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THE EFFECTS OF COMPETITION IN CONSUMER CREDIT MARKET

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ABSTRACT

This paper finds that banks and non-banks respond differently to increased competition in consumer credit markets. Increased competition and the greater threat of failure induces banks to specialize more in relationship business lending, and surviving banks are more profitable. However, non-banks change their credit policy when faced with more competition and expand credit to riskier borrowers at the extensive margin, resulting in higher default rates. These results show how the effects of competition depend on the form of intermediation. They also suggest that increased competition can cause credit risk to migrate outside the traditional supervisory umbrella.

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This paper studies the consequences of competition in local consumer credit markets. Influential theories of intermediation observe that greater competition in credit markets can generate more efficient intermediation, reduce borrowing costs and relax credit constraints for marginalized borrowers.[1] But some arguments note that more competition can also erode the profitability of incumbent financial institutions, leading to changes in credit policy that can produce 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)).[3]

The consequences of credit market competition can also depend on the sources of competition and regulation. Deposit-taking institutions like banks and credit unions engage in both relationship and arms-length or transaction banking, while non-banks, such as finance companies and securitization pools, typically focus only on transaction lending, often within specialized segments like car loans ((Benmelech, Meisenzahl et al. 2016), (Farhi and Tirole 2018)). Because relationship lending can partially insulate a bank from pure price competition, the source of competition can cause depository institutions to substitute between relationship and transaction banking (Boot and Thakor (2000)). In contrast, when faced with increased competition, non-banks, with less capacity to substitute towards other types of lending and less encumbered by regulation, might more aggressively defend their market by reducing prices and lending to riskier borrowers.

Endogenous entry into local markets—the unobserved factors that determine both entry and ex-post outcomes—makes it difficult to understand the consequences of credit market competition and assess these varied theoretical predictions. The particular setting that we use to

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[1] Academic surveys include (Allen and Gale (2004), Beck (2008), and (Vives 2012). Vives (2016) provides a book length treatment of many of the underlying theoretical ideas. (Bernanke 2009) and (Vickers 2010) discuss some of the recent policy issues surrounding financial competition within the US and international contexts respectively. Earlier work on the distributional effects of credit access is surveyed in (Aghion, Caroli et al. 1999)

[2] (Bhattacharya 1982), (Hellmann, Murdock et al. 2000), (Keeley 1990) 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 De Nicolo 2005) show that competition can lower lending rates, inducing firms to choose safer projects and thereby improving bank asset quality and safety (Martinez-Miera and Repullo 2010) point to the limits of this argument, noting that lower rates also reduce bank revenues, possibly increasing bank failure rates. A number of papers also emphasize the interaction between information asymmetries, lending standards and competition. See for example (Dell'Ariccia and Marquez 2006), (Rajan 1994), and (Petersen and Rajan 1995).

[3] Recent theories have also hypothesized more general links between the overall structure of intermediation and economic fluctuations (He and Krishnamurthy (2013), (Brunnermeier and Sannikov 2014)).

address this identification challenge is the recent changes in federal regulations that allowed some credit unions (CUs) to compete directly with banks for deposits and expand their balance sheets—the "low-income" rule. CUs are a major source of consumer finance. 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.[4]

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. CUs are traditionally restricted from intermediation outside of their common bond, thereby limiting the ability of CUs to compete directly with community banks and nearby non-banks. But under the low-income rule, some CUs that serve lower income customers are exempted from this competition restriction and can freely accept deposits outside their common bond. In 2008, the industry's federal regulator began changing 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 without deposit-taking restrictions, rose to nearly $400 billion—an almost 8-fold increase compared to 2008.

The regulatory roll-out of the low-income rule created plausibly exogenous variation in local credit market competition. Uncertainty about the low-income eligibility criteria delayed entry into the program until the regulator issued a notification letter to potentially all eligible CUs. Once notified of their low-income eligibility, over 90 percent of these institutions took-up the program within a year. Thereafter, the regulator determined each CU's eligibility for the low-income rule 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 lenders. A battery of statistical tests also corroborate the narrative that this regulatory roll-out led to exogenous variation in local credit market competition.

We find that banks and non-banks respond differently to this plausibly exogenous increase in competition. Among banks, there is a mirror decline in lending and deposit taking

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

when the number of nearby low-income credit unions (LICUs) increases—those within a five- or 10-mile radius of the bank's headquarters. To illustrate the magnitudes, consider two banks with identical loan levels in 2012Q1—just before the regulatory roll-out. Suppose that one of these banks is exposed to the growth in LICUs at the 10th percentile, while the other bank is exposed to LICU growth at the 90th percentile. The OLS point estimate suggests that the level of loans at the bank more heavily exposed to LICU competition (the 90th percentile) is about 4.3 percent less by end 2015 compared with the bank that faced less competition from LICUs. The IV point estimates, which uses a bank's potential exposure to LICU competition as an instrument for the actual growth in LICUs, are about 40 percent larger.

Moreover, increased competition is associated with greater profitability at banks. Two factors appear to explain this finding. First, banks accommodate entry in the consumer segment by substituting towards more relationship business lending, where CUs have less expertise and pricing pressures are less intense and margins higher.[5] Second, increased competition is also associated with selection pressures, as bank failure rates rise when the number of nearby LICUs increase. State tax policy appear to be a key mediating mechanism through which LICU competition induces bank failure. CUs are exempt from most state and federal taxes and in states with high tax rates, banks operate at a significant cost disadvantage when competing with LICUs. We find that the positive impact of LICU competition on the probability of bank failure is more pronounced in the higher tax states.

Regulatory balance sheet data are too aggregated to measure the impact of competition at the extensive margin or on credit policy; these data are also unavailable for most non-banks. Thus, to understand better the effects of increased competition at the extensive margin across different types of lenders, we use loan-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. These data show that competition affects an expansion in automobile lending at the extensive margin as well as a reallocation of credit towards subprime borrowers.

At the extensive margin, the estimates show that after a zip code becomes exposed to a low-income CU, the total number of newly made auto loans increase by about 3 percent in the

[5] 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)).

period 18 months and beyond, with CUs and non-banks accounting for all of this increase. Also, non-banks appear to respond relatively rapidly to greater competition, increasing lending by about 1.6 percent within 6 months of first exposure to a low-income CU in the zip code. 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.

Using information on borrower Equifax Risk Scores, we find that both CUs and non-banks expand credit at the extensive margin towards borrowers in the bottom half of the credit risk distribution. Among CUs for example, the ratio of new loans made to borrowers in the bottom half of the credit risk distribution relative to all new loans in a zip code increases by about 1.1 percentage points in the years a zip code is first exposed to a low-income CU. We also find evidence that this reallocation in automotive credit to riskier borrowers on account of increased competition is associated with a significant increase in non-performing loans (Broecker (1990)).

Our setting provides conditional support for theories that emphasize the benefits of competition in reducing the cost of credit and improving access for previously marginalized borrowers. Previously marginalized borrowers are also riskier, and our setting also highlights the possible costs of competition, as greater subprime lending leads to more defaults. But these results are nuance. Responses to competition depend greatly on the source of competition and the form of intermediation—banks versus non-banks. Also, increased competition does not always imply reduced profits, as the heightened threat of failure seem to induce bank managers to forego "the quiet life" and seek out new higher margin relationship business lending (Bertrand and Mullainathan (2003)).

Taken together, models that incorporate managerial incentives and allow for responses that differ by the form of intermediation appear to provide a more complete description of the effects of competition. Moreover, a common policy view is that enhanced supervision of the traditional banking sector allows economies to reap the benefits of increased competition while mitigating socially harmful risk-taking. But the evidence that increased competition might induce greater risk-taking in the unregulated non-bank sector suggests that this policy view might be incomplete.[6]

This is the first paper to use the lifting of deposit-taking restrictions at CUs to study the effects of competition on banks and non-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 in studying the effects of entry ((Black and Strahan 2002), (Jayaratne and Strahan 1996), (Carlson and Mitchener 2009)).[7] The most common interpretation of this literature is that increased competition among banks leads to greater efficiency and faster economic growth. In the case of consumer finance, evidence from the state deregulation waves suggests that increased competition among banks is associated with improved screening technologies, and the increased extension of consumer credit to both low and high risk customers ((Dick and Lehnert 2010)).

However, evidence drawn from variation beyond these two common sources in the literature can reveal how existing theories of competition perform in very different institutional settings. Indeed, unlike some previous studies, the current setting suggests that greater competition is associated with increased consumer credit mainly to higher risk borrowers. This setting can also help distinguish the consequences of competition from the benefits of asset diversification, which also tends to increase when geographic restrictions on lending are relaxed. Microeconomic data on credit standards and loan performance can also better distinguish the consequences of competition at the extensive margin and across different types of intermediaries from alternative explanations. Section 2 of the paper describes the institutional setting and data, while section 3 examines the impact of LICU competition on banks. Section 4 uses

[6] See the discussion in the Economist at https://www.economist.com/finance-and-economics/2009/06/25/deliver-us-from-competition. There is a broader theoretical literature on the merits of "shadow banking", with some arguing that it reflects regulatory arbitrage (Claessens, Pozsar et al. 2012) and others noting that it allows credit to bypass suboptimal regulations ((Ordoñez 2018)).

[7] There is also a sizable literature that uses cross-country variation in financial regulation to understand the effects of competition–see for example (Beck, Demirgüç-Kunt et al. 2006). Unobserved heterogeneity remains a key challenge in that setting. (Braggion, Dwarkasing et al. 2017) use historical micro data from the UK to overcome some of these identification challenges, while (Carlson, Correia et al. forthcoming) use population-based regulatory discontinuities as exogenous variation during the National Banking Era in the US for identification.

microeconomic data on auto-loans to study the effects of competition at the extensive margin for non-banks, banks and credit unions. Section 5 concludes.

2. Data and Institutional Background

2.1 Data

Credit unions (CU) are not-for-profit tax-exempt financial institutions that provide traditional relationship-based financial intermediation. Employees of a specific corporation—fraternal bonds—or residents of a specific town—geographic bond—can form a CU in order to use relationship-based financial services.[8] Credit unions mainly specialize in consumer lending and CUs and community banks are close substitutes. As Table 1 (Panels A, B and C)—drawn from Call Report data—show, both community banks and CUs are relatively small and mainly use deposits to fund their lending activities. The geographic range of lending for both types of institutions is also relatively limited. And the FDIC's definition of a community bank is based in part on the geographic range of a bank's operations, as well as the bank's size, its liabilities and asset composition. In contrast, multi-market banks are larger, more leveraged and less reliant on deposit-funding—Table IA1 in the internet appendix details the data sources. Panels D and E provide summary statistics of balance data for the low-income designated credit unions.

The second main data source is the New York Fed CCP/Equifax database. It provides loan-level data on auto lending in the U.S. Panel F provides summary statistics of the market shares of credit unions, banks and non-banks in automotive lending. The data show that the aggregate market shares across the three types of institutions remained relatively stable over the sample period. The panel also decomposes these market shares by Equifax Risk Score quartiles—generally borrowers in the bottom quartile are the highest credit risk. Non-banks, with their focus on transaction lending and securitization, generally dominate lending in the highest credit risk segment, while banks account for a much smaller share of subprime auto-lending. And as with the aggregate market shares, the market shares of the three types of institutions within the various risk categories remained relatively stable over the sample period.

[8] See (Ramcharan, Verani et al. 2016) for additional information about the industry.

2.2 Low-Income Designation: Changes in Eligibility

This subsection provides institutional details and statistical tests suggesting that the low-income rule's lifting of deposit taking restrictions among some CUs likely led to a conditionally exogenous increase in local credit market competition for community banks and non-bank suppliers of consumer credit. Under the Federal Credit Union Act of 1972, CUs designated as "low income" by the National Credit Union Administration (NCUA)—the industry's federal regulator—benefit from a relaxation of deposit-taking restrictions, and can compete directly with other financial institutions for deposits and expand their balance sheets. In 2006, well before the economic collapse and concerns about local credit demand and supply, the NCUA found the 1993 "low-income" regulation outdated and impractical--Figure 1 summarizes the key institutional changes in this rule with additional background.[9] In 2009 the NCUA thus revised the 1993 low-income rule and replaced the "household income" standard with the "family income" standard.

Under this revised rulemaking, a federal credit union qualified for "low-income" designation if more than 50 percent of its membership was low income. To be "low income", a member's family income must be less than or equal to 80 percent of the national median family income. The 2009 rule change initially had little impact on the number of LICUs (Figure 2 and Figure 3). Many credit unions were unaware of the rule change or were confused by the new family income standard.[10] In the case of the latter, few had 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 standard.[11]

[9] 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 and https://www.ncua.gov/services/Pages/resources-expansion/fom-expansion/low-income.aspx.

[10] 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.

[11] 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.

Two specific elements of the regulatory roll-out of the low-income rule feature in our identification strategy. First, a notification letter sent in the second quarter of 2012 to all 1,003 potentially eligible CUs accompanied the implementation of this revised eligibility process. The NCUA judged potential eligibility in part by whether a CU was headquartered in a relatively lower-income area and thus likely to have a membership that would qualify under the revised rulemaking. Over 900 or about 90 percent of the notified institutions selected into low-income status within a year. This high-take up rate mitigates concerns that beliefs about local demand played a role in driving the timing of selection into low income status.[12] Instead the very large take-up rate, once CUs learn of the program, reflect the benefits of accessing sources of finance external to the membership.[13]

The second element of the regulatory roll-out that features in the identification strategy is that the NCUA also linked low-income designations to the timing of the supervisory bank exam. CUs earliest on the examination schedule were notified sooner of their low-income 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 federal and state banking authorities. 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, with a discontinuous jump after the letter.

Consistent with the rule-making tying low-income designation to the relative family income of a CU's membership, column 1 of Table 2 shows that CUs in census tracts with median income below that of the national median are significantly more likely to become a LICU between 2009 and end 2015. A one standard deviation decrease in the ratio of census tract to national median income is associated with a 14 percent increase in the probability that a CU

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[12] See for example https://www.ncua.gov/newsroom/Pages/NW20131219LowIncomeCUs.aspx.

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

becomes a LICU between 2009 and end 2015. Column 2 adds standard balance sheet observables in 2008 and the log tract income itself, while column 3 includes census tract demographic variables. The relative median income of the CU's headquarters remains a significant predictor of subsequent low-income designation.

2.2 Low-Income Designation: The Statistical Evidence

This subsection shows that low-income entry likely engendered an exogenous increase in credit market competition. To this end, we first examine CU balance sheet outcomes in the period around low-income designation. An increase in intermediation after low-income designation would suggest that this relaxation in deposit-taking restrictions increased competition in local credit markets. The absence of any trends in CU balance sheet outcomes in the quarters preceding designation would be consistent with the institutional narrative of exogenous "entry" into low-income status. The subsection also examines nearby bank balance sheet outcomes in the period around first exposure to low-income credit unions (LICU), showing that LICU exposure impacted bank outcomes, but that this exposure is unrelated to past bank balance sheet trends.

These statistical tests are important, as several factors can still precipitate endogenous entry and pre-trends in balance outcomes despite the narrative evidence. For example, suppose the NCUA's 2012 Q2 notification letter targeted credit unions with poor lending opportunities or profitability on account of adverse local economic conditions. These adverse economic conditions could also lower lending and profitability at local incumbent banks, inducing a spurious correlation between low income entry and declining lending at nearby banks. Pre-trends and spurious inference can also arise if CUs in distressed areas self-selected earlier into low-income status conditional on eligibility—the standard Ashenfelter dip (Ashenfelter 1978). Of course, the 90 percent take-up rate within a year of the letter weigh against these self-selection narratives.

Pre-trends and the potential for biased inference is also possible even when entry into low-income status is linked to the timing of bank exams. The timing of these exams is orthogonal to local economic conditions, but weaker financial institutions are examined over an abbreviated exam cycle–6 months versus the standard 18-month cycle. As a result, weaker institutions could enter into low-income status earlier than eligible but stronger credit unions that are examined less frequently. This pattern can again lead to a spurious association between low-income designation and outcomes at nearby banks. But as Table 1 (Panels D and E) shows, the median LICU and non-LICU are very similar on observables, suggesting that they are unlikely to be subject to dissimilar shocks.

To evaluate the plausibility of the exogeneity low-income designation, the basic specification in equation (1) uses an indicator variable that equals 1 in the quarter *t* that a credit union *j* located in county *i* becomes low-income and 0 otherwise—$LICU_{jt}$. The baseline also includes four leads of this variable to detect pre-existing balance sheet or income trends, Δy_{ijt}, in the quarters before low-income designation. 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 designation to measure the impact of low-income designation--$Post_{jt}$. All specifications include credit union fixed effects to absorb non-parametrically pre-existing factors like the relative income of a credit union field of membership that might determine eligibility, γ_j ; we also include the county of headquarters-by-year-quarter fixed effects to absorb local economic conditions, α_{it}; standard errors are clustered at the credit union level:

$$(1) \qquad \Delta y_{ijt} = \sum_{k=-4}^{k=4} \beta_{t-k} LICU_{jt-k} + \beta_{post} Post_{jt} + \alpha_{it} + \gamma_j + e_{ijt}$$

The coefficient β_t compares the impact of low-income designation on outcome Δy_{ijt} in the quarter of designation relative to outcomes in other periods for the same CU as well as relative to outcomes among other CU-quarter observations without low-income designation. The sample consists of all CUs—the internet appendix pertubs the sample across a number of dimensions.

We report the results from these specifications in Table 3. Low income designation allowed CUs to accept deposits outside of their field of membership and the dependent variable in column 1 is the percent change or growth in deposits: the quarter on quarter change in deposits divided by deposits in the previous quarter. The individual point estimates (dots) and their 95 percent confidence bands (lines) are in Figure 4. There is robust evidence that low income designation led to a significant increase in deposit growth at CUs (column 1). Two quarters after designation, deposit growth is about 0.23 percentage points faster than otherwise—about a third of the average deposit growth in the sample.[14] The impact of low-income designation on deposit

[14] Summary statistics of variables used in the regressions are provided in the Appendix (Table A1).

growth also appears persistent. In the years after low-income designation, average deposit growth is about 0.18 percentage points faster than otherwise.

Equally important, there is no trend in deposit growth in the quarters before low-income designation. These lead variables are individually and jointly insignificant (p-value=0.19)—the cumulative sums are in the bottom panel of Figure 4. Note that the results are identical if the sample excludes CUs already designated as low-income under the 1993 rulemaking; for this subsample, the peak effect also occurs three quarters after designation (0.33 percentage points) and the one year and beyond effect is 0.22 percentage points. The lead variables are also individually and jointly insignificant (p-value=0.25). In what follows we retain the full sample of institutions. Also, note well that the results are the same when doubling the difference-in-difference window to 24 months; these are available upon request.

Balance sheet aggregates can be volatile and percent changes calculated from these aggregates are prone to outliers. We thus follow the literature and use the quarter-on-quarter change in deposits scaled by assets in the previous quarter as the baseline measure of the change in deposits and other aggregates.[15] From column 2, the results are unchanged. This increase in deposit flows external to a CU's membership can allow low-income CUs to expand lending to its membership, and column 3 uses the quarter-on-quarter change in loans scaled by assets the previous quarter—referenced henceforth as the change in lending—as the dependent variable.

Column 3 suggests that lending increased significantly after low-income designation. And again, there is no pre-trend in lending in the four quarters before designation (Figure 5). All four of these lead variables are individually and jointly insignificant (p-value=0.89). The change in lending is about 0.17 percentage points higher one quarter after designation, and remains about 0.2 percentage points higher than otherwise over the next three quarters. These magnitudes mirror those obtained when using the change in deposits, as the change in lending is about 0.15 percentage points higher in the years after designation relative to otherwise. Columns 4 and 5 show further that much of this increase in lending is concentrated in automobiles, as the change in real estate loans evince no trend in the periods around low-income designation.

[15] For example, scaling the change in lending by assets reduces substantially the volatility of the lending series—the coefficient of variation of this variable is about 50 percent smaller compared with the percent change in lending; the case of deposits is also similar. Recent papers that scale changes in lending and other bank aggregates by lagged assets include Cornett, McNutt et al. (2011) and Ramcharan (forthcoming).

Moreover, column 6 of Table 3 suggests that low-income designation and the increased access to additional sources of funding induced a relative shift towards loans in a CU's asset mix. The dependent variable is the loans to asset ratio, and this ratio is about 1.5 percentage points higher in the years after low-income designation. There is also no evidence of any trend in the loan to asset ratio in the four quarters before low-income designation. This relative shift to loans after low-income designation is also associated with increased profitability, which is about 0.2 percent higher in the years of designation (column 7).

Beyond a shift in asset composition, low-income designation is also associated with a significant balance sheet expansion, suggesting that these institutions used their easier access to deposits to finance an increase in lending at the extensive margin (column 8). The growth in assets is about 0.2 percentage points higher in the years after low-income designation, with the peak effect occurring about three quarters after designation. Note that there is one lead coefficient—out of 28 presented thus far—that is marginally significant. But this point estimate is about half that of the peak effect, and does not constitute any pre-trend—all the leads are jointly insignificant (p-value=0.19).[16]

The evidence in Table 3 suggests that the relaxation of deposit-taking restrictions relieved funding constraints at designated institutions and engendered an exogenous increase in local credit market competition on both sides of the balance sheet. That is, designated CUs likely sought deposits from traditional bank customers, and used these funds to make loans, especially car loans, to members who would otherwise borrow from banks or non-banks. Column 9 provides more direct evidence of the potential increase in competitive pressures. Marketing and advertising expenses, geared towards attracting new business, rose sharply after low-income designation and are about 6 percent higher in the years low-income designation. And as with all other cases, there are no pre-trends in marketing expenses.

Parallel Trends at Banks

Selection into low-income status at CUs might be driven by outcomes at nearby banks. For instance, a CU that observes nearby banks benefitting from plentiful deposit in-flows or lending opportunities might itself become low-income faster in order to compete for these

[16] Overdraft fees and other "fee income" can be important for CUs and small banks ((Melzer and Morgan 2015)), and in results available upon request we examine the impact of low-income designation on fee income—there is no significant evidence that designation impacted this source of income.

deposits and expand lending. Table 4 assesses this endogeneity concern. For each community bank in the sample, we draw a circle of radius 5 miles around its headquarters. We next create an indicator variable that equals 1 in the quarter that any CU within this 5-mile radius first becomes a low-income credit union (LICU) in the period after 2008; this indicator equals 0 in quarters in which no nearby CUs become low-income. This indicator variable thus captures the first exposure of a bank to a LICU. We also include four lags and four leads of this variable to detect whether outcomes at banks differ in the periods around the quarter in which banks first become exposed to LICU competition.

Low-income designation lifted deposit-taking restrictions and the dependent variable in column 1 of Table 4 is the bank-level quarter-on-quarter change in deposits scaled by assets. The results are striking. There is no evidence that the change in deposits at a bank differ significantly in the quarters before the bank first becomes exposed to a LICU. However, in the quarters after a bank's first exposure to a LICU, the change in deposits declines significantly—about a percentage point. Figure 6 depicts these effects. Similarly, the change in lending is not significantly different in the quarters before LICU exposure, but also declines significantly thereafter (Figure 7).Interestingly, despite the increase in competition on both sides of the balance sheet, there is some indication that the return on assets improves after exposure to LICUs in column 3 of Table 4.

Table 4 thus suggests that outcomes at banks do not precipitate exposure to LICU competition. But foreshadowing the results of the next section, exposure to LICUs does however impact nearby banks. Before analyzing in greater detail the effects of competition, we consider a range of additional robustness tests, which for concision we report in the Internet Appendix (Table IA.2). Notably, we show that the "parallel trend" assumption continues to hold even among those CUs most in need of external finance and thus most likely to gain from low-income designation. These additional tests also focus on different CU regulatory bonds; various tests also perturb the appropriate choice of control groups, including propensity score matching exercises; other tests focus on the role of the banking market structure and possible rents that might induce endogenous entry.

3. The Effects of Credit Market Competition: Banks

3.1 The Basic Results

To understand better the effects of exposure to LICU competition on nearby community banks, this section uses a cross-section framework that exploits the exogenous timing of the 2012 Q2 letter that precipitated the sharp rise in LICUs. Building on the timing of this letter, the analysis divides the sample into two periods—before the letter: 2008Q1-2012Q1—and after the letter: 2012Q2-2015Q4. For each of the two periods, we average various bank-level outcomes, creating a two-period panel. For example, $\overline{y}_{ipre}$ is the quarter-on-quarter percent change in lending at bank *i,* averaged over the 2008Q1-2012Q1 period. And $\overline{y}_{ipost}$ is the average of this variable for bank i in the quarters after the letter: 2012Q2-2015Q4.

To measure a bank's exposure to competition from LICUs, the baseline approach computes the log of the average number of LICUs located near the bank in each of the two periods. Concretely, we begin with a 5 mile radius so that $ln\left(\overline{LICU}_{\mathrm{i}pre}\right)$ is the log of 1 plus the average number of LICUs within 5 miles of bank i over the 2008Q1-2012Q1 period, while $ln\left(\overline{LICU}_{\mathrm{i}post}\right)$ is the log of 1 plus the average number of LICUs within 5 miles of bank i over the 2012Q2-2015Q4 period. The fixed effects and first difference estimators are identical when there are just two periods, and first differencing across the two panels, which absorbs non-parametrically bank and local time invariant unobservables, yields our cross-section estimating equation:

$$\text{(2)} \qquad \overline{y}_{ipost} - \overline{y}_{ipre} = \beta_0 + \beta_1 \left[ln\left(\overline{LICU}_{ipost}\right) - ln\left(\overline{LICU}_{ipre}\right)\right] + e_i$$

The coefficient of interest, β_1, measures the impact of the log change or growth in the number of LICUs within a 5-mile radius of the bank on the difference in average bank-level outcomes before and after the NCUA's letter.

Table 5 presents the results from estimating equation (2). The OLS specification in column 1 uses state fixed effects and standard errors are clustered at the state-level. The dependent variable in column 1 is the difference in the average quarterly percent change in lending. The point estimate in column 1 is negative and significant at the 5 percent level (p-value=0.03). It suggests that a one standard deviation increase in the growth in the average number of LICUs within a 5-mile radius of a bank after the letter is associated with about a 0.16 percentage point or 0.04 standard deviation decline in average lending growth.

To put these estimates in economic context, consider two banks with identical loan levels in 2012Q1. Suppose however that one of these banks is exposed to the growth in LICUs at the 10th percentile, while the other bank is exposed to LICU growth at the 90th percentile. The point estimate in column 1 suggests that by end-2015, the level of loans at the bank more heavily exposed to LICU competition (the 90th percentile) would be about 4.3 percent less compared with the bank that faced less competition from LICUs over the subsequent 2012Q2-2015Q4 period.

As noted earlier, balance sheet aggregates can be volatile and percent changes calculated from these variables are prone to outliers. We thus use the quarter-on-quarter change in lending scaled by assets in the previous quarter as the baseline measure of the change in lending (column 2)—the scaled changed in lending.[17] From column 2, the LICU point estimate remains negative and is more precisely estimated (p-value=0.00). Importantly, the economic magnitudes are similar when using either the percent change in lending or the change in lending scaled by assets. From column 2, a one standard deviation increase in the growth in the number of LICUs within a 5 mile radius of a bank is associated with about a 0.1 percentage point or 0.04 standard deviation decrease in the scaled change in lending.

Much of the sample period includes the Great Recession and its aftermath, and unobserved local shocks could bias these results. CUs eligible for low-income designation are more likely to be located in poorer neighborhoods. And if the demand for financial services is more depressed in poorer neighborhoods, then the growth in LICUs could well proxy for weak local latent demand. In turn, latent weak demand could then explain the negative association between an increase in exposure to low-income designation and the change in bank lending. To be sure, the theoretical relationship between income and credit demand is ambiguous. When job losses and unemployment risk rise, credit demand among lower income populations can increase to smooth consumption. And the evidence showing that CU lending actually increased after low-income designation clearly contradicts the weak demand interpretation. Nevertheless, given the

[17] Scaling the change in lending by assets reduces substantially the volatility of the lending series—the coefficient of variation of this variable is about 4.7 times smaller than the lending growth series.

tumultuous economic background in which low-income designation occurs in the sample period, it is important to directly address this latent demand concern.

An extensive literature suggests that the local variation in house price movements provides a direct and powerful way to evaluate the latent demand interpretation (Mian and Sufi, 2014). House price movements varied sharply across the country during the 2008-2015 sample period and this variation was a key driver of local economic activity and demand. Building on this literature, column 3 includes the average of the quarter-on-quarter growth in Zillow's zip code level single family house price index. The zip code is matched to the headquarters of the bank. The sample size drops by 60 percent since this index is not available for all zip codes, but the main results remain unchanged, though less precisely estimated.

It is important to note that the slight decline in the point estimate in column 3 reflects the smaller sample size rather than the inclusion of the house price index itself. Re-estimating column 2 but using the same sample from column 3 yields the same coefficient as in column 3; this is shown in column 4. Column 5 includes the log of the median income of the census tract in which the bank is headquartered, observed in 2010. The log of income directly controls for any bias that might arise from the fact that lower-income tracts experienced the largest increase in LICUs, and that these areas could also have less demand for credit. Again, the point estimate on the log change in LICUs is unchanged.

As a further robustness exercise, Table 6 gradually expands the distance window out to 50 miles. Because intermediation at CUs and community banks tend to occur within a small geographic window, we would expect the effects of increased LICU competition on bank lending to attenuate with distance. This is indeed what we find. The negative impact of exposure to LICU competition on the scaled change in lending is identical at the 5- and 10-mile radii. But the point estimate on the growth in the number of LICUs at the 20-mile radius drops by half, and is no longer statistically significant at conventional levels at the 50 mile radius (p-value=0.1). In what follows, we measure exposure to LICU competition primarily through the log number of LICUs within a 10-mile radius, as it is more precisely estimated in some cases.

3.2 Instrumental Variable Estimates

Contemporaneous shocks could still be a source of bias, and this subsection uses the pre-existing variation in LICU eligibility to identify better the effects of competition on bank outcomes. The identification strategy uses the fact that banks located near CUs that are potentially eligible for low-income conversion under the revised rulemaking would naturally become more exposed to competition after the regulatory roll-out: the 2012Q2 NCUA letter and the subsequent linking of low-income designation to bank exams. In contrast, banks located near CUs that have a simple majority of members with family income above the 80 percent threshold—ineligible CUs—would experience no growth in LICUs and face much less exposure to competition from these institutions after the NCUA's regulatory roll-out (Figure 8).

To measure a bank's potential exposure to LICU competition, we use the baseline 10-mile radius and first identify CUs within 10 miles from each bank's headquarters—a bank's CU neighbors. Among this set of neighbors, we count the number of CUs headquartered in census tracts with tract median income below the 80 percent national median income threshold—the results are the same if we use a 50 percent threshold. These are the CUs potentially eligible for LICU conversion after the NCUA's revised regulatory roll out. The log of one plus the number of CUs located in these census tracts is our measure of a bank's potential exposure to competition. To approximate better the NCUA's subsequent revised rule, which uses the 2010 Census data to establish eligibility, we use census tract and national median income data in 2010 when computing potential eligibility.

Clearly, having data on the actual income of each CU member would allow us to compute whether a simple majority of a CU's membership meet the income requirement, eliminating any measurement error in the first stage. But neither we nor the NCUA have such data. Instead, the NCUA uses a similar, but less coarse approach to ours, imputing members' income based on the median income of the census tract in which the member lives. Of course, we have already seen evidence in Table 2 that CUs located in lower income census tracts are significantly more likely to become LICUs under the revised legal standard.

The first stage results in column 1 of Table 7 is consistent with this previous evidence. The dependent variable is the difference between the log of the average number of LICUs within 10 miles of a bank's headquarters in 2008Q1-2012Q1 and the log of the average number over 2012 Q2-2015Q4. The point estimate suggests that a 10 percent increase in the number of potentially eligible CUs in 2008 is associated with a 2.3 percentage point increase in the log change in the average number of LICUs within 10 miles of a bank's headquarters (p-value=0.00). The F-statistic is 28.01in the first stage, suggesting that the instrument satisfies the relevance condition.

The evidence in Tables 3 and 4 showing no pre-trends in the balance sheets of either banks or CUs in the quarters before low-income designation strongly suggest that the exclusion restriction assumption is plausible. To wit, a bank's exposure to low-income CU competition is unlikely to be related to unobserved demand shocks at the bank. But to address further any possible violations of the exclusion restriction stemming from the fact that potentially eligible CUs are likely to be located in poorer neighborhoods with possibly weaker credit demand, we include a third order polynomial of the log of the median tract income in which the bank is located (column 2). As always, the results are invariant to these controls.

Building on this first stage evidence, column 3 presents the IV estimate of the impact of the change in the number of LICUs on bank lending; the instrument is the log number of potentially eligible CUs within 10 miles of a bank's headquarters in 2008. The IV point estimate is about 40 percent larger than its OLS counterpart and significant at the 5 percent level. The lifting of deposit restrictions was a principal component of low-income conversion, and column 4 of Table 7 uses the change in deposits scaled by assets as the dependent variable. The IV point estimate is about 90 percent larger than the corresponding OLS coefficient, and suggests that a one standard deviation increase in the growth in the number of LICUs is associated with a 0.16 percentage point or 0.07 standard deviation decrease in the average change in deposits. That is, increased competition may have led to an erosion of market share on both sides of a bank's balance sheet.

The variation in bank size can help gauge the importance of the competition hypothesis in explaining these results. CUs and smaller banks are very close substitutes. Both types of institutions operate in the same geographic markets and compete for similar customers. Under the competition hypothesis then, an increase in LICUs should have a bigger impact on geographically proximate smaller banks. Using the variation in bank sizes can also address concerns that the large scale regulatory changes in banking during the sample period might distort inference.[18] Smaller banks were exempted from most of these regulatory changes, though

[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. Liquidity regulations were formalized in early 2013 (the liquidity coverage ratio) and in 2014 (the net stable funding ratio), with gradual implementation thereafter.

the "qualified mortgage rule" could disproportionately affect these banks. But CUs were themselves not major players in this market and were equally affected by the rule.

Column 5 of Table 7 interacts the log change in the number LICUs with the log size of the bank averaged over 2007. The dependent variable in column 5 is the scaled change in lending. Consistent with the prediction that banks that are close substitutes to CUs face greater competition from newly converted LICUs, the interaction term is positive and economically and statistically significant. At the 10^{th} percentile of the bank size distribution, a one standard deviation increase in the growth in LICUs is associated with a 1.4 percentage point drop in average lending. This effect is about 75 percent smaller in absolute value for a bank at the median size (Figure 9). Column 6, which uses the scaled change in deposits as the dependent variable, reveals even larger effects. The implied effect of competition is about 90 percent larger at the 10^{th} percentile of the size distribution relative to the median (Figure 10).

3.2.1 Specialization and Selection

In the context of CUs and banks, theories of oligopolistic rent generation through substitution and specialization can further distinguish the competition hypothesis from other explanations.[19] CUs mainly specialize in consumer loans, and traditionally face regulatory barriers on expanding their business lending, such as commercial and industrial (C&I) loans.[20] The resulting increase in LICU competition concentrated in the consumer lending segment—auto and personal loans—can significantly shrink bank profit margins in this market segment. Indeed, some models of adverse selection and competition predict that the increased competition could cause banks to face expected losses from consumer lending at the extensive margin. To wit, LICUs can combine their additional lending capacity with their local knowledge to "cherry pick" the more profitable consumers, leaving the community banks with an adversely selected sample of consumers (Broecker 1990). In response to shrinking margins in the consumer segment, models of competition predict that banks would substitute lending towards market

[19] Classic references include Salop (1979) and Spence (1976).

[20] Federal regulations restrain CU competition in commercial lending, capping a credit 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. See the Credit Union Membership Access Act (CUMAA) (P.L.105-219) passed in 1998.

segments, like C&I lending, where CUs face regulatory barriers to entry and margins are higher on account of less competition.

Table 8 evaluates this substitution hypothesis. The dependent variable in column 1 is the change in C&I lending, scaled by assets. A one standard deviation increase in the growth in LICUs is associated with a 0.03 percentage point or 0.15 standard deviation increase in the change in C&I lending. Column 2 shows that exposure to LICU competition also increases the relative importance of C&I lending in the bank's loan portfolio. A one standard deviation increase in the growth in LICU exposure suggests a 0.12 standard deviation increase in the ratio of C&I to total loans. This evidence of substitution towards C&I lending among banks in conjunction with the increase in consumer lending among newly converted LICUs is difficult to reconcile with endogeneity narratives that view LICU growth as a proxy for weak local demand for credit.

Economic theory also observes that competition can affect the profitability of incumbent banks. Well known arguments predict that competitive pressures on both sides of the balance sheet can compress interest rate margins and reduce profits. Of course, competitive pressures that push incumbents to specialize in higher margin businesses, and become more efficient could have the opposite effect on profits. Moreover, the "entry" of LICUs into local banking markets could also create selection pressures, forcing inefficient or less adaptable banks to fail, merge or otherwise exit the sample, leaving behind a selected sample of the more profitable incumbents.

Column 3 of Table 8 suggests that exposure to competition is associated with increased profitability. The dependent variable is the average return on assets. The LICU growth point estimate is positive and significant in both the OLS and IV specifications. The latter suggests that a one standard deviation increase in the growth in LICUs is associated with a 0.16 standard deviation increase in the average return on assets. To understand the possible link between competition, risk-taking and profitability, column 4 uses the bank's Z-score. This is defined as the sum of a bank's return on assets plus capitalization divided by the standard deviation of the return on assets. In the absence of loan level data, the Z-score is a common albeit imperfect proxy of risk-taking, with lower values generally indicating a riskier asset profile relative to the bank's capacity to bear losses and remain solvent.

From column 4, the point estimate on the growth in the number of LICUs is positive, suggesting that not only did the return on assets increase in the period after banks became more exposed to competition, but that incumbent banks' earnings became less volatile relative to their capacity to bear losses. Column 5 provides more direct evidence of this channel, using the standard deviation of the return on assets computed for each of the two periods as the dependent variable. It shows that increased competition from LICUs is associated with a decline in the realized volatility of earnings.

Non-interest expenses are another dimension through which competition might affect profitability. Increased competition and the compression of interest rate margins might force banks to reduce non-interest expenses to augment profitability. But in the current context the effects of competition can be ambiguous, as marketing, information gathering costs and other adjustment expenses related to the substitution away from consumer lending and into C&I and other higher margin businesses could increase. To gauge the effects of competition on these expenses, column 8 uses the ratio of non-interest expense to assets—a common measure of efficiency—as the dependent variable. The growth in exposure to LICUs is associated with an increase in this ratio.

3.2.2 Tax Rates

In addition to moving into possibly higher margin C&I loans, economic theory also observes that selection pressures from increased competition can increase the probability of failure among banks not able to shift easily their lending to higher margin businesses. This selection effect could also explain the increased profitability among the surviving banks. Moreover, CUs are exempt from most state and federal taxes and the variation in tax rates across states is likely a key mediating mechanism through which LICU competition affects bank solvency. In states with high tax rates, banks operate at a significant cost disadvantage when competing with LICUs. For example, the relative tax advantage of LICUs in these states might allow LICUs to undercut banks in loan pricing. The state-level variation in corporate taxes thus provides another means of identifying the effects of increased LICU competition on bank outcomes.

Table 9 investigates the effects of competition, selection pressures and tax-rates on bank-level outcomes. Columns 1 and 2 estimate separately the baseline change in lending specification separately for banks in below median corporate tax states and for those in above median states. There is significant evidence that the negative impact of LICU competition on changes in bank lending is significantly larger in higher tax states. The point estimate on the growth in the number of LICUs in column 2—the high tax states—is twice the size of the coefficient in column 1—the latter itself is not significant at conventional levels (p-value=0.14).

This loss of lending opportunities due to competition can cause some banks to exit the sample and we focus on possible selection pressures. The dependent variable in column 3 equals 1 if a bank failed between 2012Q1 and 2015Q4—the period in which LICU conversion began—and 0 otherwise. Column 3 uses the full sample of states and the LICU growth coefficient is positive but not statistically significant (p-value=0.17). However, column 4 (5) re-estimates the specification separately for banks headquartered in states with below (above) median tax rates. Among the banks headquartered in low-tax states, the LICU growth point estimate is both economically and statistically insignificant, suggesting that competition from these institutions has no effect on the probability of failure. But for banks headquarted in higher-tax states (column 5), there is robust evidence that competitive pressures from LICUs increased the probability of failure (p-value=0.03). A one standard deviation increase in the growth in the number of LICUs is associated with a 2.1 percent increase in the probability of failure in this subsample.

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

Increased competition from LICUs is associated with greater efficiency and profitability at community banks, as well as a contraction in overall intermediation among these banks. In part, this reflects banks' substitution towards possibly higher margin businesses like C&I lending, as well as the exit of smaller banks, especially those that operate at a tax disadvantage relative to CUs. However, this evidence on the effects of competition is incomplete. Regulatory balance sheet data are too aggregated to measure whether competition expands credit at the extensive margin. Balance sheet aggregates also make it difficult to measure the effects of competition on risk-taking. For example, the Z-score might take several years to detect a bank's shift in credit policy favoring riskier borrowers. Equally important, non-bank financial institutions, such as captives and other finance companies, are major suppliers of consumer credit and go unmeasured in most regulatory data.

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 only at the 6 month frequency.[21] While the CCP does not identify the lender, in this version of the data set, 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 use a difference-in-difference specification similar to equation (1). We first compute the log number of newly financed cars at the zip code level in half-year intervals, and then define an indicator variable that equals 1 in the half year interval that a zip code is first exposed to a low-income CU and zero otherwise. We also include leads of this first exposure variable to capture any pre-existing trends and lags that measure the impact of first exposure on car originations at the extensive margin. We use county by time fixed effects to absorb all demand shocks to the county within each half-year interval. The baseline also includes the log number of CUs itself in each zip code.

Table 10 shows that increased competition is associated with an expansion in automobile lending at the extensive margin. Column 1 uses the log of one plus total originations from all sources of finance. In the first 6-month interval that a zip code is exposed to a low-income CU, the number of car originations increase by 1.2 percent; this effect increases to about 2.2 percent one year afterwards, and the total number of car originations is about 3 percent higher 18 months or more after a zip code is first exposed to a low-income CU. There is no evidence of any pre-trend. Column 2 uses only car loan originations by CUs, and in this case, the long-run impact of

[21] This is the FRBNY CCP/Equifax auto trade line data which covers all the auto loans at the account level.

low-income competition is similar: the number car loans originated by CUs increase by about 2.5 percent 18 months and beyond after first exposure.

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, the non-bank response to competition appears immediate. First exposure to a low-income CU in the zip code suggests a 1.6 percent increase in the number of car loans originated by non-banks in that half-year. In the long run, non-bank originations rise by about 4 percent. 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.

Table 11 suggests that this expansion in auto credit in response to competition is tilted towards riskier borrowers—those with below median Equifax Risk Scores. 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. We continue to use the same difference-in-difference setup. Column 1 uses loans made by all kinds of lenders, while the remaining columns disaggregate by CUs, banks and non-banks. It shows that 18 months and beyond after first exposure to a low-income CU, the ratio of new loans to borrowers with below median Risk Scores relative to all new loans increases by 0.74 percentage points in the zip code. Among CUs (column 2) this long run effect is about 1.1 percentage points, while non-banks increase this ratio by about 0.6 percentage points. As before, there is no significant response among banks, and there is no evidence of any pre-trend.

Table 12 shows that this increase in automotive credit on account of greater 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 (columns 5 – 8) also measures non-performing loans in terms of the share of total loans–the results are similar.

Table 13 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.

5. Conclusion

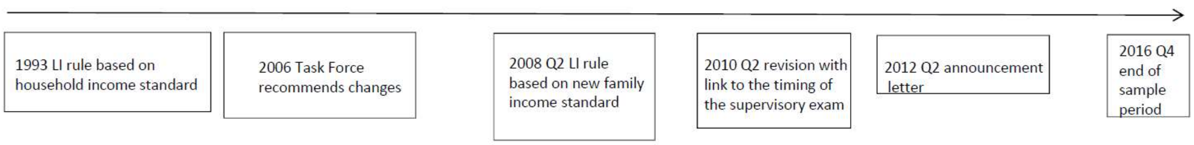
This paper has studied the effects of increased competition using regulatory changes that lifted deposit-taking restrictions at credit unions. We find that increased competition in the consumer credit segment from credit unions elicited very different response between banks and non-banks. In response to this competition, banks increasingly specialized in relationship business lending, and surviving banks became more profitable, as competition increased failures among banks in higher tax states. In contrast, non-banks aggressively fought entry in the auto-loan segment, resulting in a reallocation of automotive credit towards riskier borrowers. 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 reallocation 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 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. We also leave it to future research to understand better how management incentives within banks determine their shift to business lending in response to competition in the consumer segment.

Figures and Tables

Figure 1: Low Income Rule Regulatory Timeline and Background

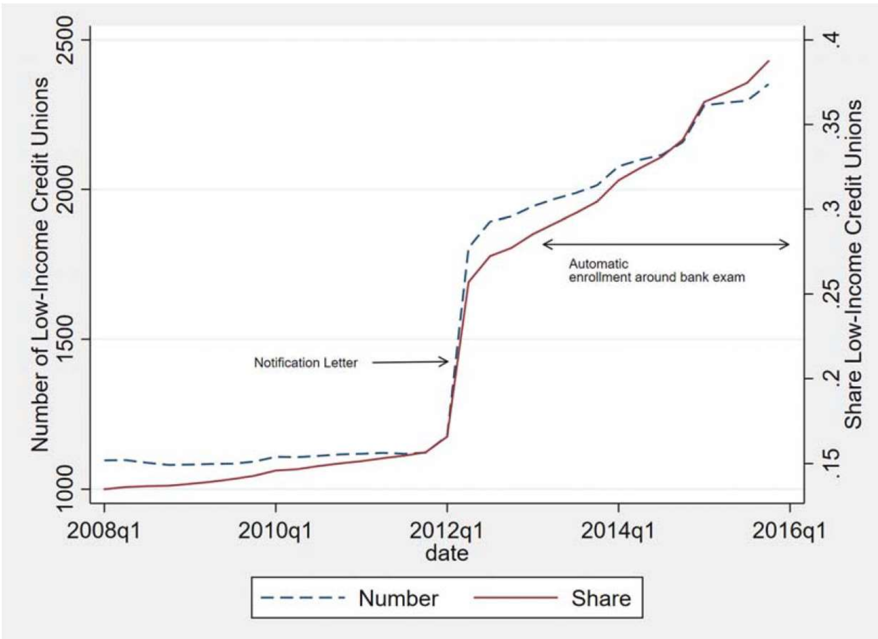


This figure shows the timeline of the regulatory changes surrounding the low income credit union rule. The 1993 rule was based on the "household income" standard: If 50 percent or more of a CU's membership had household income below 80 percent of the national median income, then the CU was eligible for "low-income" designation. Cost-of-living adjustments were possible using the Department of Labor's administrative data. The NCUA's 2006 task force noted that this 1993 rule was inconsistent with the subsequent adoption of the family income standard by other federal agencies when defining economically undeserved areas. The NCUA also noted that the Department of Labor based adjustment for high cost areas was geographically incomplete. The 2010 Q2 linking of eligibility to the supervisory exam notes that:

> "*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." (*

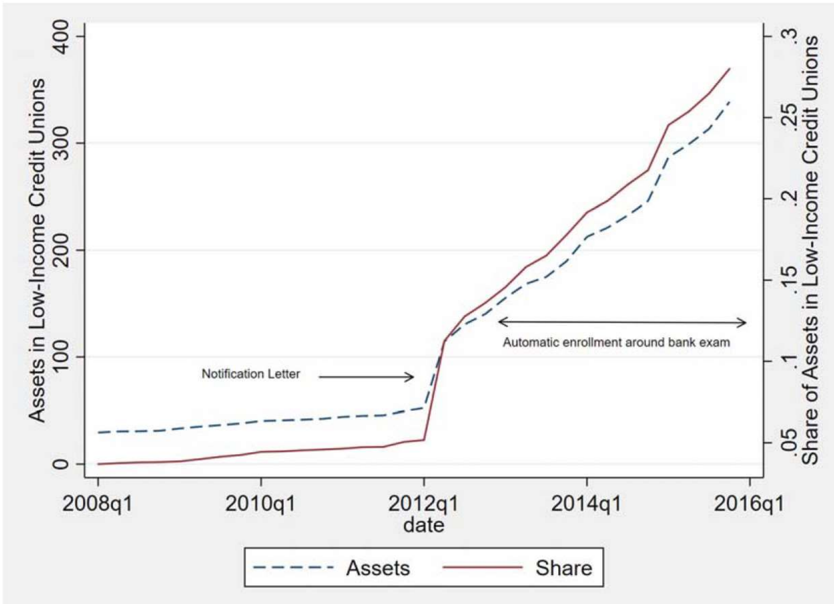
Additional Background:
Competitive pressures between banks and CUs have long led to legal and legislative battles. Beginning in the mid 1970s, the American Bankers Association (ABA) sued to stop CUs from offering interest bearing checking accounts; Congress eventually sided with the CU industry. In the 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.

Figure 2: Low Income Credit Unions, by Number 2008Q1-2016Q1



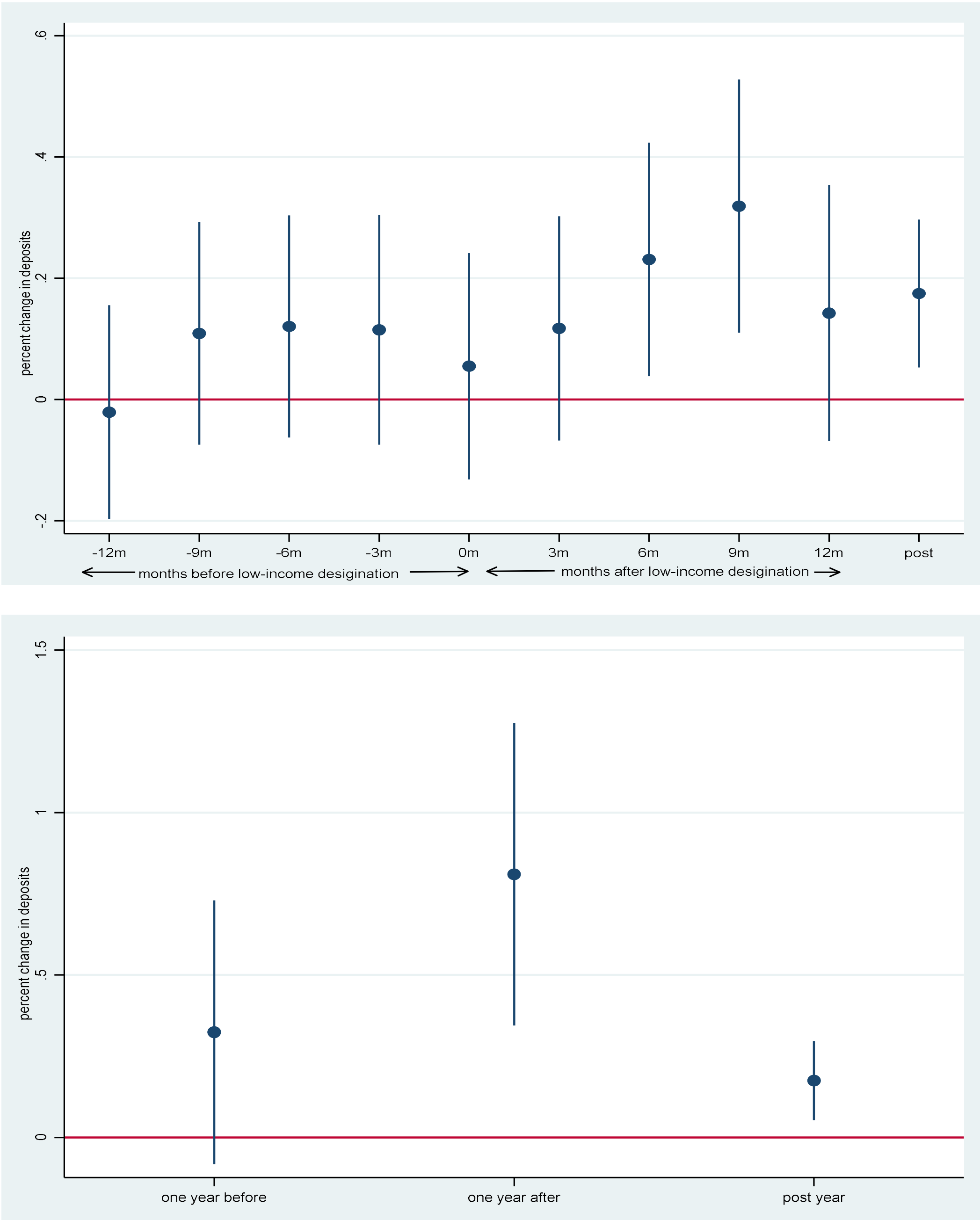
Note: This figure plots the number of credit unions designated as low-income credit unions between 2006 and 2016 as well as the ratio of low-income credit unions to the total number of credit unions. The letter notifying credit unions of their low-income eligibility was sent in the second quarter of 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 Credit Unions, by Assets 2008Q1-2016Q1



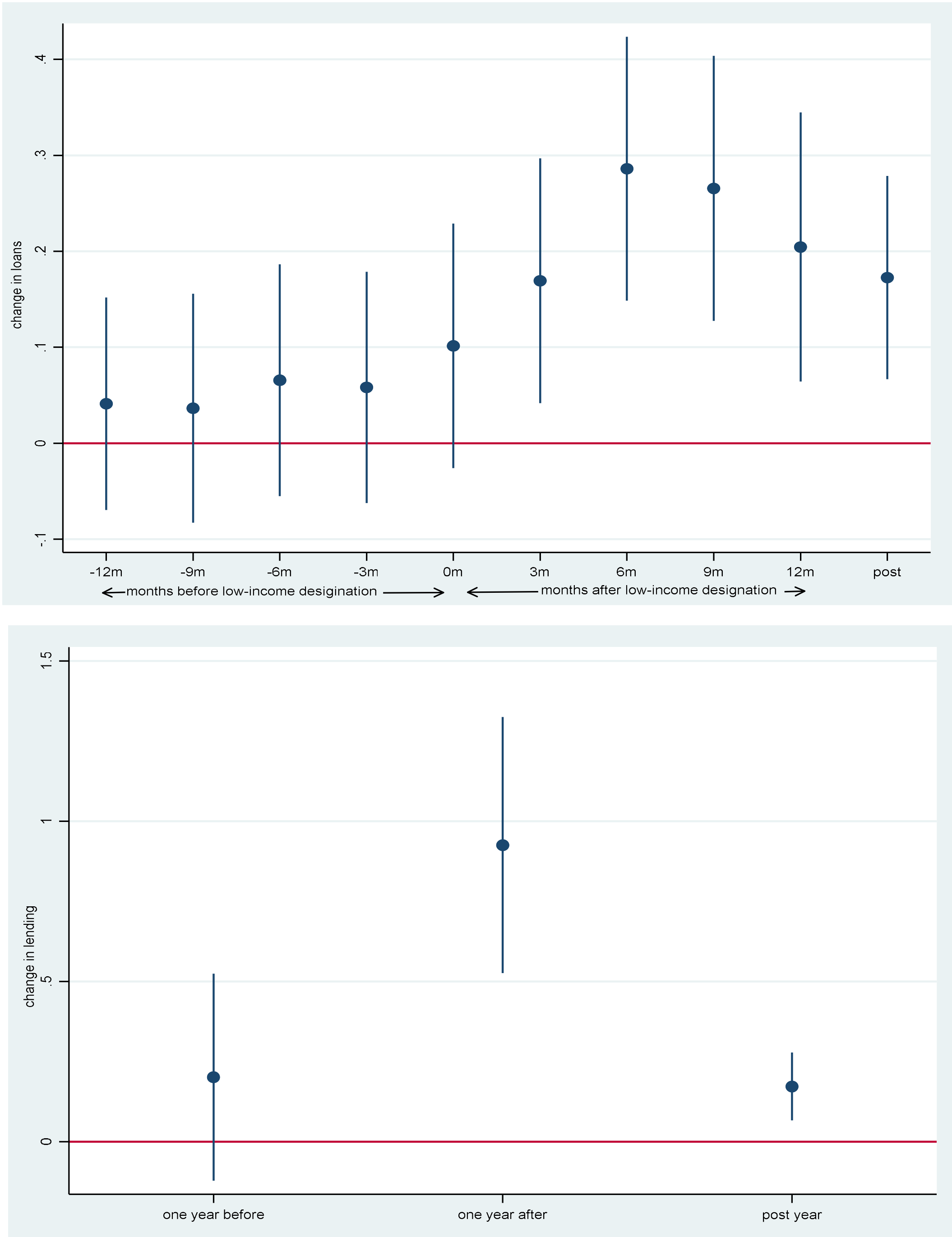
Note: This figure plots total assets of credit unions designated as low-income credit unions between 2006 and 2016 as well as the ratio of low-income credit unions to the total number of credit unions. The letter notifying credit unions of their low-income eligibility was sent in the second quarter of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

Figure 4: The impact of low-income designation on the percent change in deposits at CUs



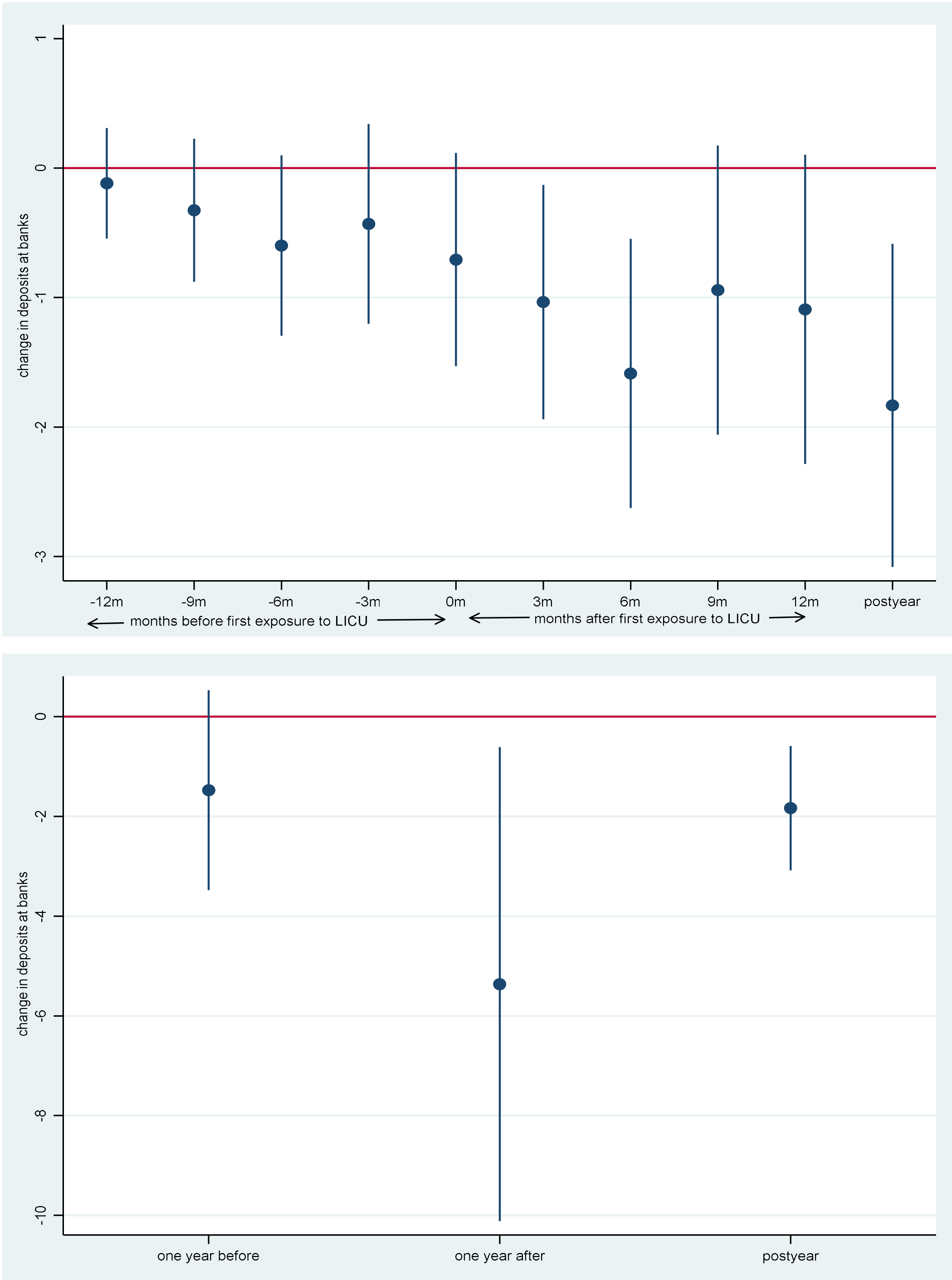
This figure plots the regression estimates of the impact of low income designation on the percent change in deposits of credit unions over the sample period of 2009-2015, as in column 1 of Table 3. The top panel plots the individual point estimates (dots) and 95 percent confidence intervals (lines) of the low income designation dummy and its lead and lag values around the designation. The bottom panel plots the cumulative sum of the individual coefficients in the year before; the year after and more than one year after low-income designation.

Figure 5: The impact of low-income designation on the change in lending at CUs



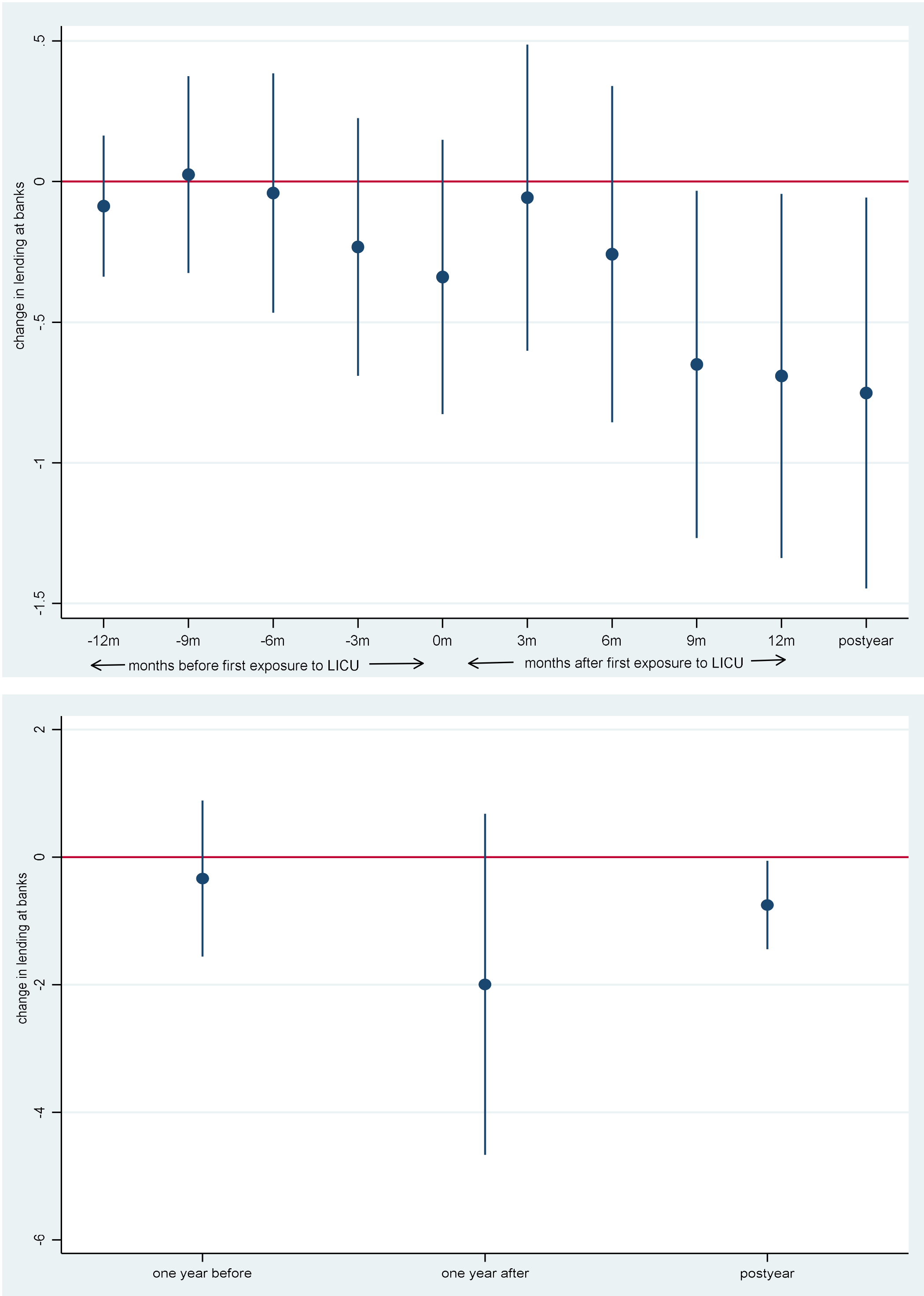
This figure plots the regression estimates of the impact of low income designation on changes in lending (scaled by assets in the previous quarter) of credit unions over the sample period of 2009-2015, as in column 3 of Table 3. The bottom panel plots the cumulative sum of the individual coefficients in the year before; the year after and more than one year after low-income designation.

Figure 6: First exposure to LICUs and the change in deposits at banks



This figure plots the regression estimates of the impact of banks' first exposure of low income credit unions on changes in deposits (scaled by assets in the previous quarter) of banks over the sample period of 2009-2015, as in column 1 of Table 4. The top panel plots the individual point estimates (dots) and 95 percent confidence intervals (lines) of the low income designation dummy and its lead and lag values around the designation. The bottom panel plots the cumulative sum of the individual coefficients in the year before; the year after and more than one year after low-income designation.

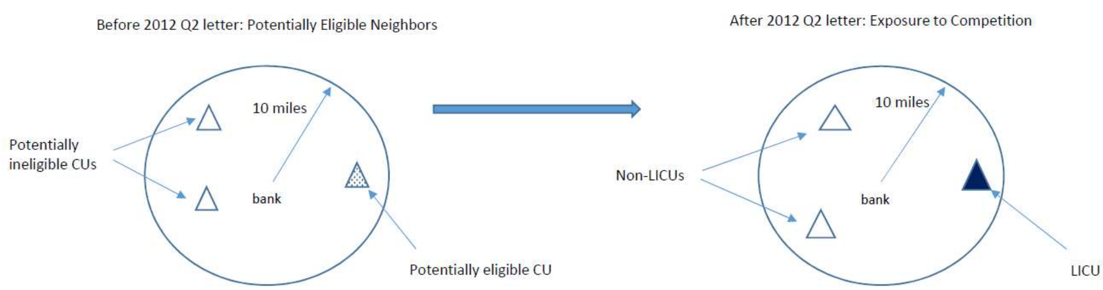
Figure 7: First exposure to LICUs and the change in lending at banks



This figure plots the regression estimates of the impact of banks' first exposure of low income credit unions on changes in lending (scaled by assets in the previous quarter) of banks over the sample period of 2009-2015, as in column 2 of Table 4. The top panel plots the individual point estimates (dots) and 95 percent confidence intervals (lines) of the low income designation dummy and its lead and lag values around the designation.

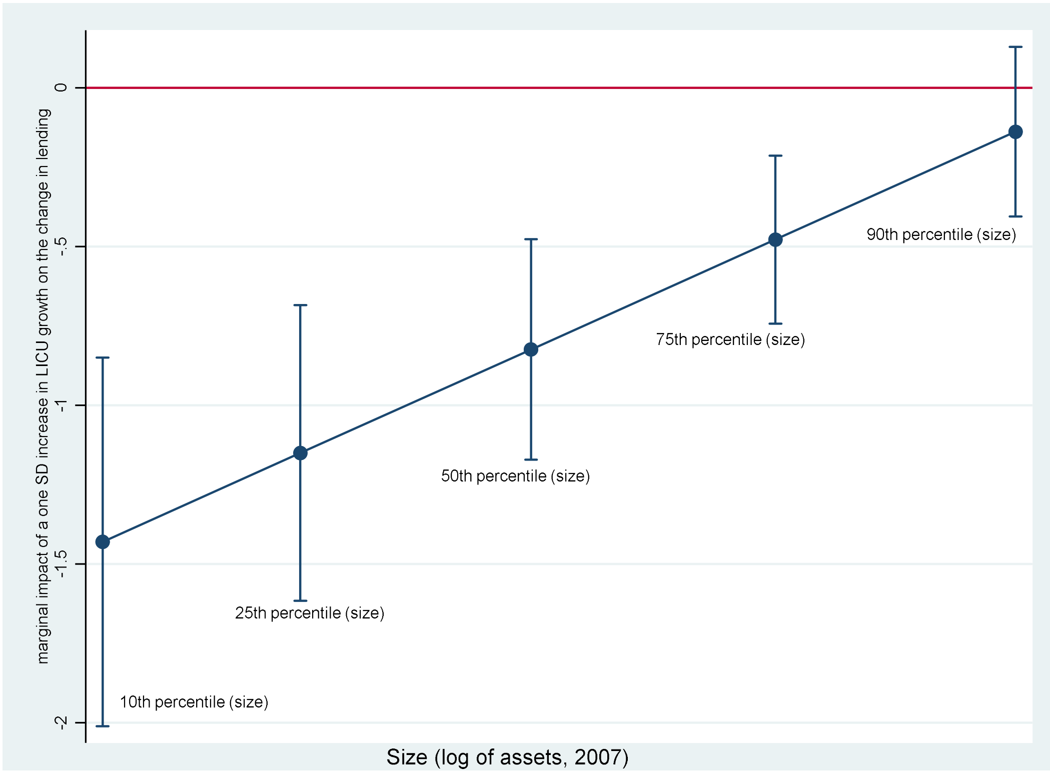
Figure 8: Using Potential Eligibility to Determine a Bank's Exposure to LICU Competition

A. B.



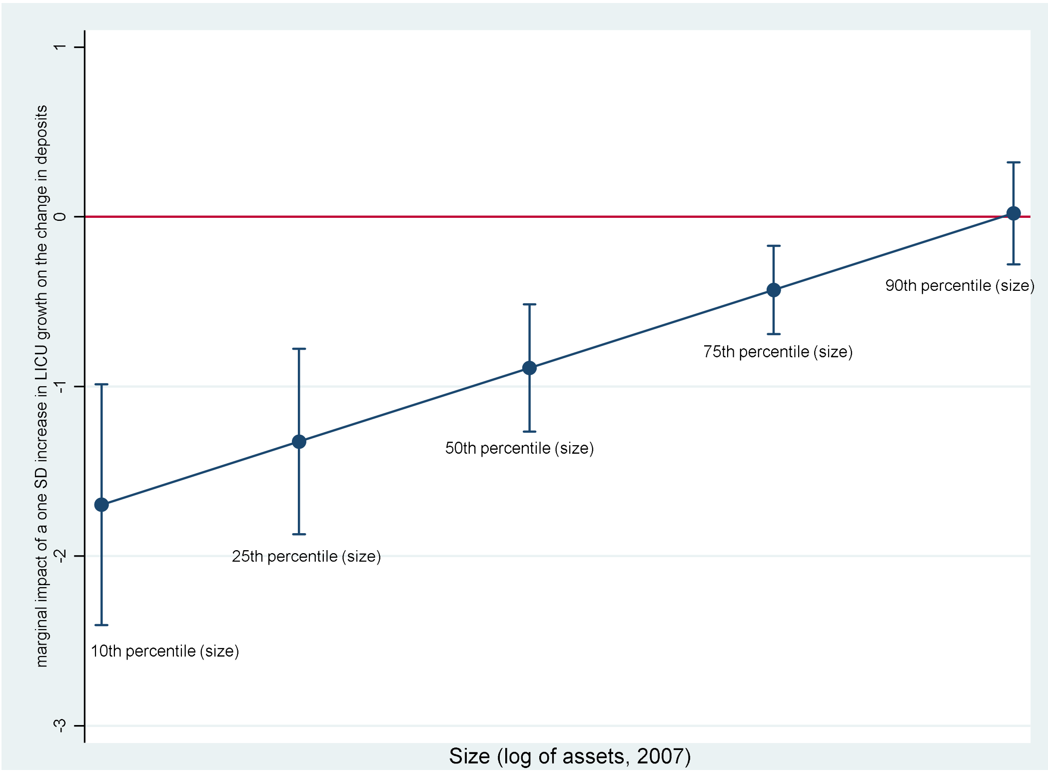
This figure illustrates the identification strategy in Table 7. In panel A, three CUs are located within 10 miles of the bank. Of the three, one CU is headquarted in a census tract with median income that is 80 percent or less of the national median income (the hatched triangle). This CU is thus potentially eligible for low-income designation after the 2012 Q2 regulatory roll-out. Panel B shows the bank's exposure to LICU competition after this 2012 Q2 roll-out, and the conversion of the potentially eligible CU to low-income status (dark triangle).

Figure 9: The marginal impact of low-income credit union growth on lending at banks



This figure plots the marginal impact of a one standard deviation increase in LICU growth on the change in lending at different sized banks using the estimates from column 5 of Table 7. The dots are the estimated impact and the bars denote their 95 percent confidence bands.

Figure 10: The marginal impact of low-income credit union (LICU) growth on deposits at banks



This figure plots the marginal impact of a one standard deviation increase in LICU growth on the change in deposits at different sized banks using the estimates from column 6 of Table 7. The dots are the estimated impact and the bars denote their 95 percent confidence bands.

Table 1: Summary Statistics

Panel A. Summary Statistics for Credit Unions, 2009-2015				
	Total Assets	Loans/Assets	Deposits/Assets	Total Equity/Assets
mean	125,263	0.53	0.85	0.14
median	16,342	0.54	0.87	0.12
25th percentile	4,385	0.41	0.83	0.09
75th percentile	61,861	0.66	0.90	0.16
standard deviation	758,010	0.18	0.07	0.07
Observations	8,161	8,161	8,161	8,161

Panel B. Summary Statistics Community Banks, 2009-2015				
	Total Assets	Loans/Assets	Deposits/Assets	Total Equity/Assets
mean	311,336	0.62	0.84	0.12
median	150,441	0.64	0.85	0.12
25th percentile	75,968	0.54	0.81	0.10
75th percentile	314,701	0.72	0.88	0.13
standard deviation	604,727	0.14	0.07	0.29
Observations	7,732	7,709	7,732	7,709

Panel C. Summary Statistics for Multi-Market Banks, 2009-2015				
	Total Assets	Loans/Assets	Deposits/Assets	Total Equity/Assets
mean	10,247,080	0.53	0.66	0.09
median	667,834	0.63	0.77	0.11
25th percentile	162,192	0.36	0.65	0.03
75th percentile	2,762,236	0.74	0.84	0.13
standard deviation	69,744,006	0.28	0.28	0.07
Observations	1,205	1,205	1,205	1,205

Panel D. Summary Statistics for Low-Income Designated CUs, 2012-2015				
	Total Assets	Loans/Assets	Deposits/Assets	Total Equity/Assets
mean	121,497	0.52	0.86	0.13
median	19,291	0.53	0.88	0.11
25th percentile	4,898	0.39	0.84	0.09
75th percentile	73,257	0.66	0.90	0.14
standard deviation	378,871	0.18	0.06	0.06
Observations	2,640	2,640	2,640	2,640

Panel E. Summary Statistics for Non-Low-Income Designated CUs, 2012-2015				
	Total Assets	Loans/Assets	Deposits/Assets	Total Equity/Assets
mean	170,579	0.50	0.86	0.13
median	23,670	0.50	0.88	0.11
25th percentile	6,896	0.37	0.84	0.09
75th percentile	85,337	0.63	0.90	0.15
standard deviation	1,003,952	0.18	0.07	0.07
Observations	6,049	6,049	6,049	6,049

Panel F. Automotive lending, market shares for credit unions, banks and non-banks		
	2009-2017	2012-2017
	Overall Market Share	
Credit Unions	0.25	0.25
Banks	0.28	0.27
Non-Banks	0.47	0.48
	Market Share, by Equifax Risk Score Quartiles	
	2009-2017	2012-2017
1st quartile		
Credit unions	0.18	0.17
Banks	0.15	0.14
Non-banks	0.67	0.69
2nd quartile		
Credit unions	0.28	0.28
Banks	0.27	0.26
Non-banks	0.45	0.46
3rd quartile		
Credit unions	0.27	0.28
Banks	0.35	0.34
Non-banks	0.38	0.38
4th quartile		
Credit unions	0.27	0.27
Banks	0.32	0.31
Non-banks	0.41	0.42

Panel A of this table reports summary statistics for all credit unions over the period 2009-2015. Panel B reports summary statistics for the sample of community banks, as defined by the FDIC. Panel C focuses on the non-community (multi-market) banks in the sample period. Panel D reports summary statistics for those credit unions that eventually became "low-income" between 2012Q1 and end-2015. Panel C focuses on the sample of credit unions that did not become "low-income". "Total assets" are in thousands of dollars. Panel F uses data from the FRBNY CCP/Equifax Data to report the market shares for credit unions, banks and non-banks in aggregate automotive lending for various sample periods. It also reports market shares by Equifax Risk Score quartiles; "1st quartile" are Equifax Risk Scores in the bottom quartile ("highest credit risk").

Table 2: Probability of Low Income Designation and Census Tract Relative Income, 2009-2015

VARIABLES	(1)	(2)	(3)
ratio of tract to national median income	-0.695***	-0.560**	-1.558***
	(0.147)	(0.285)	(0.599)
median income of census tract, log, 2010		-0.143	-0.318
		(0.203)	(0.279)
total equity/assets, 2007-2008		-2.604***	-3.123***
		(0.922)	(0.980)
average assets, 2007-2008, log		-0.00940	-0.00744
		(0.0300)	(0.0303)
average ROA, 2008-2007		-0.728	-1.002
		(1.092)	(1.126)
average loans/assets, 2007-2008		0.279	0.382
		(0.272)	(0.294)
percent of African-Americans			0.338
			(0.544)
population per square mile			0.0311***
			(0.00516)
Observations	4,450	4,450	4,094

This table studies the determinants of low-income credit union (LICU) conversion. The dependent variable equals 1 if a CU becomes a low-income credit union (LICU) between 2009 and 2015 and 0 otherwise. The sample consists of all CUs that are not LICUs in 2008. The estimates are obtained using logit, and all regressions include state fixed effects and the standard errors are clustered at the state-level; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. "tract income" is the median income of the census tract in which a CU is headquartered. All demographic and income data come from the 2010 US Census. The CU balance sheet data come from the CU call report and are averaged over the 2007-2008 period.

Table 3: The Impact of Low Income Designation on Credit Unions' Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Deposits								
VARIABLES	% change	scaled by assets	Loans	Cars	Real Estate	Loans/Assets	ROA	Assets	Marketing Expenses
more than one year after designation	0.175***	0.149***	0.173***	0.0800**	0.0346	1.495***	0.0234**	0.196***	0.0564***
	(0.0622)	(0.0525)	(0.0541)	(0.0381)	(0.0227)	(0.369)	(0.00935)	(0.0556)	(0.0184)
4 quarters after designation	0.143	0.114	0.204***	0.179***	-0.0126	0.862***	0.0433**	0.174*	0.0508***
	(0.108)	(0.0909)	(0.0715)	(0.0513)	(0.0278)	(0.319)	(0.0217)	(0.0931)	(0.0177)
3 quarters after designation	0.319***	0.279***	0.265***	0.144***	0.0308	0.738**	-0.00491	0.328***	0.0414**
	(0.107)	(0.0905)	(0.0704)	(0.0505)	(0.0289)	(0.302)	(0.0175)	(0.0929)	(0.0173)
2 quarters after designation	0.231**	0.189**	0.286***	0.152***	0.0544*	0.693**	0.0154	0.273***	0.0400**
	(0.0982)	(0.0831)	(0.0701)	(0.0478)	(0.0283)	(0.288)	(0.0154)	(0.0859)	(0.0167)
1 quarters after designation	0.117	0.102	0.169***	0.124***	-0.00749	0.514*	0.0146	0.106	0.0204
	(0.0942)	(0.0797)	(0.0651)	(0.0453)	(0.0264)	(0.269)	(0.0225)	(0.0824)	(0.0156)
quarter of designation	0.0551	0.0417	0.101	0.0442	0.0290	0.376	0.00788	0.0473	0.0286*
	(0.0952)	(0.0801)	(0.0650)	(0.0446)	(0.0267)	(0.256)	(0.0112)	(0.0824)	(0.0147)
1 quarters before designation	0.115	0.110	0.0583	0.0553	0.0125	0.317	0.00905	0.122	0.00912
	(0.0966)	(0.0817)	(0.0615)	(0.0446)	(0.0262)	(0.239)	(0.0132)	(0.0839)	(0.0140)
2 quarters before designation	0.121	0.0840	0.0656	0.0604	-0.0296	0.262	0.0159	0.115	0.0179
	(0.0934)	(0.0790)	(0.0616)	(0.0439)	(0.0252)	(0.224)	(0.0110)	(0.0818)	(0.0131)
3 quarters before designation	0.109	0.0980	0.0365	0.0493	-0.0138	0.219	0.0124	0.142*	-0.00413
	(0.0937)	(0.0786)	(0.0609)	(0.0419)	(0.0251)	(0.207)	(0.0173)	(0.0812)	(0.0129)
4 quarters before designation	-0.0208	-0.0209	0.0412	0.078	-0.00653	0.244	0.0240**	0.00669	0.00279
	(0.0899)	(0.0765)	(0.0565)	(0.0400)	(0.0235)	(0.190)	(0.00994)	(0.0788)	(0.0121)
Observations	192,455	192,455	192,455	192,332	192,455	192,455	192,453	192,455	192,097
R-squared	0.380	0.385	0.325	0.279	0.297	0.915	0.100	0.372	0.969

This table estimates the difference-in-difference framework in equation (1) using quarterly data on credit unions over the sample period 2009-2015. Columns 2-5 uses the quarter-on-quarter change in the variable scaled by assets in the previous quarter and multiplied by 100; columns 1 and 8 are percent changes. All columns include credit union and county-by-year-quarter fixed effects. Standard errors are clustered at the credit union level (7,064 clusters); and (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). Figures 5 and 6 plot the coefficients (dots) and 95 percent confidence banks (lines) in columns 1 and 3 respectively.

Table 4: The impact of first exposure to low-income credit unions (LICUs) on banks

	(1)	(2)	(3)
	change in:		
VARIABLES	deposits	Loans	ROA
postyear	-1.833***	-0.752**	0.0487
	(0.637)	(0.355)	(0.0319)
4 quarters after exposure to LICU	-1.092*	-0.691**	0.0340
	(0.610)	(0.330)	(0.0310)
3 quarters after exposure to LICU	-0.943*	-0.650**	0.0423
	(0.570)	(0.315)	(0.0283)
2 quarters after exposure to LICU	-1.587***	-0.258	0.0283
	(0.531)	(0.305)	(0.0282)
1 quarters after exposure to LICU	-1.035**	-0.0572	0.0306
	(0.462)	(0.278)	(0.0242)
first exposure to LICU	-0.708*	-0.339	0.0258
	(0.420)	(0.249)	(0.0232)
1 quarters before exposure to LICU	-0.432	-0.232	0.00958
	(0.394)	(0.234)	(0.0222)
2 quarters before exposure to LICU	-0.598*	-0.0407	0.0247
	(0.356)	(0.217)	(0.0193)
3 quarters before exposure to LICU	-0.326	0.0247	0.0211
	(0.282)	(0.179)	(0.0150)
4 quarters before exposure to LICU	-0.118	-0.0874	0.000104
	(0.218)	(0.128)	(0.0143)
Observations	175,296	174,831	175,837
R-squared	0.321	0.470	0.678

This table estimates the impact of community banks' first exposure to a low-income credit union (LICU). The variable "first exposure to LICU" equals one in the quarter a bank first becomes exposed to a LICU that is within 5 miles of the bank's headquarters; this variable is 0 otherwise. The sample period is 2009-2015. Columns 1 and 2 multiply the quarter-on-quarter change in the dependent variable by 100 and divide by assets in the previous quarter. "ROA" is the return on assets. All columns include bank-by-year fixed effects; year by quarter fixed effects and county fixed effects. Standard errors are clustered at the bank level (7,427 clusters); and (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). Figures 6 and 7 depict the coefficients (dots) and 95 percent confidence banks (lines) in columns 1 and 2 respectively.

Table 5: The impact of low-income credit union (LICU) growth on nearby banks in the cross-section, OLS

	(1)	(2)	(3)	(4)	(5)
		change in loans scaled by assets			
VARIABLES	percent change in loans	baseline	house prices	constant sample	income
growth in number of LICUS, 5 miles	-0.567**	-0.256**	-0.185*	-0.171	-0.256**
	(0.239)	(0.0992)	(0.112)	(0.111)	(0.0998)
average change in house prices			0.0477		
			(0.0396)		
log of tract income					-0.262***
					(0.0838)
Observations	5,944	5,945	2,393	2,393	5,386
R-squared	0.067	0.048	0.060	0.060	0.054

This table estimates the impact of the growth in the number of LICUs within 5 miles of a bank's headquarters on the average change in the bank's lending—Equation (2) in the text. The unit of observation is a bank. The analysis divides the sample into two periods: 2008Q1-2012Q1 and 2012Q2-2015Q4. For each bank, the change in lending is averaged over each of the two periods. The dependent variable is the difference in the average change in lending between the two periods. The growth in the number of LICUs is the difference between the log of 1 plus the average number of LICUs within 5 miles a bank between the two periods. All regressions include state fixed effects and standard errors are clustered (49 clusters) at the state-level. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table 6: The impact of low-income credit union (LICU) growth on nearby bank lending in the cross-section, OLS, various distances

VARIABLES	(1) 5 miles	(2) 10 miles	(3) 20 miles	(4) 30 miles	(5) 40 miles	(6) 50 miles
growth in number of LICUS	-0.256**	-0.204**	-0.101	-0.131*	-0.114**	-0.112
	(0.0992)	(0.0843)	(0.0808)	(0.0681)	(0.0560)	(0.0663)
Observations	5,945	5,945	5,945	5,945	5,945	5,945
R-squared	0.054	0.054	0.052	0.053	0.053	0.053

This table estimates the impact of the growth in the number of LICUs, within various miles from a bank's headquarters, on the average change in the bank's lending—Equation (2) in the text. Column (1) uses a 5 mile radius; column 2: 10 miles; column 3: 20 miles; column 4: 30 miles; column 5: 40 miles; column 6: 50 miles. The unit of observation is a bank (Equation (2)). The analysis divides the sample into two periods: 2008Q1-2012Q1 and 2012Q2-2015Q4. For each bank, the change in lending is averaged over each of the two periods. The dependent variable is the difference in the average change in lending between the two periods. The growth in the number of LICUs is the difference between the log of 1 plus the average number of LICUs within a given radii from a bank between the two periods. All regressions include state fixed effects and standard errors are clustered (49 clusters) at the state-level. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table 7: The impact of low-income credit union (LICU) growth on nearby banks in the cross-section, IV

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	first stage		change in lending	change in deposits	change in lending	change in deposits
log number of eligible CUs, 2008	0.232***	0.229***				
	(0.0276)	(0.0278)				
growth in number of LICUS, 10 miles			-0.305*	-0.380*	-6.279***	-8.144***
			(0.154)	(0.198)	(1.433)	(1.913)
growth in number of LICUS*size					0.468***	0.622***
					(0.112)	(0.152)
Observations	5,945	5,386	5,386	5,386	5,219	5,219
R-squared	0.441	0.444	0.057	0.062	0.121	0.121

The dependent variable in columns 1 and 2 is the growth in the number of LICUs within 10 miles of a bank's headquarters. The "log number of eligible CUs, 2008" is the log of 1 plus the number of CUs located within 10 miles of a bank that are themselves (the CUs) headquartered in census tracts with median income that is 80 percent or less of the national median income (all income data are from 2010 US census). Columns 2-6 includes a third order polynomial of the log median income of the census tract in which the bank is headquartered. "size" is the log of average assets in 2007. Columns 3-6 instrument the "growth in number of LICUs, 10 miles" with the "log number of eligible CUs, 2008". The "first stage" F-statistic is 28.01 (p-value=0.00). Note that the unit of observation remains the bank. As before, the analysis divides the sample into two periods: 2008Q1-2012Q1 and 2012Q2-2015Q4. For each bank, the change in lending or deposits is averaged over each of the two periods. The dependent variable is the difference in the average change in lending or deposits between the two periods. The growth in the number of LICUs is the difference between the log of 1 plus the average number of LICUs within 10 miles a bank between the two periods. All regressions include state fixed effects and standard errors are clustered (49 clusters) at the state-level. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). The marginal impact of the growth in the number of LICUs on the dependent variable in columns (5) and (6) as a function of size are in Figures 9 and 10. The change in lending has a mean of 0.21 with a standard deviation of 1.87. The change in deposits has a mean of -0.78 with a standard deviation of 1.95.

Table 8: The impact of low-income credit union (LICU) growth on nearby banks in the cross-section, extension 1.

Panel A. IV

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	change in C&I loans	C&I loans/loans	ROA	Z-Score	ROA StDev	Non-Interest Expenses
growth in number of LICUS, 10 miles	0.0823***	1.213***	0.121***	1.51**	-0.0772***	1.834*
	(0.0173)	(0.333)	(0.0222)	(0.703)	(0.0204)	(0.998)
Observations	5,386	5,385	5,386	5,276	5,276	5,386
R-squared	0.020	0.028	0.072	0.016	0.050	0.016

Panel B. OLS

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	change in C&I loans	C&I loans/loans	ROA	Z Score	ROA StDev	Non-Interest Expenses
growth in number of LICUS, 10 miles	0.0396***	0.786***	0.0536***	0.829**	-0.0389***	1.115*
	(0.0105)	(0.212)	(0.0103)	(0.396)	(0.00999)	(0.562)
Observations	5,386	5,385	5,386	5,276	5,276	5,386
R-squared	0.025	0.030	0.079	0.017	0.052	0.017

Panel A instruments the “growth in number of LICUs, 10 miles” with the “log number of eligible CUs, 2008”. The “first stage” F-statistic is 28.01 (p-value=0.00). “C&I” loans are “commercial and industrial loans”. All changes are quarter on quarter and scaled by assets in the previous quarter. The Z-score is defined as the sum of a bank’s return on assets plus leverage divided by the standard deviation of the return on assets. “ROA” is the return on assets and “ROA StDev” is the standard deviation of the return on assets. Note that the unit of observation remains the bank. Panel B repeats Panel A using OLS. As before, the analysis divides the sample into two periods: 2008Q1-2012Q1 and 2012Q2-2015Q4. For each bank, the change in lending is averaged over each of the two periods. The dependent variable is the difference in the average between the two periods. The growth in the number of LICUs is the difference between the log of 1 plus the average number of LICUs within 10 miles a bank between the two periods. All regressions include state fixed effects and standard errors are clustered (49 clusters) at the state-level. (*** p<0.01, ** p<0.05, * p<0.1).

Table 9: The impact of low-income credit union (LICU) growth on nearby banks in the cross-section, Extension 2

Panel A. IV

	(1)	(2)	(3)	(4)	(5)
	change in lending		probability of failure		
VARIABLES	low-tax states	high-tax states	full sample	low-tax states	high-tax states
growth in number of LICUS, 10 miles	-0.0867	-0.546**	0.0208	-0.000701	0.0520*
	(0.177)	(0.227)	(0.0158)	(0.0135)	(0.0255)
Observations	3,067	2,319	5,386	3,067	2,319
R-squared	0.071	0.039	0.017	0.029	0.002

Panel B. OLS

	(1)	(2)	(3)	(4)	(5)
	change in lending		probability of failure		
VARIABLES	low-tax states	high-tax states	full sample	low-tax states	high-tax states
growth in number of LICUS, 10 miles	-0.156	-0.105	0.00446	-0.00470	0.0181
	(0.103)	(0.135)	(0.00846)	(0.00926)	(0.0138)
Observations	3,067	2,319	5,386	3,067	2,319
R-squared	0.071	0.046	0.020	0.029	0.015

Panel A instruments the "growth in number of LICUs, 10 miles" with the "log number of eligible CUs, 2008". The "first stage" F-statistic is 28.01 (p-value=0.00). "low-tax states" have below median corporate tax rates in 2009. In columns 3-5, the dependent variable equals 1 if a bank failed between 2012Q2 and 2015 Q4. . The growth in the number of LICUs is the difference between the log of 1 plus the average number of LICUs within 10 miles a bank between the two periods. Panel B repeats Panel A using OLS. All regressions include state fixed effects, and a polynomial of median income in the census tract in which a bank is headquartered; and standard errors are clustered (49 clusters) at the state-level. (*** p<0.01, ** p<0.05, * p<0.1). The change in lending has a mean of 0.21 with a standard deviation of 1.87.

Table 10: Low-income credit unions (LICUs) and the number of auto loans in a zip code at the extensive margin

	(1)	(2)	(3)	(4)
	all institutions	credit unions	banks	non-banks
12 months before exposure	0.0076	0.0059	0.015	0.0086
	(0.0052)	(0.011)	(0.011)	(0.0072)
6 months before exposure	0.0061	-0.0044	0.025**	0.0088
	(0.0055)	(0.011)	(0.011)	(0.0076)
first exposure to LICU	0.012**	0.017	0.0077	0.016**
	(0.0058)	(0.012)	(0.011)	(0.0079)
6 month after exposure	0.017***	0.0052	0.012	0.022***
	(0.0060)	(0.013)	(0.013)	(0.0076)
12 months after exposure	0.022***	0.020	0.0085	0.033***
	(0.0067)	(0.013)	(0.013)	(0.0083)
18 months or more after first exposure	0.029***	0.025**	0.015	0.039***
	(0.0057)	(0.011)	(0.0099)	(0.0066)
N	389914	389914	389914	389914
R-sq	0.967	0.910	0.878	0.949

This table estimates the impact of first exposure to a low-income credit union (LICU) on the log number of originated auto loans (plus 1) inside a zip code-half year unit of observation between 2009 and 2017. "first exposure to LICU" is an indicator variable that equal 1 in the 6 month period in which a zip code first has a low-income CU and 0 otherwise. We also include two lags and leads of this indicator variable, as well as an indicator for 18 months and beyond from when a zip-code first gets a low-income CU. Column 1 uses the log of 1 plus the number of all auto loans originated in the zipcode-6 month period; column 2 uses only the log of 1 plus the number of loans originated by credit unions inside the zipcode-6 month period; column 3 uses only loans originated by banks, while column 4 uses the log of one plus the number of loans originated by non-banks in a zipcode-6 month unit. 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 FRBNY CCP/Equifax database. The differences between banks, non-banks and credit unions at the 18 month exposure level are significant at the 5 percent level.

Table 11: Low-income credit unions (LICUs) and auto-loan portfolio risk

	(1) All institutions	(2) Credit unions	(3) Banks	(4) Non-banks
12 months before exposure	0.0019	0.0015	0.0016	0.0015
	(0.0024)	(0.0060)	(0.0055)	(0.0033)
6 months before exposure	0.0034	0.0018	0.0018	0.0035
	(0.0023)	(0.0063)	(0.0056)	(0.0032)
first exposure to LICU	0.0040*	0.0071	0.0068	-0.00036
	(0.0024)	(0.0058)	(0.0057)	(0.0032)
6 month after exposure	0.0045*	0.015**	0.0069	-0.0017
	(0.0024)	(0.0063)	(0.0058)	(0.0032)
12 months after exposure	0.0078***	0.013*	0.0075	0.0062*
	(0.0027)	(0.0068)	(0.0059)	(0.0033)
18 months or more after first exposure	0.0074***	0.011**	0.0014	0.0059**
	(0.0020)	(0.0048)	(0.0042)	(0.0025)
N	389914	309314	336042	357848
R-sq	0.778	0.439	0.461	0.700

This table estimates the impact of first exposure to a low-income credit union (LICU) on the share of riskier loans at the zip code level. The unit of observation is zip code by half-years and the sample period is 2009-2017. 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 individuals 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; column 2 focuses only on loans originated by credit unions, column 3 computes the share for loans by banks, while column 4 uses non-banks. 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 FRBNY CCP/Equifax database.

Table 12: Low-income credit unions and non-performing 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

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. 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 2017. All regressions control for the change in number of credit unions between 2010 and 2013 in a zip code and county demographics in 2013 (percent of African American, unemployment rate, county median income, county median income growth, poverty rate, changes in poverty rate, population size, density and growth rate). Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The source of the auto loan data is the FRBNY CCP/Equifax database.

Table 13: Low-income credit unions and non-performing 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

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 overdue by institution types in the second half of 2017. All regressions control for the change in number of credit unions between 2010 and 2013 in a zip code and county demographics in 2013 (percent of African American, unemployment rate, county median income, county median income growth, poverty rate, changes in poverty rate, population size, density and growth rate). Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The source of the auto loan data is FRBNY CCP/Equifax database.

Appendix

Table A1: Summary Statistics of Variables in Regressions

Variables	Notes	Mean	Standard deviation
Table 3: Credit unions			
Deposits	% change	1.04	4.01
Deposits	change scaled by assets * 100	0.89	3.40
Loans	change scaled by assets * 100	0.28	2.29
Car loans	change scaled by assets * 100	0.10	1.60
Real estate loans	change scaled by assets * 100	0.10	0.94
Loans/Assets	loans divided by assets	0.52	0.18
ROA	return on assets	0.03	1.97
Assets	change scaled by assets * 100	0.01	0.03
Marketing expenses	change scaled by assets * 100	2.37	2.11
Table 4: Banks			
Deposits	change scaled by assets * 100	1.11	4.65
Loans	change scaled by assets * 100	0.56	3.18
ROA	return on assets	0.15	0.33
Table 5: Growth in LICUs			
Loans	% change	0.03	4.98
Loans	change scaled by assets * 100	0.21	1.87
Growth in number of LICUs	difference between the log of 1 plus the average number of LICUs within 5 miles of a bank between the two periods	0.12	0.32
Table 8: 2SLS			
Change in C&I loans	change scaled by assets * 100	0.04	0.23
C&I loans / loans	C&I loans divided by total loans	0.10	0.45
ROA	return on assets	0.08	0.31
Z-score	sum of a bank's return on assets plus leverage divided by the standard deviation of the return on assets	33.23	134.82
ROA StDev	standard deviation of the return on assets	-0.11	0.30
Non-Interest expenses	change scaled by assets * 100	0.25	8.45

Note: This table provides summary statistics for variables used in Tables 3, 4, 5, and 8 in the main text.

Internet Appendix

Table IA1: Data Sources

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 IA2. The Impact of Low Income (LI) Designation on Credit Unions' (CU) Outcomes, Additional Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
						loans/deposit ratio	
VARIABLES	single bond CUs	multiple common bond CUs	exclude pre-2008 LICUs	LICU counties	LICU tracts	above median	below median
more than one year after designation	0.00197*	0.00153**	0.00137**	0.00173***	0.00181***	0.00224**	0.000505
	(0.00101)	(0.000730)	(0.000560)	(0.000536)	(0.000645)	(0.000922)	(0.000779)
1 quarters after designation	0.000783	0.00254***	0.00157**	0.00169***	0.00147*	0.00250***	0.000505
	(0.00141)	(0.000785)	(0.000653)	(0.000646)	(0.000794)	(0.000963)	(0.000994)
2 quarters after designation	0.000742	0.00334***	0.00268***	0.00286***	0.00265***	0.00268**	0.00313***
	(0.00153)	(0.000839)	(0.000708)	(0.000696)	(0.000827)	(0.00108)	(0.00105)
3 quarters after designation	0.00325**	0.00277***	0.00238***	0.00266***	0.00288***	0.00259**	0.00202*
	(0.00151)	(0.000857)	(0.000707)	(0.000698)	(0.000845)	(0.00112)	(0.00105)
4 quarters after designation	-0.000224	0.00285***	0.00190***	0.00205***	0.00262***	0.00394***	-0.000400
	(0.00140)	(0.000906)	(0.000722)	(0.000709)	(0.000856)	(0.00109)	(0.00107)
quarter of designation	0.000290	0.00116	0.00107	0.00100	0.00112	0.00147	0.000891
	(0.00132)	(0.000812)	(0.000652)	(0.000645)	(0.000775)	(0.000958)	(0.000992)
1 quarters before designation	-0.00195*	0.00143*	0.000391	0.000572	0.000774	0.000886	-0.000197
	(0.00119)	(0.000795)	(0.000617)	(0.000610)	(0.000740)	(0.000954)	(0.000900)
2 quarters before designation	-0.000741	0.00107	0.000634	0.000639	0.000660	0.000785	0.000937
	(0.00123)	(0.000809)	(0.000624)	(0.000612)	(0.000740)	(0.000961)	(0.000916)
3 quarters before designation	0.000588	0.000105	0.000267	0.000355	0.000154	0.00108	-0.000597
	(0.00129)	(0.000745)	(0.000614)	(0.000604)	(0.000700)	(0.000920)	(0.000914)
4 quarters before designation	-0.000108	0.000876	0.000234	0.000406	0.000563	-0.000106	0.00130
	(0.00117)	(0.000693)	(0.000568)	(0.000560)	(0.000660)	(0.000854)	(0.000851)
Observations	57,278	122,970	167,039	173,952	134,825	78,810	78,006
R-squared	0.365	0.356	0.326	0.315	0.352	0.398	0.321

This table extends Table 3 (main text) and estimates the difference-in-difference framework in equation (1) using quarterly data on credit unions over the sample period 2009-2015. The dependent variable is the quarter-on-quarter change in loans divided by the one quarter lag in assets. Columns 1 and 2 estimate separately the impact of LICU designation for CUs that are based on single bonds versus those based on multiple bonds. Column 3 excludes all CUs that were LICU before 2008. Column 4 restricts the sample to CUs located in counties that had at least one LICU designation after 2008. Column 5 restricts the sample to CUs located in census tracts with median income below that of the national median income (all income observed from 2010 census). Columns 6 and 7 estimate separately the main specification for CUs above the median loans/deposit ratio (in 2007) and those below this ratio. All columns include credit union and county-by-year-quarter fixed effects. Standard errors are clustered at the credit union level (7,064 clusters); and (*** p<0.01, ** p<0.05, * p<0.1).

Table IA4. The Impact of Bank Market Structure on the Geographic Variation in LICUs

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

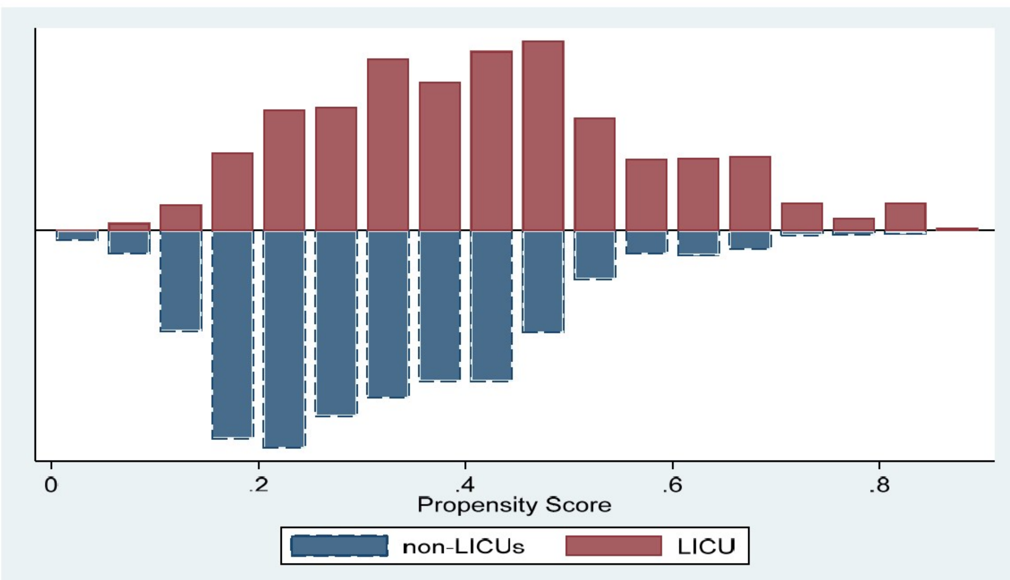
This table examines the impact of bank market structure in 2008 at the county-level on the 2015 Q4 ratio of low-income credit unions to all credit unions in the county. The dependent variable in this table is the share of LICUs to all CUs in a county in 2015 Q4. All regressions include state fixed effects and standard errors are clustered at the state-level.*** p<0.01, ** p<0.05, * p<0.1

Table IA5. Propensity Score Matching

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 2009-2015. Specifically, the dependent variable equals 1 if a credit union is designated as “low-income" over the sample period, 2009Q1-2015 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.

	(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

Propensity Score Matching Overlap



This figure is based on column 4 of Table IA.3. To compute the propensity to become a LICU during the sample period, we use the predicted probabilities from column 4 of Table IA.3. This figure shows the support of these predicted probabilities for both LICUs and the nearest-neighbor non-LICUs.

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.

	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

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