0.82	0.37	0.0055
Contemporaneous + lag 1 + lag2	coefficient	0.027***	0.019**	0.0070	0.042***
	p-value	0.00000019	0.042	0.46	1.0e-11

Note: This table is the full table corresponding to panel A of Table 8 in the main text. It examines the impact of low income designation of credit unions on the number of new auto loans at the zip code level. The unit of observation is zip code by half-years. The dependent variable is the log number of auto loans plus one. The table reports all the coefficient estimates as well as the 4-quarter cumulative effect of the low income designation on auto loan issuance. All regressions control for the total number of credit unions in a zip code, zip code fixed effects, and county by time fixed effects. Standard errors are clustered at the zip code level and are reported in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). The source of the auto loan data is the NY Fed CCP/Equifax database.

Table IA.16: Low Income Designation and Number New Auto Loans

		Panel B: 1st quartile in Equifax Risk Score				Panel C: 2nd quartile in Equifax Risk Score			
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Log number of new car loans		all institutions	credit unions	banks	non-banks	all institutions	credit unions	banks	non-banks
Log number of designated credit unions		0.046***	0.052**	0.041	0.048***	0.016	0.021	0.0019	0.034**
		(0.013)	(0.024)	(0.026)	(0.014)	(0.011)	(0.020)	(0.021)	(0.015)
Log number of designated credit unions (lag 1)		-0.0097	0.011	0.0029	-0.010	-0.0055	-0.0013	0.026	-0.031
		(0.016)	(0.029)	(0.033)	(0.019)	(0.015)	(0.026)	(0.027)	(0.020)
Log number of designated credit unions (lag 2)		0.030**	-0.018	-0.023	0.043***	0.025**	0.043**	-0.018	0.044***
		(0.013)	(0.023)	(0.025)	(0.015)	(0.013)	(0.021)	(0.022)	(0.016)
Log number of credit unions		-0.020***	-0.025**	-0.0061	-0.022***	-0.014**	-0.029***	0.0063	-0.016**
		(0.0066)	(0.010)	(0.011)	(0.0074)	(0.0061)	(0.0096)	(0.010)	(0.0074)
Observations		557828	557828	557828	557828	557828	557828	557828	557828
R-squared		0.91	0.75	0.59	0.90	0.90	0.81	0.71	0.87
Cumulative effects: contemporaneous + lags 1-2	coefficient	0.067***	0.044***	0.021	0.081***	0.035***	0.062***	0.0096	0.047***
	p-value	3.5e-16	0.0025	0.16	6.8e-20	0.000036	0.0000025	0.48	0.0000050

		Panel D: 3rd quartile in Equifax Risk Score				Panel E: 4th quartile in Equifax Risk Score			
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Log number of new car loans		all institutions	credit unions	banks	non-banks	all institutions	credit unions	banks	non-banks
Log number of designated credit unions		0.0013	-0.022	-0.0098	0.033**	0.025**	0.040**	0.023	0.041**
		(0.012)	(0.021)	(0.019)	(0.017)	(0.012)	(0.020)	(0.021)	(0.018)
Log number of designated credit unions (lag 1)		0.028*	0.030	0.021	0.026	-0.031*	-0.069**	-0.028	-0.030
		(0.015)	(0.025)	(0.027)	(0.021)	(0.016)	(0.028)	(0.028)	(0.022)
Log number of designated credit unions (lag 2)		0.00052	0.0025	0.0066	-0.000071	0.0047	0.026	-0.00026	0.0056
		(0.013)	(0.021)	(0.022)	(0.018)	(0.013)	(0.021)	(0.023)	(0.018)
Log number of credit unions		-0.0094	-0.016*	0.0025	-0.014*	0.0035	0.0039	0.0047	0.0087
		(0.0060)	(0.0096)	(0.0088)	(0.0076)	(0.0060)	(0.0095)	(0.0093)	(0.0075)
Observations		557828	557828	557828	557828	557828	557828	557828	557828
R-squared		0.90	0.81	0.76	0.86	0.92	0.82	0.79	0.87
Cumulative effects: contemporaneous + lags 1-2	coefficient	0.030***	0.011	0.018	0.058***	-0.0011	-0.0028	-0.0051	0.016
	p-value	0.00029	0.41	0.14	0.00000013	0.89	0.83	0.69	0.12

Note: This table is the full table corresponding to panels B-E of Table 8 in the main text. It examines the impact of low income designation of credit unions on the number of new auto loans at the zip code level. The unit of observation is zip code by half-years. The dependent variable is the log number of auto loans plus one. The table reports all the coefficient estimates as well as the 4-quarter cumulative effect of the low income designation on auto loan issuance. All regressions control for the total number of credit unions in a zip code, zip code fixed effects, and county by time fixed effects. Standard errors are clustered at the zip code level and are reported in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). The source of the auto loan data is the NY Fed CCP/Equifax database.

Table IA.17: Low Income Designation and Auto Loan Portfolio Risk

Panel A: all institutions			
		(1)	(2)
Share of new car loans		below median	above median
Log number of designated credit unions		0.0049*	-0.0049*
		(0.0028)	(0.0028)
Log number of designated credit unions (lag 1)		-0.0031	0.0031
		(0.0035)	(0.0035)
Log number of designated credit unions (lag 2)		0.0067**	-0.0067**
		(0.0028)	(0.0028)
Log number of credit unions		-0.0036***	0.0036***
		(0.0013)	(0.0013)
Observations		557828	557828
R-squared		0.74	0.74
Four quarters cumulative effect	coefficient	0.0085***	-0.0085***
	p-value	0.0000044	0.0000044

Panel B: credit unions			
		(1)	(2)
Share of new car loans		below median	above median
Log number of designated credit unions		0.0081	-0.0081
		(0.0073)	(0.0073)
Log number of designated credit unions (lag 1)		0.0044	-0.0044
		(0.0094)	(0.0094)
Log number of designated credit unions (lag 2)		0.00034	-0.00034
		(0.0077)	(0.0077)
Log number of credit unions		-0.0051	0.0051
		(0.0035)	(0.0035)
Observations		391283	391283
R-squared		0.43	0.43
Four quarters cumulative effect	coefficient	0.013***	-0.013***
	p-value	0.0064	0.0064

Panel C: banks			
		(1)	(2)
Share of new car loans		below median	above median
Log number of designated credit unions		0.0061	-0.0061
		(0.0069)	(0.0069)
Log number of designated credit unions (lag 1)		-0.0032	0.0032
		(0.0090)	(0.0090)
Log number of designated credit unions (lag 2)		-0.0011	0.0011
		(0.0071)	(0.0071)
Log number of credit unions		-0.00047	0.00047
		(0.0029)	(0.0029)
Observations		429458	429458
R-squared		0.45	0.45
Four quarters cumulative effect	coefficient	0.0019	-0.0019
	p-value	0.64	0.64

Panel D: non-banks			
		(1)	(2)
Share of new car loans		below median	above median
Log number of designated credit unions		0.0019	-0.0019
		(0.0038)	(0.0038)
Log number of designated credit unions (lag 1)		-0.0059	0.0059
		(0.0047)	(0.0047)
Log number of designated credit unions (lag 2)		0.012***	-0.012***
		(0.0038)	(0.0038)
Log number of credit unions		-0.0047***	0.0047***
		(0.0018)	(0.0018)
Observations		473350	473350
R-squared		0.68	0.68
Four quarters cumulative effect	coefficient	0.0076***	-0.0076***
	p-value	0.0010	0.0010

Note: This table is the full table corresponding to Table 9 in the main text. It examines the impact of low income designation of credit unions on the number of share of riskier loans at the zip code level. The unit of observation is zip code by half-years. The dependent variable is the share of loans with below median Equifax Risk Scores within each institution type. The table reports all the coefficient estimates as well as the 4-quarter cumulative effect of the low income designation on auto loan issuance. All regressions control for the total number of credit unions in a zip code, zip code fixed effects, and county by time fixed effects. Standard errors are clustered at the zip code level and are reported in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). The source of the auto loan data is the NY Fed CCP/Equifax database.

Table IA.18: Low Income Designation and Non-performing Auto Loans

	log number of non-performing auto loans in 2017				log non-performing auto loan rate in 2017			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	all institutions	credit unions	banks	non-banks	all institutions	credit unions	banks	non-banks
Change in log number of designated credit unions between 2010 and 2013	1.18***	0.71***	0.56***	1.13***	0.011***	0.0086***	0.0067**	0.015***
	(0.12)	(0.074)	(0.074)	(0.12)	(0.0036)	(0.0031)	(0.0027)	(0.0045)
Change in log number of credit unions between 2010 and 2013	-0.93***	-0.57***	-0.41***	-0.90***	-0.0078**	-0.012***	-0.0023	-0.0053
	(0.11)	(0.084)	(0.049)	(0.10)	(0.0034)	(0.0042)	(0.0027)	(0.0047)
Percent African American	1.83***	0.31**	0.55***	1.95***	0.100***	0.035***	0.045***	0.098***
	(0.20)	(0.12)	(0.11)	(0.19)	(0.0078)	(0.0069)	(0.0097)	(0.011)
Unemployment rate	-0.0082	-0.016***	-0.0088	-0.0080	-0.00030	-0.00053	-0.00031	-0.00041
	(0.013)	(0.0057)	(0.0058)	(0.012)	(0.00058)	(0.00033)	(0.00030)	(0.00090)
County median income (log)	0.10	0.099	-0.089	0.028	-0.021***	-0.015**	-0.0072	-0.030***
	(0.17)	(0.13)	(0.082)	(0.17)	(0.0074)	(0.0058)	(0.0058)	(0.010)
County median income growth	-0.57	-0.72***	0.10	-0.37	0.037**	0.012	0.022**	0.033
	(0.37)	(0.23)	(0.17)	(0.34)	(0.014)	(0.011)	(0.0081)	(0.023)
Poverty rate	0.0038	-0.015*	0.0088	0.0055	0.0015**	0.00047	0.0017**	0.00095
	(0.011)	(0.0078)	(0.0054)	(0.012)	(0.00056)	(0.00059)	(0.00062)	(0.00069)
Poverty rate changes	0.21	0.40***	-0.097	0.16	-0.0029	-0.0038	-0.014*	0.018*
	(0.19)	(0.10)	(0.10)	(0.20)	(0.0067)	(0.0076)	(0.0071)	(0.0095)
Population density	-0.0000074**	-0.0000083***	0.00000017	-0.0000063**	-0.00000042***	-8.0e-09	-0.00000012*	-0.00000076***
	(0.0000028)	(0.0000018)	(0.0000019)	(0.0000029)	(0.000000084)	(0.000000066)	(0.000000060)	(0.00000016)
Population growth	2.15***	1.42***	0.58***	2.02***	0.044***	-0.0013	0.016***	0.079***
	(0.28)	(0.17)	(0.16)	(0.30)	(0.011)	(0.0071)	(0.0056)	(0.015)
Population (log)	0.20***	0.071***	0.11***	0.21***	0.0020***	0.00034	0.00096**	0.00059
	(0.020)	(0.011)	(0.010)	(0.020)	(0.00066)	(0.00047)	(0.00041)	(0.0011)
Observations	23346	23346	23346	23346	23346	20270	21344	22262
R-squared	0.181	0.108	0.111	0.197	0.076	0.010	0.026	0.053

Note: This table is the full table corresponding to Table 10 in the main text. It examines the impact of the change in the number of low income designation of credit unions between 2010 and 2013 on the number of non-performing auto loans in 2017 at the zip code level. The dependent variable for columns (1)–(4) is the log number of auto loans that are 30+ days over due by institution types in the second half of 2007. The dependent variable for columns (5)–(8) is the fraction of auto loans that are 30+ days over due divided by the total number of auto loans in a zip code, by institution types in the second half of 2007. Standard errors are reported in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). The source of the auto loan data is the NY Fed CCP/Equifax database.