# ARE (NONPROFIT) BANKS SPECIAL?
# THE ECONOMIC EFFECTS OF BANKING WITH CREDIT UNIONS*

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**Abstract**

Nonprofit banks in the U.S. are primarily organized as credit unions (CUs) and have grown steadily over the last two decades, increasing their share of total lending to U.S. households. This paper studies the economic effects of banking with CUs using consumer credit report data merged to administrative data on originated mortgages and detailed data on the locations and balance sheets of CUs. To estimate causal effects, I construct a novel instrument for banking with a CU using a distance-weighted density measure of nearby CUs. I find that banking with a CU causes borrowers to have fewer mortgage delinquencies, higher credit scores, and a lower risk of bankruptcy several years later. I find support for several mechanisms behind these results: CUs charge lower interest rates, price in less risk-sensitive ways, are less likely to resell their originated mortgages in the secondary market, and are more likely to accommodate borrowers that become past due. These results suggest that CUs behave differently than for-profit banks, that many consumers experience different outcomes by banking with CUs, and are inconsistent with CUs behaving as "for-profits in disguise." JEL codes: L30, G21, G50, H25

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# 1 Introduction

Economists have long been interested in the nonprofit organization as a notable deviation from the standard model of the firm (Hansmann, 1980; Newhouse, 1970; Pauly and Redisch, 1973; Rose-Ackerman, 1996). In trying to explain why nonprofit organizations exist, economists have put forward theories with divergent implications about the value of nonprofits. The more optimistic among them presumes altruism among some entrepreneurs and views the nonprofit form as a natural vehicle for their objectives. Less optimistically, others argue that non-profits overcome market failures stemming from insufficient trust in for-profits. Most pessimistically, others suggests profit-seeking entrepreneurs engage in tax and reputational arbitrage by disguising themselves in the nonprofit form (Weisbrod, 1975; Hirth, 1999; Duggan, 2000).

Understanding why nonprofits exist and how they behave is important for various reasons. First, nonprofits represent an increasing share of economic production: the U.S. nonprofit sector has grown from 1% to 6% of U.S. gross domestic product since the beginning of the post-war era (Bureau of Economic Analysis, 2021). This statistic understates the increasing importance and pressure that firms face to engage in actions that are "pro-social" and, by intimation, not necessarily profit driven (New York Times, 2018). A second broad cause for interest is the potential erosion of trust in the legitimacy of the nonprofit organizational form. A third, more direct, cause for interest in the underlying objective function of nonprofits is the potentially misdirected tax policy, which currently exempts nonprofits from paying income taxes.

The U.S. banking industry is an interesting setting to study these questions. In the U.S., nonprofit banks are principally organized as Credit Unions (CUs), and they have grown their market shares in various consumer lending markets since the early 2000s. They hold about 8% of the banking industry's assets under management and, as of 2017, more sizeable shares of various lending markets: 26% in personal loans, 13% in mortgage originations, and 28% of auto loans

(Experian, 2017). Furthermore, in 2020, CUs had over 124.3 million memberships, a figure that suggests an even larger fraction of the U.S. adult population are customers of nonprofit banks (National Credit Union Administration, 2020). Unlike with nonprofits in general, CUs have the measurable (putative) objective of providing better prices and banking services to their customers. Last, unlike for many other industries with high nonprofit participation rates, high-quality data are available for the banking sector.

CUs are also organized as member-only cooperative organizations. Alongside their configuration as nonprofits, this is the second feature of their organizational structure that distinguishes them from for-profit banks. Formally, only individuals who can identify under a particular CU's field(s) of membership can become its members, owners, and customers. Fields of membership are defined in terms of an occupation, association, or geography, and any given CU has one or two fields. This membership requirement is a possible channel by which individuals with more advantageous and hard-to-measure creditworthiness may be systematically selecting into banking with CUs. Therefore, CUs are also an interesting setting to study long-standing questions in finance related to the costs and benefits of relationship banking (Petersen and Rajan, 1994) and private information (Hauswald and Marquez, 2006).

The rise of CUs has been met with the policy concern that their nonprofit status disguises for-profit behavior and their tax exemption unfairly provides a competitive disadvantage to profit-seeking banks. CUs defend the tax exemption on the basis that "credit unions are democratically owned and controlled not-for-profit cooperative financial institutions that take pride in their 'People Helping People' philosophy" (Credit Union National Association, 2021). For-profit banks disagree; they claim CUs have long abandoned their mandate and that they "look and act like banks, yet they do not pay taxes or abide by the same rules as banks" (American Bankers Association, 2021).

Using administrative data, this paper presents an empirical analysis of nonprofit banks, their effects on borrowers, and the role of information in consumer banking. My primary data sources are the Home Mortgage Disclosure Act (HMDA) data and an anonimyzed 10% sample of credit records provided by TransUnion, one of the major national credit rating agencies. Using these and other supplementary data sources, I study three aspects of CU participation in mortgage markets: the market segments they focus on, pricing, and the quality of credit outcomes of individuals who bank with them. In each of these, I compare CUs to banks with assets in the same range as CUs (hereafter, "small" banks) and relate the results to an inference on whether CUs are nonprofits in disguise, by controlling for the role that selection into CUs may play.[1]

The HMDA data are a quasi-universe of the mortgages originated in the U.S., and therefore provide a good way to evaluate differences in the market segments that CUs and banks focus on. Overall, the distributions of loans both lenders originate are much more alike than they are different. On average, CUs originate mortgages that are slightly smaller and to individuals with slightly lower incomes, but the distributions of loan size and borrower income are strikingly similar. CU and bank loans are distributed across similar geographic measures of creditworthiness, income, and urbanity. Together, these facts suggest two interesting conclusions. First, CU membership requirements do not seem to affect the overall pool of CU mortgage borrowers; that is, any potential differential selection into CUs is not strong enough to manifest itself in the aggregate data. Second, because CUs seem to be competing with banks for similar customers, increasing access to credit is not a central feature of CU participation in the mortgage market.

List-price data suggest that CUs have offered their customers better interest rates on HELOCs, auto loans, and CDs over the last 20 years. Since 2009, CUs have priced HELOCs and auto loans at more than one interest rate point less than banks. Mortgages are an exceptional product in this regard, as banks and CUs post similar list prices. However, HMDA data show that prior to 2010 CUs originated significantly less "high-interest" mortgages than banks. Since 2010, banks and CUs are equally likely to report high-interest mortgages. This fact suggests a nuanced dynamic in

[1] Although small banks are the principal comparison group, I also compare CUs with larger banks in some analyses.

which pricing is changing across time and across credit-risk segments. Given these descriptive facts and the relatively liquid secondary market for mortgages, the mortgage setting is a particularly interesting one to study whether CUs comport with nonprofit behavior.

Going beyond interest rates, this paper takes a household finance perspective and thinks about credit outcomes post origination as a measure of quality that CUs may offer their customers.[2] Using a novel dataset, this paper shows that, in fact, individuals with CU-originated mortgages do experience better credit-profile outcomes up to four years after origination. Three years after origination, bank mortgages are three times as likely as CU mortgages to be 90+ days past due, and they owe three times as much. CU mortgages appear less likely to be charged off or sent into collections than small bank mortgages, but not than big bank mortgages. The better performance by CU-originated loans spills over into the individual's overall credit profile. The credit scores of individuals with a CU mortgage improve by one percentile point more than the credit scores of individuals with bank mortgages. Most notably, the likelihood of having a bankruptcy record is lower for individuals with CU mortgages.

Despite the descriptive evidence that these populations appear similar in aggregate measures, the differences in interest rates and credit outcomes cannot necessarily be attributed to different behavior by CUs post origination. In principle, these differences are due to both mutual selection effects on unobservable dimensions and bank treatment post origination. Given the membership requirements of CUs, lower list prices and better credit outcomes could be due to CUs selecting customers with an unobservably lower risk profile and not necessarily reflect lower prices or higher quality performance conditional on individual characteristics.

Credit record data allow me to evaluate whether CUs in fact charge lower interest rates and provide better credit outcomes after controlling for individual risk, an impediment in the literature and policy debate thus far. To allay concerns about selection on characteristics that are unobserv-

[2]Studying individual credit outcomes in with this perspective is arguably analogous to the way in which health outcomes are used as a measure of hospital quality.

able in my data, I instrument for whether the individual originates with a CU versus a bank. The instrumental variable (IV) is a distance-weighted density measure of CU branches within 10 kilometers of the address of the new mortgage. The instrument correlates with and is predictive of CU choice. The argument for the instrument's validity relies on the assumption that individuals do not choose the property they buy based on factors correlated with the density of CU branches around it, and that CU density only affects the individual credit outcomes via the choice of mortgaging with a CU. Based on the logic that borrowers choose where to live based on considerations that do not include CU branch locations per se, I argue for and show evidence that lends credence to these assumptions.

In my sample, CUs charge an unconditional 0.189 interest rate points less than small banks do on average. Accounting for risk and selection, however, I estimate that CUs charge 0.295 percentage points less than small banks do. Under reasonable assumptions, this difference implies cost savings of approximately 0.5% of the mortgage loan's principal amount. From a bank's balance sheet perspective, this difference in interest rates is similarly economically meaningful.

I apply the same technique of controlling for observable risk and selection to the credit outcomes event studies, focusing on the comparison of CUs and small banks. For the overall credit profile outcomes, this specification amounts to an IV-difference-in-differences research design. Although the IV estimates imply no detectable difference in the likelihood of a mortgage being charged off or sent into collections, they otherwise confirm —or at least do not refute— many of the suggestive conclusions from the descriptive event studies.

In an extension to another domain, I show that these results hold in the market for auto loans. Auto loan borrowers pay lower interest rates and experience better credit outcomes. The caveat is that, because there is no equivalent to the HMDA data for auto loans, the set of variables I can analyze in the auto loans sample is reduced. Most notable is the absence of a lender identifier. Nevertheless, I can control for borrower creditworthiness, loan terms, and geographic factors –

including the CU density instrumental variable.

Having compiled evidence of little differential selection into CUs and a CU treatment effect on interest rates and borrower credit outcomes, I further explore the different ways in which CU behavior in the mortgage market may differ from bank behavior and may be indicative of the mechanisms by which these differences arise.

I analyze whether CUs' pricing function differs from banks' pricing function. First, CU interest rates show a flatter gradient on credit score. Second, prior to 2009, the sample period during which bank interest rates were highest, CUs charged lower interest rates, but then CU and bank pricing seems to have converged post 2011. Third, contrary to banks, CU interest rates are lower in areas with high mortgage application rejection rates and higher in areas with high creditworthiness. Together these findings suggest that the *slope* of the CU pricing function is less sensitive to variation in the observable risk characteristics of the borrower and the lending environment. Using an estimated pricing function, I also show that the expected *level* of counterfactual CU interest rates is lower across the entire support in my sample. I interpret these results to mean that CU pricing seems to be less optimized around profit seeking than for-profit bank pricing.

CUs are drastically less likely to resell mortgages onto the secondary market, consistent with them following a different mortgage banking model. I correlate all lenders' mortgage resell rates to credit outcomes and find that loans from lenders with low resell rates experience better outcomes – although these improvements do not spill over onto the borrower's credit profile. This finding is consistent with the idea that banks that keep mortgages on their balance sheet better internalize incentives to originate good risk *and* improve outcomes post origination. In particular, maintaining the loan on balance sheet creates incentives for the lender to originate good risk and to resolve repayment issues post origination.

The causal estimates suggest that CUs do something after mortgage origination to yield better borrower credit outcomes. Among mortgages that become past due, CUs are more likely to accommodate the borrower's circumstance by granting the loan a forbearance, deferment, or declare it affected by a natural disaster. Similarly, CUs are less likely to foreclose, repossess, charge-off or send a loan to collections when it is past due. These findings suggest that CUs yield better borrower outcomes by being *relatively* accommodating and forgiving when their loans are behind on payments.

Motivated by the finding that CUs were less likely to charge high interest rates prior to 2010, I explore heterogeneity in CU effects across time. I segment the data by whether a mortgage was originated in $2004 - 2008$, $2009 - 2011$, and $2012 - 2017$. The CU effect on credit outcomes was greatest between 2004 and 2008. One interpretation of these results –consistent with a growing body of evidence on poor underwriting standards prior to the Great Recession– is that the quality of bank-originated mortgages was then at its lowest relative to CUs. That is, when demand and ex-ante profit opportunities seemed high, CU prices were at their relative lowest and their quality was its relative highest.

The remainder of the paper proceeds as follows. Section 1.1 reviews the literature on nonprofit organizations, its main application being to the hospital industry, and then the brief literature on CUs. Section 2 provides institutional background on CUs in the U.S. Section 3 presents a simple economic framework that motivates and guides the empirical work. Section 4 describes the main data sources and the results of merging HMDA data with credit records data. Section 5 presents aggregate facts about CUs' market focus and suggestive evidence that CUs offer better interest rates and quality in terms of credit outcomes. Section 6 presents the causal research design and its results. Section 7 presents evidence on mechanisms and heterogeneity behind the results. Section 8 concludes.

## 1.1 Literature Review

In a helpful review, Malani et al. (2003) synthesize the literature on nonprofit organizations. They categorize its theories according to the key substantive assumptions that explain the existence of nonprofits: altruism, cooperatives, and noncontractible quality.[3]

Altruism is perhaps the most intuitive concept behind the nonprofit firm —even if how to specify altruism in the objective function is less intuitive. Since Newhouse (1970), a common way to specify altruism has been to model the entrepreneur as maximizing a combination of product quantity and quality. More recent iterations generalize this model to consider objective functions with preferences for both altruism and profits/consumption (Lakdawalla and Philipson, 2006). One general prediction of altruism-based models is that firm size will be larger. Assuming no tax advantages and perfect competition, the altruism model predicts prices will be the same for both nonprofits and for-profits, but nonprofits will provide additional quantity or quality.

In trying to rationalize facts about nonprofit hospitals, Pauly and Redisch (1973) model the nonprofit as a cooperative effort by physicians to eliminate an outside investor's residual claims on hospital revenue. The cooperative form is then a way for key employees to gain control of the organization. The model can accommodate physicians with either altruistic or profit-oriented preferences, or both. Their model suggests that when the physician cooperative restricts its number of members, physicians are able to extract rents. When the physician cooperative is open to new members, however, physicians are paid their marginal product even if they only care about profits.

Hansmann (1980) argues nonprofits exist to solve a market failure arising from noncontractible quality. The logic of this explanation is that when customers cannot observe the quality of a product, the supplier has opportunities to profiteer. Because customers anticipate this incentive,

[3] This review focuses on the existence and behavior of *commercial* nonprofit firms, and largely ignores theories for the existence of donation-based nonprofits. Weisbrod (1975) argued that donation-based nonprofits provide public goods for which there is heterogeneous demand. Because the government supplies public goods at the level satisfying the median voter, there is unmet residual demand which nonprofits emerge to supply.

they are less likely to purchase, and the market for the product potentially unravels. The nonprofit form, defined by the "non-distribution constraint," curbs the incentive to profiteer and signals to the customer that the firm can be trusted not to shirk on quality. An implication of this model is that nonprofits produce higher quality than for-profits.

As already suggested above, health care and, in particular, hospitals have been a focal setting for the study of nonprofits. Nonprofits not only represent a large fraction of hospitals, they also account for a large share of the nonprofit sector.[4] In particular, policy interest in hospital pricing has placed acute attention on the economics of hospitals, both for- and nonprofit. Unfortunately, because these models ignore the tax exemption and assume perfect competition, the models reviewed are not set up to expect differences in observable prices.[5]

An interesting point of coincidence in the three models reviewed above is that they all predict nonprofits will produce higher quality products. In the health-care context, the most widely accepted measure of quality is health outcomes. The empirical evidence on whether nonprofit hospitals provide better health outcomes is mixed (Malani et al., 2003).

Duggan (2000) studies a policy change in California during the 1990s that created opportunities for hospitals to profit by treating indigent patients. He finds both for-profit and private nonprofit hospitals were equally likely to pursue the financial incentives without improving the quality of care for the poor. He concludes that nonprofit hospitals are no more altruistic than their for-profit counterparts. In the sense that this paper provides evidence on whether CUs act as for-profits in disguise, Duggan (2000) is an analogue in the hospital literature.

Overall, the literature seems to support the view that nonprofit hospitals do not provide better prices or quality for patients than for-profit hospitals. In fact, a more recent strand in the literature argues theoretically (Philipson and Posner, 2009) and empirically (Capps et al., 2020) that nonprofit

[4] As of 2016, hospitals and primary care facilities account for close to one half of total public charities' expenses and revenue (Urban Institute, 2020).

[5] The noncontractible quality model predicts nonprofits will charge higher prices, but not after conditioning on quality.

hospitals should not receive leniency in antitrust scrutiny. However, recent evidence in Garthwaite et al. (2018) suggests nonprofit hospitals disproportionately provide the bulk of uncompensated care to the uninsured, which is generally covered by forgoing profits. This argument runs counter to the literature's otherwise impression that nonprofits are for-profits in disguise, because it suggests nonprofit hospitals play a distinctive, welfare-enhancing role for a critical population.

The literature on nonprofit banks is less developed than the hospital literature. Because CUs are formed around fields of membership, one can expect more heterogeneity in their objective functions. The CU literature has been heavily influenced by the question of whether CUs merit the tax exemption. Researchers continue to debate the extent to which the CU tax exemption is in fact passed along to CU members, or whether it is consumed via perquisites and inefficient operations. DeYoung et al. (2019) construct a structural model and conclude that between 50% and 90% of the tax subsidy is passed on to CU members. Frame et al. (2003) find community-based CUs redirect some of the tax exemption to "expense preferences," or perquisites.

The literature has taken many approaches to modeling the specific nonprofit form of CUs. Smith (1981) models CUs as size maximizers, Flannery (1974) and Leggett and Stewart (1999) model CUs as balancing the interests of savers and borrowers, and Cororaton (2019) and van Rijn and Li (2019) model CUs as maximizing a combination of returns and member utility.

In similar spirit to this paper, Cororaton (2019) and van Rijn et al. (2019) provide evidence that CUs have different objective functions than banks. Cororaton (2019) finds CUs are able to grow lending by forgoing profits. van Rijn et al. (2019) argue that, in alignment with their mission, CUs offer their executives less powerful incentives to pursue profits. Consistent with my empirical results in the mortgage setting, van Rijn et al. (2021) use the Survey of Consumer Finances to show CUs charge lower auto loan rates.

## 2 Institutional Background

When considered jointly, five characteristics distinguish CUs from other financial institutions (U.S. Treasury, 2001). First, CUs are member-owned cooperatives and each member is entitled to one vote in electing members of the board of directors. Second, CUs do not issue capital stock; instead they create capital via retained earnings. Third, CUs rely on almost exclusively volunteer, unpaid boards of directors whom the members elect from their membership ranks. Fourth, CUs are nonprofit instead of shareholder-owned institutions. That is, earnings can be retained as capital or returned to members in the form of interest on share accounts, lower interest on loans, or via other products and services (e.g., financial education or micro-loans). Finally, CUs may only accept as members individuals identified in the CU's articulated field of membership. According to the National Credit Union Association, the CU regulator and provider of deposit insurance, CU membership is limited to individuals who share a common bond of occupation, association, or community (i.e., a geography).

Within these defining features, CUs are a heterogeneous class of banks. The table below provides one example of a CU for each field of membership category. CUs are very heterogeneous in asset size, as they range from US $149 billion in assets under management to one with a balance sheet of US $20,000, resembling a household in size. As membership rules have been relaxed, many CUs now have dual fields of membership, and fields of membership are stretched to include the family members of those directly included in the field. Other CUs have converted to geographic-based fields, presumably when doing so is conducive to membership growth. As the example below shows, community-based CUs can be liberal with respect to what it means to be located in a geography.

**Examples of Credit Unions**

| Name | Category | Assets Under Management | Membership | Field of Membership |
|---|---|---|---|---|
| Navy Federal | Occupational | US $149 billion | 10 million | Armed forces & their families |
| Adirondack Regional | Community | US $50 million | 7,000 | Individuals who live, work, own a business, worship, or attend school in Clinton, Essex, Franklin, or St. Lawrence County of NY state, & their families |
| Holy Trinity Baptist | Associational | US $20 thousand | 100 | Church members |

The NCUA states that the "Federal Credit Union Act expects this national system [of Credit Unions] to meet 'the credit and savings needs of consumers, especially persons of modest means.'" Thus, credit unions have an explicit social objective in their mandate, which is not the case for for-profit banks. Historically, some have interpreted the rationale that CUs would receive special tax treatment on the basis that they would serve a restricted consumer base, would focus on low- to middle-income customers, and would offer a small set of products (Internal Revenue Service, 1979). The statistics presented earlier suggest that CUs have grown their consumer base since the early 2000s. On the whole, CUs generally offer a smaller set of products and features than the more technologically advanced and large banks.

The extent to which this policy-mandated goal is relevant today is a matter of debate. Bankers have long complained the tax exemption is an unfair competitive advantage that allows CUs to charge below-market interest rates on loans and offer above-market deposit rates (American Bankers Association, 2021).They argue that, after taking into account size, portfolio concentration and other related indicators, CUs are not substantively different from commercial banks. Because this argument is generally made on behalf of community banks or similarly-sized banks, I principally compare CUs with "small" banks, which I define as banks with assets in the same range of assets as CUs.

Since the early 2000s, the National Credit Union Administration has relaxed the rules on how fields of membership can be defined. It has also simplified the process by which CUs can change their field of membership, hold multiple fields at once, and convert to geographic-based fields of membership. In the last two decades, close to one thousand CUs converted to a community-based charter; from 1997 to 2017, community charters grew from 6.5% to 30.3% of all federally charted CUs (van Rijn, 2018).

## 3 Economic Framework

To guide and interpret empirical results, in this section I develop some of the empirical implications of two theories of nonprofit organizations and discuss the role of selection into nonprofit banks.

The first theory goes back to Newhouse (1970) and presumes the altruistic motivations of entrepreneurs who choose to run nonprofits. Although there are variations, the original altruism-based theory assumes entrepreneurs have a preference for quantity and quality, instead of profits. I use this theory as the standard for an honest nonprofits' behavior. The second theory originates with Hansmann (1980) and posits that profit-seeking entrepreneurs use the nonprofit organizational form to overcome a problem of noncontractible quality. Entrepreneurs choose between the perquisite profits they can extract under the nonprofit form and the cash profits they could get as a for-profit. While they generally prefer cash over perquisites, they face a trade-off because the nonprofit form enables them to sell higher quantities of the good at higher prices. I use this second theory as the theoretical implementation of a nonprofit in disguise. In brief: the altruism theory predicts nonprofits will have higher quality and lower prices, while the noncontractible quality theory predicts nonprofits will have higher prices and higher quality.

In the context of banking, quality is a relatively novel outcome to focus on. In part, the focus on credit outcomes as a measure of quality is motivated by the literature's emphasis on their importance to understanding nonprofit firms. Properly conceptualized and when limited to the aspects a bank can influence, individual credit outcomes can be viewed as measures of a loan's quality that a firm expends on. Examples of such quality include: lenders being willing to modify loan terms ex post to improve the borrower's position, especially at a cost to the lender; lenders extending financial education and/or ease of payments to aid the borrower in maintaining good credit history; lenders being unwilling to originate a loan to an applicant at terms that they consider high-risk for the applicant, given that the lender may understand the consequences of missed payments better than the applicant.

Selection is also an interesting object of study in this context. Although I find little theoretical guidance on how to understand selection into nonprofits, the policy debate presumes that nonprofits serve the customers who are not being serviced by the for-profit sector. The institutional features of CUs, however, do not seem to be designed around this idea. In particular, selection into CUs is determined by fields of membership which are not necessarily representative of under-banked populations. Altogether, these ideas together generate ambiguous predictions about selection into CUs.

In what remains of this section, I describe how altruism-based theories can be applied to banking services in a perfectly competitive environment. Then, I describe the general features of the theory of noncontractible quality. Last I compare the predictions of the two theories and argue for the importance of considering potential selection in this setting.

### 3.1 Altruism

Banks intermediate between the supply of deposits and the demand for loans, both measured in quantity of dollars. For-profit banks maximize profits and nonprofit banks maximize quantities subject to a break-even constraint.

While both types of banks face the same direct intermediating costs, for-profit firms face higher opportunity costs and, therefore, total costs: $C^{fp} > C^{np}$. The idea that for-profit banks face higher opportunity costs is the key feature that distinguishes nonprofits from for-profits. As maximizers of quantities of a specific good, nonprofit banks are assumed to have fewer ways to pursue their objective than for-profits banks. This assumption comes from the idea that profits can be pursued in the market for any good, but if nonprofit banks have a specific interest in promoting bank services, they have fewer alternatives to do so. Another distinguishing assumption is that, relative to total demand, nonprofits are capacity constrained. This assumption is motivated by the idea that there is a limited number of suppliers with an intrinsic interest in providing banking services.

In order to maximize the quantities they intermediate while breaking even, nonprofits keep their price at cost, with or without competitive pressures. For-profit banks also set their prices at cost, but they do so out of market pressure in a competitive environment. Because of the differences in costs and capacity, nonprofits charge lower prices than for-profits.

In keeping with the literature, we further assume that the nonprofit entrepreneur has an intrinsic preference for producing goods of higher quality. On the margin, achieving this higher quality comes at a positive and arbitrarily small cost. Therefore, so long as the cost of providing higher quality is not too high, nonprofits charge lower prices and offer higher quality products.

In this model of honest nonprofit firms, nonprofits seek and generate no profits. Therefore, whether the nonprofit is subject to an income tax or not is irrelevant to the firm. Of course, this model abstracts from the reality that, even if only for operational reasons, an honest nonprofit will often have excess income over expenses. By definition and law, nonprofits cannot distribute excess income over expenses, so this money becomes retained earnings. So, an income tax is actually best thought of as a tax on the retained earnings of nonprofit firms as opposed to a tax on profits.

A more realistic model of nonprofits would therefore specify the intertemporal preferences of the nonprofit and model the effect that an income tax has on the nonprofit's ability to grow its supply over many periods. In such a model it is possible for a nonprofit firm to charge the same prices as a profit maximizing firm in early periods so that it accumulates retained earnings that will allow it to increase its supply in future periods. Notwithstanding this example, an honest nonprofit would still charge lower prices across its lifetime.

Altogether, the insights from these models suggest that: a) at least over a long-horizon, nonprofits should charge lower prices than for-profits do, and b) although on any given year a nonprofit may charge the same prices as profit-maximizing firm does, it would never charge a higher price.

### 3.2 Noncontractible Quality

I present a stylized version of the theory in Glaeser and Shleifer (2001), which models exchange and production as proceeding in three periods. In the first period, a consumer agrees to purchase a unit of a good at a fixed price. In the second period, the firm's owner engages in cost-cutting effort to reduce the quality of the good along its non-observable dimension. The firm's choice of optimal cost-cutting effort in the second period is summarized by the trade-off between the cost of effort and the benefit of increased profits (from reduced product costs). In the third period, the firm delivers the good.

In period zero, an entrepreneur has the choice of adopting the for-profit or nonprofit organizational form. If the entrepreneur chooses the nonprofit form, they adopt the nondistribution constraint, which prevents them from disbursing profits to themselves in the form of cash. An entrepreneur choosing the nonprofit form can still extract profits, but they would be limited to in-kind or perquisite profits. By assumption, the entrepreneur values perquisites less than their cash equivalent.

Why would the profit-seeking entrepreneur choose to adopt the nondistribution constraint? The argument is based on equilibrium behavior of consumers. Consumers anticipate that profit-seeking firms will shirk on quality to cut costs and increase profits. This will cause the market for the product based on profit-seeking to partially unravel. The nonprofit form is a solution to this market failure because the nondistribution constraint curbs the incentive to shirk on quality.

Because perquisite profits are less desirable than cash profits, the entrepreneur is less inclined to expend the effort it takes to cut costs and reduce unobservable quality. Consumers anticipate this and, thus, are more likely to trust in the unobservable quality of a nonprofit firm's product.

In equilibrium, nonprofits can command higher prices for their products because consumers rationally expect them to be of higher quality. Therefore, from this theory we derive a prediction that entrepreneurs who choose the nonprofit form will charge higher prices for products of higher quality.

### 3.3 Predictions: Prices, Quality, and Selection

Both the altruism and noncontractible quality theories predict that nonprofit firms will offer higher quality. While the assumption of a preference for quality appears ad-hoc in the context of the altruism theory, it has a long history in the literature which suggests nonprofits are motivated to provide higher quality. Perhaps most importantly, though, in this context the assumption allows me to align and better contrast the altruism theory with the noncontractible quality theory, where it is inherent. The two theories generate different nonprofit price predictions, which creates an opportunity to discriminate between them empirically. Specifically, altruism predicts lower nonprofit prices while noncontractible quality predicts higher nonprofit prices.[6]

From the perspective of making price and credit outcome comparisons, selection is something that needs to be controlled for. More broadly, though, differential selection into CUs is an interesting object of understanding in its own right. Although the literature notes that nonprofits are more likely to arise in markets for personalized services, the theories presented earlier and the literature in general do not address selection directly. From a welfare perspective, one way to conceptualize a nonprofit organization is to assume that its preferences are equivalent to those of a utilitarian

[6]While both theories have edge cases that unwind or complicate these predictions, these predictions are at the core of the assumptions that motivate those theories. These predictions thus capture the principal logical implications of the underlying thrust of the theories.

social planner. If so, a nonprofit's best course of action, on the margin, would be to pursue the redistributive goal of extending access to credit to those who cannot get it from the for-profit sector. This would imply that a nonprofit's customers would have the characteristics of the under-banked population. This is one way to rationalize the underlying premises of tax policies that differentially benefit nonprofit banks.

However, the field-of-membership nature of CUs is not necessarily aligned with the would-be goal of reaching the most under-served populations. The membership model selects customers based on their affinity and/or ability to save deposits and take out loans. Once a membership is established, the organization generally has little incentive to reach out to more costly customers and becomes in-group focused. Hence, because CUs are nonprofits *and* cooperatives, there are competing selection forces at play, and predictions are ambiguous.

# 4 Data

The two main data sources for this paper are the HMDA data and anonymized individual credit record data provided by TransUnion.

## 4.1 Credit Records Data

TransUnion is one of the three nationwide consumer credit-reporting agencies in the U.S. The data analyzed in this paper comes from a 10% sample of individual monthly records gathered by TransUnion from 2001 to 2020. If an individual is observed in the sample, they are in the sample for as many months as TransUnion observes them. TransUnion gathers data on an individual's credit lines from lenders, servicers, and public sources to construct individual credit reports.[7] Thus, credit records include data on how the evolution of balances and repayment behavior for each line of credit (in this case, specific to the mortgage) as well as the aggregated data about the individual.

[7]According to the Consumer Financial Protection Bureau (2016), close to 90% of the U.S. adult population has a credit file.

These aggregated data are used to evaluate individual creditworthiness.

The table below lists the seven variables I select to study credit outcomes.

**Credit Outcomes**

| **Category** | **Name** | **Units** |
|---|---|---|
| Mortgage-Specific | Mortgage is 90+ days past due | Binary |
| Mortgage-Specific | Amount 90+ days past due | USD thousands |
| Mortgage-Specific | Mortgage is charged-off or sent into collections | Binary |
| Credit Profile | Number of trades 90+ days past due | Number |
| Credit Profile | Amount 90+ days past due | USD thousands |
| Credit Profile | Credit score | Percentiles |
| Credit Profile | Number of public bankruptcy records | Number |

Whether and by how much an individual is past due on their mortgage captures the most immediate adverse potential consequence of opening a mortgage. A mortgage is charged off and/or sent into collections when the lender or servicer no longer considers pursuing repayments to be worthwhile. This decision has negative consequences for the individual's creditworthiness because credit reports include these events and are generally perceived negatively. The rest of the variables are aggregates and help me investigate whether adverse mortgage outcomes spill over into the overall credit profile.[8] The number of trades and total amount past due are analogous to the mortgage-specific outcomes. Of interest is whether something other than a one-to-one relationship exists between the mortgage-specific and credit-profile versions. The credit score is a numeric representation of an individual's creditworthiness, constructed by credit rating agencies. Credit scores are important factors that lenders use in deciding whether to extend credit to individuals and, if so, how much to charge in interest. Last, I study whether the adverse mortgage outcomes translate into increased public bankruptcy records. Although individuals choose to file bankruptcy for good reasons, from the

[8]Although perhaps unlikely, in principle it is possible for negative outcomes on a mortgage to not spill over into aggregate outcomes. One way in which this may occur is that a negative mortgage outcome may be offsetting a negative outcome from another credit line.

perspective of an individual taking on a mortgage, the prospect of filing for bankruptcy a few years later is a negative one.

Credit records data do not contain information on prices. Yet, for many of the mortgages I study, working out the interest rate paid on the mortgage is possible. To back out interest rates, I use various mortgage-specific variables including the term, the initial balance, and the evolution of the remaining balances.

In a mini-study toward the end of the paper, I also use a sample of auto loans derived from TransUnion data to investigate whether the main results from the mortgage market carry over to the auto loans market. I study the same set of outcome variables and can control for individual, loan, and geographic characteristics of the loan. A relative limitation of this sample is that, because there is no equivalent to the HMDA data for auto loans, I cannot obtain the specific identity of the lender; I can only identify whether the lender is a CU or a bank.

### 4.2 Home Mortgage Disclosure Act Data

Since 1975, the HMDA has required many lenders to report application-level mortgage data. The HMDA data cover approximately 90% of mortgages originated in the U.S. (Board of Governors, 2017). Supplementing the credit records data with HMDA data enriches the information I observe on individuals.

Although the reporting requirements have changed over time, I use the following variables, which are available in my sample time period: the loan amount, applicant's income, loan type (conventional, FHA, VA, or FSARHS), loan purpose (home purchase, improvement, or refinancing), lien status (first, subordinate, or non-secured), property type (one-to-four family, manufactured, or multifamily), whether the property will be owner occupied, the census tract of the property, the identity and principal regulator of the lender, the lender's assets under management, whether the application was approved, and whether the loan was resold in the secondary market.

Furthermore, HMDA data allow me to construct two measures of credit health at the level of geography: the fraction of mortgage applications that were accepted by census tract and year and the mean credit score at the tract-year level. I can also construct similar measures at the lender level: lender-year mortgage application acceptance rates and secondary market resell rates.[9,10]

### 4.3 Merge of Credit Records and HMDA Data

I combine the mortgage credit records and HMDA data with a "fuzzy" merge based on three variables: the year of origination, the census tract, and the loan amount rounded to the nearest thousand. The merge requires equality of the three variables and uniqueness in both datasets. The requirement that records be unique combinations of the values of these three variable cells in each dataset provides a high degree of confidence that the resulting matches are accurate, because the HMDA data amounts to a near universe of mortgages. Furthermore, the requirement that mortgages be unique combinations of tract-year-amount excludes many observations from the merge, which means no attempt is made to find their corresponding credit records.

Appendix Figure A1 shows the fraction of originated mortgages in HMDA that I am able to match. Because the credit records data are a 10% sample, this imposes an upper bound on the match rate. On a yearly basis, the match rate oscillates between 1% and 7%, and is notably higher since 2009.[11] The most obvious reason my match rate is not closer to 10% is the requirement that loans be unique combinations of amount, tract, and origination year. Because I would not be able to have a confident match on non-unique loans, I do not attempt to merge them.

The dataset resulting from the fuzzy merge contains approximately 5.1 million mortgages orig-

[9]The resell indicator is censored as the HMDA data only record a resell if it occurs in the same calendar year in which the mortgage was originated.

[10]Another added benefit of incuding HMDA data is that it increases the confidence of the identity of the lender. Credit record data are often provided by servicers and not necessarily the originating lenders. Although I do not analyze individual lenders and am only interested in them as a class, HMDA data ensure I can identify the lender type that originated a mortgage.

[11]TransUnion introduced improvements to data as of 2009, which may be related to the marked improvement in the match rate.

inated between 2004 and 2017. After restricting to loans which a) are conventional, b) are for one-to-four family properties, c) are owner occupied, and d) have standard terms of 10, 15, 20, or 30 years, the sample contains approximately 3.4 million loans. I further restrict the data to bank originated loans (i.e., mortgage company loans are excluded) and the final sample includes approximately 2.3 million mortgages.

Despite the clear limitations of a fuzzy merge, the merge quality is good. Appendix Figure A2 shows the fraction of CU-originated mortgages in the HMDA and fuzzy-merged sample are similar across all years. The first part of Table 1 compares the mean value of variables in my matched sample and in the HMDA universe. I show these variables by CU, small bank and large bank. The mean loan amount and applicant income are larger in the matched sample than in HMDA. That this difference is present for all lender types suggests my sample is skewed toward larger loans, but not in a differential way across lender types. Loan resell rates are also slightly higher in the matched sample for CUs and small banks. Overall, though, the remaining variables suggest my matched sample is sufficiently representative of the HMDA universe.

### 4.4 Backing Out Implied Interest Rates from Credit Records

Although credit data do not report prices, calculating implied interest rates from a subset of variables in the data is possible. For a loan $l$ that is observed over multiple months $t$, observing its term $T_l$ and remaining balance $Balance_{lt}$ is sufficient to back out the interest rate $IntRate_l$ and monthly payment amount $Payment_l$.[12] The following asset price identity holds for any $l$ and $t$, and links the two observed variables to the two unknown values:

$$Balance_{lt}(1 + IntRate_l)^{T_l - t} = \frac{Payment_l((1 + IntRate_l)^{T_l - t} - 1)}{IntRate_l}.$$

[12]The monthly payment amount reported to credit agencies usually includes the sum of payments for mortgage interest and principal, taxes, and other fees collected by the loan servicer (e.g., home owner association fees). Therefore, it cannot be used to infer interest rates directly.

For any given month, this equation has two unknowns and is under-determined. With multiple months of data, however, we can pin down the two unknowns by combining any pair of months $t$ and $t'$ such that $t \neq t'$. Therefore, we use the same equation to incorporate another month's observation:

$$Balance_{lt'}(1 + IntRate_l)^{T_l - t'} = \frac{Payment_l((1 + IntRate_l)^{T_l - t'} - 1)}{IntRate_l}.$$

Combining the two previous equations and observations generates a system of two equations with two unknowns. I solve numerically for the pair $(Payment_l, IntRate_l)$ that satisfies the system above.[13]

Two months of data are technically sufficient to identify both the interest rate and payment amount. Empirically, however, any one pair of observations may lead to an incorrect estimate for many reasons, including the following (a) recording errors, such as delays, in the variables; (b) missed payments; and (c) whether the interest rate is variable or fixed is unobserved. Having more than two months of observations is therefore useful because it allows me to estimate a single loan's interest rate multiple times, once for each pair of months, and apply quality controls to the estimates. For each mortgage $l$, the calculation proceeds as follows:

1. **Restrict the data to observations between months 2 and 7.**

   This restriction serves two purposes: it reduces the probability that the data are affected by delayed payments and it restricts attention to the period during which even adjustable rate mortgages often have fixed interest rates.

2. **Solve the system of equations for each month pair.**

[13]One can also solve for the interest rate without solving for the payment amount by using a root-solver on the following equation, which is be obtained by dividing the first and second equations above:

$$\frac{Balance_{lt}}{Balance_{lt'}} = \frac{(1 + IntRate_l)^{T_l - t} - 1}{(1 + IntRate_l)^{T_l - t} - (1 + IntRate_l)^{t' - t}}$$

Let $\tau := (t, t')$ be a pair of months such that $t, t' \in \{2, 3, 4, 5, 6, 7\}$ and $t \neq t'$. Let $\Psi$ be the set of all 15 possible $\tau$. For each $\tau \in \Psi$, estimate the solution to the system and denote it by

$$\left(IntRate_l^{\tau}, Payment_l^{\tau}\right).$$

To estimate the solution, I used the Newton-Rhapson method and set an interest rate of 3.5% and payment of \$600 as starting values and limited the search to strictly positive solutions.

3. **Exclude implied interest rates for month pairs with unlikely values.**

   From the set of interest rates $IntRate_l^{\tau} : \tau \in \Psi$, discard $IntRate_l^{\tau}$ if it is greater than 15% or less than 1%.

4. **Exclude implied interest rates for mortgages with inconsistent rates across month pairs.**

   To increase confidence in the estimation, I discard mortgages for which the coefficient of variation of implied interest rates is greater than 0.4; that is, I consider calculating an interest rate impossible if:

$$\frac{StDev_{\Psi}\left(IntRate_l^{\tau}\right)}{Mean_{\Psi}\left(IntRate_l^{\tau}\right)} < 0.4.$$

5. **Take the mean of implied interest rates across all month pairs.**

   For the $l$ not discarded in step 4, the estimated implied interest rate is the mean of $IntRate_l^{\tau}$ across all remaining $\tau \in \Psi$.

Given the quality restrictions imposed, the algorithm produces an estimate of the implied interest rate for 67% of the mortgages in the matched sample. Appendix Table A1 reports the results from a regression of an indicator variable for whether I am able to calculate an interest rate on the main set of controls $X$. I expect the main reason for my inability to calculate an interest rate to be due to some irregularity in the timely reporting of information to the credit bureau. The explanation is that incorrectly timed reports can cause implied interest rates to be far from their true value.

These results are informative of the external validity of the exercise of relating interest rates to CU versus bank prices. They speak to the question of how does the 67% of observations I am able to calculate a rate for differ from the total sample. Appendix Table A1 shows I am more likely to be able to calculate rates for mortgages with a CU, from tracts with higher credit scores, that were resold, for a home improvement, with a higher loan amount, from borrowers above 60 and below 35. The remaining variables are negatively correlated with having a calculated interest rate.

Appendix Figure A3 compares the monthly mean of calculated interest rates with the market-wide monthly average of 30-year fixed-rate mortgages. This comparison is a useful check on the validity of the approach to extracting interest rates, because nothing in the algorithm would mechanically make interest rates align over time. Therefore, the fact that the plot shows a high degree of temporal correlation is very encouraging because it shows that, on average, this method accurately backs out implied interest rates.

### 4.5 Other Data Sources

I primarily use FDIC and NCUA Call Reports and Summary of Deposits for banks' asset size and branch locations. To complement branch-location data of CUs, I use the geocodes provided in the "Your-economy Time Series" by the Business Dynamics Research Consortium. I use S&P Ratewatch data to compile descriptive, aggregate statistics on CU and bank prices, independently from my other data sources. Ratewatch data are branch-level surveys of interest rates and fees for various deposit and loan products. Finally, I use the 2010 Census tract data on the urban versus rural population and the 2012 five-year American Community Survey to gather data on a tract's median income.

## 5 Aggregate Facts and Suggestive Evidence

This section documents aggregate facts about CUs along three dimensions: CU mortgage market segments and banking model, CU pricing across various consumer lending products, and credit outcomes from mortgage originations. For each of these, I contrast CUs to banks —and, in some cases, I distinguish between small and large banks.[14]

### 5.1 Mortgage Market Segments and Banking Models

Using the HMDA universe of data, Figure 1 plots the distributions of many features of mortgages originated between 2004 and 2017. I separately plot the distribution for each bank type. For the bank and geographic features, the distributions are weighted by the number of originated mortgages.

Panels (a) and (b) show CUs offer notably smaller loans to applicants with slightly lower income. Although both of these differences in means are directionally consistent with the policy mandate that CUs focus on individuals of modest means, their distributions show a high degree of overlap. Additionally, cross-referencing with Table 1, the mass at the lower end of the CU loan size distribution is in part explained by the larger fraction of mortgages dedicated to home improvement. CUs seem to more evenly distribute their mortgage originations across purposes (home purchase, improvement, or refinance) and are more likely to originate mortgages that do not have a first lien on the property.

Panels (c) and (d) show CUs follow different mortgage banking models. Although CUs and banks have similar mean rejection rates, the mortgages originated by CUs suggest more variation among CUs in their likelihood of rejecting applicants —especially relative to large banks. Mortgages originated by CUs are drastically less likely to be resold in the secondary market. This finding is interesting because of the argument that the secondary market incentivized loose underwriting

[14] "Small" banks are defined with the goal of creating a comparable group in asset size to CUs. Specifically, I define a small bank as one that has no more than 105% the asset size of the largest CU in each year.

standards, especially prior to the financial crisis of 2008 (Acharya et al., 2011).

Panels (e)–(h) summarize geographic characteristics of the mortgages. CU- and bank-originated mortgages are located in areas with very similar rates of application rejections and creditworthiness. This finding suggests CUs do not expand access to credit by focusing on geographies with disadvantageous aggregate creditworthiness. Relative to large banks, CUs' geographic focus is less urban (86% vs. 81%) and lower income (US $73K vs. US $67K). Relative to small banks, however, CUs' geographic focus is more urban (78% vs. 81%) but of an equal income level (US $67K vs. US $67K). To benchmark these means differences, note 80.7% of the U.S. population lives in an urban area, and tracts with median incomes of US $73K and US $67K are at the 79th and 73rd percentile of tracts, respectively.

To emphasize the role of CUs and small banks at different levels of these distributions, Appendix Figure A4 displays the fraction of CU and small bank mortgages by the level of the distribution. Panels (e) and (f) show CUs disproportionately supply loans in tracts with high mortgage rejection rates and low credit scores. At the same time, panel (g) shows CUs provide relatively few of the loans in tracts with the lowest income.

To summarize, although CUs offer smaller loan amounts to individuals with lower income, the population that they serve overlaps considerably with that of banks. CUs are much more likely to keep loans that they originate on their balance sheet. Overall, CUs and banks, especially small ones, seem to be present in similar geographies, and their market focus is, on the whole, quite similar. The significant degree of overlap in CU and bank market segments suggests CUs are not sharply focused on providing banking services to those who could not get serviced by a bank.

Although this evidence is not conclusive, it suggests CUs largely do not extend access to credit along the extensive margins of new markets or segments of consumers. Yet, because CUs restrict their members to fields of membership, they may have an informational advantage on their members relative to banks and their borrowers, and that they may be able to extend access along the intensive margin. That is, conditional on income, credit score, and on receiving a loan, CUs may be able to offer higher loan sizes. However, I find evidence that is inconsistent with CUs increasing access to credit on the intensive margin. Appendix Figure A5 shows CU and small bank conditional loans sizes are no different.

Whether extending credit to those who do not have access is the *raison d'etre* of CUs is unclear from the law and policy discourse. From a conceptual economic perspective, however, increasing access to credit would perhaps be the largest way in which nonprofit banks could be creating value. I offer three non-exclusive ways to interpret the results, suggesting CUs do not extend access to new credit in mortgage markets. One is that for-profit banks have the capacity to reach all market segments, and so no space is left for nonprofits to "open" new markets or segments. The active discourse on banking deserts suggests this explanation is unlikely (Federal Reserve Bank of St. Louis, 2017). Another possibility is that CUs' mission is not centered on extending access, but rather on serving their current fields of membership, which may not include individuals without access to credit. Last, although HMDA cover approximately 90% of mortgages, a significant fraction of small CUs are excluded from the sample I analyze because of HMDA's reporting requirements. It is therefore possible that borrowers at the bottom of the income and credit distribution are disproportionately served by CUs that do not report to HMDA. Although the criteria are complex, usually only lenders with at least $28 million in assets under management report to HMDA. Because approximately one third of CUs do not meet the reporting requirements, CUs are disproportionately excluded from the HMDA data and they do not reveal the full extent of their activities.

### 5.2 Interest Rates

Using survey data from S&P RateWatch, Figure 2 (a) plots the mean bank interest rates of various savings and loan products from 2001 to 2019. Figure 2 (b) plots the interest rate differential between CUs and banks for each product. For many products, CUs offer better list prices than for-profit banks. CU CD rates have been consistently higher, although the rates on other deposit products have compressed since the financial crisis. Most remarkably, CU interest rates on HELOCs and auto loans have been over 1% lower since 2010.

Perhaps due to the presence of a highly liquid secondary market, mortgages are an exception among loan products in that CUs charge similar interest rates. As shown in Appendix Figure A6, however, HMDA data show that, prior to 2010, CUs originated significantly fewer "high-interest" mortgages than banks did. This fact suggests a more complex dynamic in which pricing differentials vary across time and credit risk segments. In short, the descriptive evidence on CU interest rate pricing is mixed.

There is a limit on what one can infer from aggregate price data and posted list-price data. Sustained lower CU prices could be explained by various factors: tax advantages, a lower-cost pool of customers, and willingness to sacrifice profits when they have market power. In Section 6 I apply causal techniques to distinguish selection from treatment in CU pricing.

A general limitation of my analysis of prices is it only includes interest rates and does not account for origination fees. If adjustments to interest rates are limited due to broader contextual factors, one would expect competition on dimensions other than the interest rate. The model in Section 3 suggests an honest nonprofit bank seeking to differentiate itself from profit-seeking banks would offer better origination fees and/or higher quality products. Appendix Figure A7 shows CUs and banks charge roughly the same amount in mortgage origination fees, which is true both across time and interest-rate levels. Thus, product quality is the remaining dimension along which CUs may be differentiating themselves. I explore whether CU customers experience credit outcomes of higher quality in the next section.

### 5.3 Credit Outcomes

Using the matched sample of mortgages, Figure 3 plots the evolution of the seven credit outcomes described in Section 4.1 by bank type. Panels (a)–(c) show the means for the mortgage-specific outcomes every six months up until four years after origination. Panels (d)–(g) show the mean of quarterly credit profile outcomes, four years before and after origination.

Focusing on outcomes at the three-year mark, CU mortgages have a 0.7% chance of being 90+ days past due, whereas small bank mortgages have a 1.4% chance and large bank mortgages have a 1.6% chance of the same event. Similarly, the mean amount past due for individuals with CU mortgages is US \$118, whereas the average amount past due for those with small and large bank mortgages is US \$297 and US \$356, respectively. Conditional on being behind on payments, the average amount owed is approximately US \$16,850, US \$21,200 and US \$22,250, for CUs, small banks, and large banks, respectively. This finding suggests the primary way in which CU-originated mortgages are different is in the likelihood that they fall behind on their payments.

The likelihood that any mortgage is charged-off or sent into collections at the three-year mark is roughly 0.2%. Small bank mortgages have a slightly higher probability of being charged-off or sent into collections, than both CUs and large banks, which show no difference between them.

Panels (d) and (e), which show the mean individual number of trades 90+ days past due and total amount past due, show the mortgage-level differences spill over onto the credit profile.

Panel (f) shows the mean individual credit scores. The credit scores of individuals with a CU mortgage grow by more than individuals with bank mortgages. At three years, CU credit scores are 1.5 percentile points higher than small bank credit scores and 0.75 percentile points higher than large banks scores. This contrasts with three months prior to origination, when large bank scores were 0.3 percentile points greater than CUs and small bank scores were 0.6 percentile points lower. Overall, CU mean credit scores grew about 1 percentile point more than mean bank scores.

Panel (g) shows the mean number of individual public bankruptcy records. At three years, 1 in 40 individuals in the CU group will have one bankruptcy record, whereas approximately 1 in 34 individuals in both bank groups will have one record.

Prior to origination, individuals in the CU group seem to be improving both credit scores and the number of bankruptcy records faster than both bank groups. This suggests caution in attributing these differences to CU behavior post origination and that scope for differential selection by bank type exists.

## 6 Causal Evidence

This section builds on the aggregate, correlational analysis in the previous section by controlling for an individual's risk characteristics observable in their credit profile and adjusting for remaining endogenous sorting into CUs versus banks.

The pretrends in Figure 3 panels (f) and (g) suggest the possibility of advantageous selection into CUs that goes beyond what is observable in a credit report immediately prior to origination. The process of searching for a mortgage immediately prior to origination exposes individuals and the lender to information that might induce endogenous sorting into types of banks. Furthermore, the field of membership requirement means not all individuals can join any given CU.[15] This identification challenge motivates a research design based on an IV that isolates quasi-random variation in the type of bank that individuals get a mortgage from. I describe the construction of the instrument in Section 6.1. In Section 6.2 I present the results from applying the instrument to the estimate of the "CU effect" on interest rates. In Section 6.3 I combine the event studies with the instrument to tease out the "CU treatment effect" on credit outcomes. For mortgage-specific outcomes, this approach amounts to a standard IV research design, but for credit profile outcomes

[15] CU membership requirements are loose enough that any individual can likely find *a* CU that they can join —even if they cannot join every CU. Because I treat CUs as a class of banks, the restrictions imposed by fields of membership are less of a concern in this context.

the research design is an application of an IV to difference-in-differences (IV-DiD).

### 6.1 Instrumental Variable: CU Branch Density

Using geocoded bank and CU branch data, I construct the instrument, which I refer to as "CU Density." For each mortgage $i$ in my matched sample, I restrict attention to the CU and bank branches within a 10-kilometer radius of each address for which the mortgage was originated.[16] I compute the distance $d(i,l)$ of each branch of lender $l$ to the individual's new address. The instrument is then the density of CU branches over all CU and bank branches, weighted by the inverse of their distance from the new address:

$$CuDensity_i = \frac{\sum_{l \in CU} \frac{1}{d(i,l)}}{\sum_{l \in CU} \frac{1}{d(i,l)} + \sum_{l \in Bank} \frac{1}{d(i,l)}}.$$

The validity of the instrument relies on the standard arguments of relevance and monotonicity, and exogeneity and independence.

#### 6.1.1 Relevance and Monotonicity

The relevance assumption formalizes the idea that the *CuDensity* instrument is positively associated with the probability that an individual chooses to bank with a CU. The monotonicity assumption formalizes the requirement that no individual chooses against banking with a CU as a result of having a higher *CuDensity* value. Let $CU$ be an indicator function for whether an individual chooses to bank with a CU, and let $X$ be a vector of individual controls. Both these assumptions can be formalized as follows:

$$CU\left(z', X\right) \geq CU\left(z, X\right) \;\; \forall z, z' \in CuDensity \text{ s.t. } z' > z.$$

[16]For the small set of mortgages whose address has no branches within a 10-kilometer radius, I use the 20 nearest branches to it within a 200-kilometer radius.

Figure 4 plots the fraction of individuals who choose a CU by bin of *CuDensity* without conditioning on $X$. For the instrument values of the vast majority of the population, the fraction choosing a CU is monotonically increasing in the instrument. Although the relationship seems to become partially negative for $CuDensity > 0.6$, this range contains less than 0.7% of the sample and is measured imprecisely. A notable exception is that the CU fraction of those with *CuDensity* values below 0.01 is lower than of those with values between 0.01 and 0.04. Overall, Figure 4 suggests the instrument is strongly associated with CU choice, consistent with the assumption above. The exceptions identified above are handled by controlling for a vector of controls $X$, which include various geographic measures. As reported later in the paper, the F-statistic of the first-stage regression of CU on instrument and controls is well above 8,000 in the sample comparing CUs with small banks and over 500 when comparing with large banks.[17]

I rationalize the relevance of the instrument through a model of bounded search for lenders within a proximate geography. Individuals sample quotes from a fixed number of lenders in their vicinity and then choose a lender from among those they quoted. The intuition is straightforward: if an individual samples a limited number of quotes from banks or CUs around them, the fraction of CU quotes they will sample will be a function of the fraction of total CUs around them, and thus, so will their choice.[18]

The model is driven by two assumptions: (1) The probability that an individual quotes a lender is inversely related to the distance between them, and (2) borrowers sample a limited number of lenders for quotes. Both of these assumptions have empirical validation. Approximately 60% of mortgage borrowers conduct business in person, and the median distance between lender and borrower was seven miles in 2003 (Federal Reserve Board, 2008b).[19] Mortgage borrowers typically

[17]As another measure of the instrument's relevance, Appendix Figure A8 plots the histogram of the instrument value for the CU, small bank, and large bank mortgages in the matched sample. The CU distribution of *CuDensity* first-order stochastically dominates that of both other bank types.

[18]Another way to rationalize the relevance of the instrument is with a mortgage-choice model in which individuals have a distaste for lender distance.

[19]Although technological changes likely have decreased the magnitude of the effect of physical distance on lending

only contact one or two lenders, and generally not more than four or five (Woodward and Hall, 2012; Federal Reserve Board, 2008a; Lacko and Pappalardo, 2007).

For any given individual $i$, assume a total of $B$ bank lenders and a total of $C$ of CU lenders that operate within an arbitrary geographic radius around $i$. I index either lender type by $l$ and $L = B + C$.[20] An individual $i$ chooses to gather an exogenous number $n < L$ of mortgage quotes from among $L$. Let $q(i,l)$ be an indicator function for whether $i$ quotes from $l$, and let $d(i,l)$ denote the physical distance between them. The probability that $i$ quotes a lender is proportional to the inverse distance between them:

$$\mathbf{Pr}\left[q(i,l) = 1\right] \propto d(i,l)^{-1}.$$

Treating CUs and banks each as groups, the probability that $i$ quotes a CU is equal to the fraction of CU branches weighted by their inverse distance:

$$\rho := \mathbf{Pr}\left[l \in C \mid q(i,l) = 1\right] = \frac{\sum_{l\in C} \frac{1}{d(i,l)}}{\sum_{l\in C} \frac{1}{d(i,l)} + \sum_{l\in B} \frac{1}{d(i,l)}}.$$

Let $c \leq n$ denote the number of CUs that $i$ quotes. The probability that $i$ quotes any given number $c$ of CUs is given by the binomial distribution:

$$\mathbf{Pr}\left[c|n\right] = \frac{n!}{c!(n-c)!}\rho^c(1-\rho)^{n-c}.$$

Using the mean of the binomial distribution, the expected number of CUs that get quoted as a fraction of all quotes is

$$\frac{\mathbb{E}\left[c|n\right]}{n} = \rho.$$

This equation clarifies the economic meaning of the *CUDensity* instrument in the context of

relationships, research suggests that even as late as 2017, physical proximity is positively associated with higher mortgage lending volumes (Rehbein and Rother, 2020).

[20] I abuse notation and use $B$, $C$, and $L$ to denote the set of lenders as well as the size of each set.

this model. The instrument can be interpreted as the fraction of $i$'s quotes that are from a CU, in expectation. To microfound its empirical relationship to CU choice, therefore, I analyze how the fraction of CU quotes can be related to CU choice. I consider three ways in which $i$ chooses a lender from among those quoted.

- **Choice is uniformly random among quotes**

  Assume an individual chooses from among the quoted lenders randomly. That is, the probability of choosing a CU from among the quoted lenders is the fraction of CUs among quoted lenders: $\frac{c}{n}$. Then, prior to sampling quotes, the overall probability that $i$ chooses a CU is equal to the instrument value:

$$\mathbf{Pr}\left[i \longrightarrow C|n, B, C\right] = \rho.$$

- **Choice is the most preferred quote**

  Assume an individual chooses the quote that they most prefer. Further assume CUs are systematically, but probabilistically, more (or less) likely than banks to provide the best quote. More specifically, the borrower chooses a CU with probability $\frac{c}{\pi n}$, for some factor $\pi$. Prior to sampling, the probability that $i$ chooses a CU is equal to the instrument value divided by $\pi$:

$$\mathbf{Pr}\left[i \longrightarrow C|n, B, C\right] = \frac{\rho}{\pi}.$$

- **Choice is uniformly random, conditional on membership eligibility**

  Assume that, after receiving quotes from lenders, $i$ learns they are unable to join a fraction $\mu$ of CUs because of membership restrictions and is otherwise indifferent between lenders. More specifically, the borrower chooses a CU from among those quoted with probability $\frac{(1-\mu)c}{n}$. Prior to sampling, the probability that $i$ chooses a CU is equal to the instrument value multiplied by $1 - \mu$:

$$\mathbf{Pr}\left[i \longrightarrow C | n, B, C\right] = (1 - \mu)\rho.$$

Although these different scenarios above all rely on specific functional form assumptions, they are meant to illustrate that, even in the presence of frictions, an expected relationship between the instrument and CU choice exists.

Using the terminology of Angrist et al. (1996), the monotonicity assumption implies no instrument "defiers." That is, no individuals are less inclined to use a CU because they live in an area with higher CU density. Effectively this assumption means the data contain three types of individuals: (a) those who, regardless of CU density, always use a bank (never takers); (b) and those who, likewise, always use a CU (always takers); and (c) those who use a bank when in a low CU density area and use a CU when in a high CU density area (compliers). Assuming that heterogeneous treatment effects of banking with a CU, then the recovered IV estimates will reflect marginal treatment effects for those who are compliers on the relevant margin of $CuDensity$.

Although the individual compliers are not identifiable in the data, Appendix Table A2 describes some characteristics of them as a group. For ease of interpretation, I discretize the continuous instrument into a binary variable based on its median value and follow the method in Angrist and Pischke (2009). Overall, approximately 10% of the sample are compliers and 20% of the treated are compliers. For each control variable, the table shows the percentage of compliers among the observations with a "high" value of the variable. For binary variables, a high value is a 1, and for continuous variables, a high value is one that is above the median. On the whole, compliers are relatively balanced across the distribution of controls. With the exception of bank loan resell rates, compliers are never less than half or more than twice the fraction of overall compliers in the high category of a variable. Compliers are less likely to have higher loans, income, and resold loans;

they are less likely to come from areas with high credit scores and income; and they are less likely to go to CUs with high loan resell rates and assets. On the whole, compliers are roughly balanced across the credit score distribution.

### 6.1.2 Independence and Exclusion

The independence and exclusion assumptions formalize the idea that, after controlling for $X$, $CuDensity$ is as good as randomly assigned and that it only affects outcomes $Y$ by way of its influence on $CU$:

$$(CuDensity \perp\!\!\!\perp Y, CU(z) \ |X) \quad \forall z \in CuDensity.$$

Distance-based instruments do not generally satisfy the independence and exclusion restrictions unconditionally, and thus, many of their applications are conditional on a vector of geographic controls (Mountjoy, 2021; Card et al., 2020). Because CUs are more likely than small banks to be located in urban areas, controlling for factors related to geography and urbanization seems *a priori* important.

Although directly testing the instrument's conditional exogeneity is not possible, I present two analyses which support the assumption. The first is based on the logic of coefficient and R-squared movement when including additional controls ((Altonji et al., 2005; Oster, 2015) to test for omitted variable bias. The second analysis is similar in its underlying logic, and compares the predictiveness of controls to the instrument versus CU choice. The intuition of these analyses is that there should be little correlation between the instrument and the controls we do not expect to have a relationship. Then, to the extent that these observable controls are indicative of the relationship to unobservables, this helps support the assumption that the instrument only affects outcomes via $CU$.

The set of controls I use includes the following: the logarithm of the bank's total assets; a bank-year's mortgage resell and rejection rates; the census tract-year mortgage application rejection rate, its mean credit score, its fraction of urban residents, and its median income; a dummy for whether the individual mortgage was resold; dummies for the loan's purpose, lien status, and terms; the logarithm of the loan amount; dummies for whether the loan was originated before 2009, after 2011, or in between; dummies for whether the applicant was under 35, over 60, or in between; and dummies for whether the applicant's credit score prior to origination was in the top quartile, the third quartile, or below the median.

Table 2 reports the results of various "first-stage" regressions of CU choice on $CuDensity$. In the first column, with no controls, the intercept suggests 17% of individuals choose a CU when $CuDensity = 0$, and changing $CuDensity$ from 0 to 1 would increase this percentage by 45 points. To give a more relevant interpretation of the magnitude, moving across the interquartile range of $CuDensity$, from .075 to .229, changes predicted CU choice from 20% to 27%. This is consistent with the evidence presented in the previous section that the relevance assumption holds. Columns (2) and (3) show the loan- and tract-characteristic controls help purge the instrument of potentially confounding relationships, as anticipated. Relative to column (3), however, columns (4) through (8) show that even as the coefficient on the instrument is relatively stable from (0.36 to 0.33), the R-squared increases when additional controls are included (from 0.12 to 0.18). Then assuming we can draw information from the observed controls added in columns (4) through (8) about the effect that adding unobserved controls would have, this analyses suggest no cause for concern about the validity of the independence and exclusion assumption.

Table 3 compares the predictiveness of the controls on CU choice relative to the instrument. The first column reports the results of an OLS regression of $CuDensity$ on $X$ and the second regresses $CU$ on $X$. This is a helpful analysis because the second regression serves as a benchmark for the degree of correlation between the controls and the instrument. As shown by the R-squared of each regression, the controls are less predictive of the instrument than they are of of $CU$ choice.

If this was the opposite, it would be a cause for concern about the instrument's validity.

A few other facts are consistent with the instrument's exogeneity. First, the results from Section 5.1 do not suggest different location choices by CUs and banks based on credit-related geographic variables. This helps allay concerns that CUs choose branch locations based on different criteria than banks. Second, the instrument varies at the individual level and so can capture individual variation in otherwise similar broader geographies. Third, although individuals sometimes consult with a lender before choosing which home to buy, it seems reasonable that the decision of which lender to go to is conditional on them extending loans in the area they are interested in purchasing a house in (or already live in), and not vice versa.

#### 6.1.3 Instrument Specification Robustness

As a measure of robustness to the arbitrary nature of some of the choices in constructing the instrument, I construct various alternative CU branch density instruments. Each instrument differs in the specification of geographic catchment and distance weighting. I construct a total of nine instruments based on three different geographic catchment definitions —10-kilometer radii, nearest 20 branches, and either— and three different distance weighting measures —inverse distance, the exponential of negative distance multiplied by 0.1, and uniform weights regardless of distance.[21] Appendix Figure A9 plots the correlations between these nine instruments and shows all of them are highly correlated.

### 6.2 The CU Effect on Interest Rates

This section builds on section 5.2, which showed correlational evidence that CUs charge lower interest rates on many loan products except mortgages. Thus far, academic and policy analyses comparing bank and CU interest rates have not been able to go beyond the correlational observa-

[21] The nearest 20 branches are restricted to branches within 200 kilometers. All instruments that restrict attention to 10 kilometers supplement the few properties with no branches within 10 kilometers using the 20 nearest branches.

tions such as the one made in Section 5.2, because they are unable to control for individual risk characteristics and selection. I am able to calculate interest rates for approximately two thirds of the sample, and Appendix Figure A3 shows that, on average, the algorithm matches market-wide interest rates quite well. Thus, credit data along with the identification strategy allow me to causally explore whether a "CU effect" on interest rates exists.

First, I run a simple OLS regression of interest rates on a dummy variable $CU$ for whether the originator is a CU. Second, I run an OLS regression with the same $CU$ dummy, but adding a host of controls to account for various individual risk characteristics and bank controls. Third, I run a two-stage-least-squares IV regression in which I instrument for $CU$ with $CuDensity$, while maintaining the aforementioned controls.

The equations below summarize the approach, where equations (3) and (4) are the second and first stages of the 2SLS regression. In all cases, I am interested in the coefficient $\beta_1$ and in interpreting it as the causal effect of CUs on interest rates, relative to banks.

$$InterestRate_i = \beta_0 + \beta_1 CU_i + \epsilon \tag{1}$$

$$InterestRate_i = \beta_0 + \beta_1 CU_i + \boldsymbol{\alpha} X_i + \epsilon \tag{2}$$

$$InterestRate_i = \beta_0 + \beta_1 \widehat{CU_i} + \boldsymbol{\alpha} X_i + \epsilon \tag{3}$$

$$CU_i = \gamma_0 + \gamma_1 CuDensity_i + \boldsymbol{\delta} X_i + \varepsilon \tag{4}$$

Table 4 shows the estimates for $\beta_1$ in all three regressions. The first panel shows results relative to small banks and the second relative to large banks. The unconditional difference between CUs and small banks in the matched sample is $-0.189$, controlling for observable risk characteristics changes the estimate to $-0.107$, and adjusting for risk and selection via the instrument further changes the estimate to $-0.295$. All these estimates are statistically significant, and Appendix Table A3 shows the IV estimate is robust to the specifics of the construction of the instrument.

To help interpret the value of an interest rate difference of 0.295 from the borrower perspective, consider the example of two 30-year mortgages held for seven years, one with an interest rate of 5% versus another with a rate of 4.705%. As a percentage of the principal, the implied present value cost of the second mortgage is 0.60% lower under a 20% personal discount rate (Warner and Pleeter, 2001). For an average mortgage loan of US $\$200,000$, the present value of savings amounts to approximately US $\$1,190$. From the perspective of a banks' balance sheet, this difference is a significant reduction in interest revenue. The estimates relative to large banks are qualitatively similar; although the IV estimate suggests an effect of a larger magnitude, but with weak statistical significance. Relative to the correlational evidence, this analysis suggests that, conditional on credit score and selection, CUs charge meaningfully lower interest rates.

### 6.3 The CU Effect on Credit Outcomes

This section builds on Section 5.3, which showed correlational evidence that individuals who originated mortgages with a CU experienced better credit outcomes up to four years after origination. Like Section 6.2, this section builds on the descriptive analysis of credit outcomes in two steps. First, by controlling for observable risk characteristics with an OLS regression. Second, by accounting for potential endogenous selection with the instrument. In this section, I combine these controls and instrument with the event-study approach. In all cases, I am interested in the evolution of the differential effect of having a CU mortgage on outcomes post origination.

I generically denote the seven credit outcome variables as $Y_{it}$. The OLS specification includes the same set of controls $X$ as in Section 6.2 and is specified as follows:

$$Y_{it} = \boldsymbol{\beta} CU_i \psi_{\tau(t,i)} + \boldsymbol{\delta} \psi_{\tau(t,i)} + \boldsymbol{\alpha} X_i + \epsilon_{it}. \tag{5}$$

$\psi_{\tau(t,i)}$ are event-time dummy variables that capture the number of months after origination that the credit outcome is being observed. The three mortgage-specific credit outcomes are limited to $\psi_{\tau(t,i)} > 0$, as the credit-profile outcomes include both pre- and post-event time dummies.

The IV specification is

$$Y_{it} = \boldsymbol{\beta} \widehat{CU_i \psi_{\tau(t,i)}} + \boldsymbol{\delta} \psi_{\tau(t,i)} + \boldsymbol{\alpha} X_i + \epsilon_{it} \tag{6}$$

$$CU_{it} \psi_{\tau(t,i)} = \boldsymbol{\gamma^{post}} CuDensity_i \psi_{\tau(t,i)>0} + \boldsymbol{\gamma^{pre}} CU_i \psi_{\tau(t,i)<0} + \boldsymbol{\delta} X_i + \epsilon_{it}, \tag{7}$$

where equations (6) and (7) are the second and first stages, respectively. Because of the event time coefficients, Equation (7) is a system of as many equations as there are event time dummies. Note the instrument is only applied to the CU variable post-origination, as is standard in IV-DiD specifications applied to event-study frameworks (Hudson et al., 2017).

Figure 5 plots the $\boldsymbol{\beta}$ coefficients of equations (5) and (6) by event time, comparing CUs with small banks. The estimates of ordinary least squares (OLS) with controls corroborate the results from Section 5.3. The IV estimates are also consistent with those results but have wider confidence intervals. The results in this section lend credence to the idea that CUs are doing something post origination to affect credit score outcomes in an advantageous way for their customers. Although a pre-trend remains on the number of public bankruptcy records even after controlling for risk characteristics, the instrument allows us to interpret the effect as causal. Appendix Figure A10 shows the same results comparing CUs to large banks. Relative to large banks, the causal evidence is more mixed, but altogether leans in the same direction and confirms the qualitative conclusion that individuals with a CU mortgage experience better credit outcomes as a result of a CU effect.

## 7 Extensions, Mechanisms, and Heterogeneity

This section begins with a mini-study of the auto loans market, in which I apply the analyses in the previous section of the mortgage market to a sample of auto loans derived from the TransUnion data.

I afterward deepen the analysis of the mortgage market by exploring variation in the results from the previous sections to shed light on what mediates CU effects on prices and credit outcomes. First, I present an analysis meant to identify ways in which CUs differ from banks in setting interest rates. Second, I study the differential propensity to accommodate loans that become past due. Third, I investigate whether bank loan resell rates are related to credit outcomes. Last, I investigate whether the effects on credit outcomes vary by time period: prior to 2009, post 2011, or in between these two years.

### 7.1 Extension: Auto Loans Mini-Study

Auto loans are the second largest category of consumer loans primarily supplied by commercial lenders (Federal Reserve Bank of New York, 2023). Although the data sample of auto loans I study does not have lender identifiers, the auto loans market is another important setting to study CUs because a) CUs have a larger market share of auto loans than mortgages and b) individuals of lesser means are potentially more represented in the auto loans market. I analyze the approximately 7.8 million auto loans originated by either CUs or commercial banks found in the TransUnion data sample.

Table 5 reports the results from the IV specification in equation (6) on the interest rates at origination and loan and credit outcomes three years after origination. The results imply that interest rates at CUs are 0.460 interest rate points lower than at banks, which is a very similar magnitude found for mortgages. The results on differences in loan and credit outcomes are also consistent with the equivalent for mortgages. CU loans are less likely to become past due and charged off or sent into collections. CU borrowers have lower amounts past due, higher credit scores, and fewer bankruptcies. Although I do not detect statistically significant effects on the number of trades past due, these results suggest a very consistent inference on the effect of banking with CUs and lend credence to the idea of a CU effect.

In Appendix Figure A11 I show that, among the variables that I can analyze, the distribution of the characteristics of auto loans is similar for CUs and banks. Although these data are limited to the sample in TransUnion data (i.e., they are not close to the universe, like in HMDA) and I can analyze fewer variables, the similarity between banks and CUs is even stronger in auto loans than it is in mortgages. Altogether, this pair of results suggests that the takeaways about CUs from the mortgage market apply also to the auto loans market.

### 7.2 Mechanism: Pricing Function

This section builds on Section 6.2 and analyzes whether CUs differ in setting interest rates. Figure 6 plots predicted interest rates for CUs and banks by credit score ventile from an OLS regression with no controls. Although CUs charge lower interest across the entire score distribution, they charge notably less than banks to those with credit scores in the bottom 30% to 40%. Given the importance of credit scores in determining prices, this finding by itself suggests lower prices as well as less risk-sensitive pricing.

To better understand the differences between CUs' and banks' pricing functions, the following analysis investigates whether CUs price differently based on each covariate I use. For each control variable $x \in X$, I estimate the following 2SLS regressions:

$$InterestRate_i = \beta_0 + \beta_1 \widehat{CU_i} + \beta_2 \widehat{CU_i \times x} + \boldsymbol{\alpha} X_i + \epsilon \tag{8}$$

$$CU_i = \gamma_0 + \gamma_1 CuDensity_i + \gamma_2 CuDensity_i \times x + \boldsymbol{\delta} X_i + \varepsilon \tag{9}$$

$$CU_i \times x = \gamma_0 + \gamma_1 CuDensity_i + \gamma_2 CuDensity_i \times x + \boldsymbol{\delta} X_i + \varepsilon. \tag{10}$$

These equations are similar to equations (3) and (4), but they add an interaction between $x$ and $CU$ that reveals a potentially different way in which CUs load on those variables to set interest rates.

Equations (9) and (10) are the two first stage equations, both of which rely on the *CuDensity* instrument, and equation (8) is the second stage. For each regression, I am interested in the coefficients $\beta_2$ and $\alpha^x$, the banks' coefficient corresponding to $x$. The coefficient $\alpha^x$ captures how a bank's interest rates are affected by $x$, and $\beta_2$ captures how CUs potentially differ from banks on this specific dimension.

Figure 7 plots, for each regression, the $\alpha_x$ coefficients in black squares and the $\beta_2$ coefficients in blue diamonds. Although my data are insufficiently powered to make definitive claims, many variables also suggest CUs price in less risk-sensitive ways than banks. Below, I highlight the variables that support this claim:

- **Tract characteristics:** Bank interest rates are higher in tracts with higher rejection rates and lower in tracts with high mean credit scores. These coefficients are consistent with pricing based on costs or risk. The CU coefficient on interest rates leans in the opposite direction. Neither bank nor CU interest rates seem affected by a tract's urban fraction or its median income.

- **Loan purpose:** Relative to mortgages for a home purchase, banks charge lower interest on home improvement and refinancing loans. By contrast, CUs do not differentiate interest rates for refinancings and charge higher interest on home improvement loans.

- **Credit Score:** Relative to banks, CUs charge lower interest rates to both below median and top quartile CU individuals.

- **Loan Term:** Relative to banks, CUs charge higher interest rates on 10-year term mortgages, approximately the same on 15-year term mortgages, and less on 20-year term mortgages (although 20-year mortgages only account for 7% of all CU mortgages). Overall, CUs price more uniformly in relation to the length of the mortgage.

- **Time Period:** Bank interest rates were highest prior to 2009, and CUs offered lower prices at this time. Post 2011, when bank interest rates decreased, CU interest rates converged with bank rates.

The remaining variables suggest no (detectable) differential CU effect. As a more complete way to perform this exercise, I estimate counterfactual interest rates at CUs and banks for all individuals, and compare the predicted interest rates individuals would get under the two types of lenders after controlling for all covariates. The regression is the same one specified in equations (8)-(10) but estimated for all controls at once ($x := X$). Figure 8 shows a scatter plot of the predicted interest rates for all individuals at banks versus a CU. The horizontal axis plots predicted rates for individuals, which are counterfactual for CU borrowers. The vertical axis plots the difference between predicted rates at a CU and at a bank, counterfactual for individuals who borrowed from the "other" lender. The black solid line plots the OLS fitted line, and the hollow circles show the mean value of the difference for the bin. The plot shows the mean predicted CU rate is lower across the entire empirical support of predicted rates, and the CU difference is larger for higher interest rates.

Overall, CUs vary interest rates as banks do based on risk factors, but they seem to do so at a lower degree of sensitivity than banks. Although there are other potential explanations, such as a less sophisticated pricing machinery, these results are consistent with CUs being less profit maximizing.

### 7.3 Mechanism: Accommodations and Credit Outcomes of Mortgages Past Due

The results in Section 6 suggest that CUs do something, other than selection, which contributes to the improved outcomes among its borrowers. For example, CU advocates claim that they provide financial education to their borrowers and members. Another such action may be to modify a borrower's loan terms when doing so would be beneficial to the borrower. Although I cannot study these with the data available, I can investigate something close in spirit to the latter example: for mortgage that are past due, a) what is the likelihood that they ever received any accommodation? and b) what is the likelihood that they experienced an even more negative outcome?

I restrict attention to mortgages that are at least 90+ days past due. Accommodations include forbearance, deferment, being reported as affected by a natural disaster. Negative credit outcomes include foreclosure, repossession, being charged-off, or being sent to collections. The first column of Table 6 reports that overall, CU loans are approximately 40% less likely to be past due than small bank originated loans (0.0114 versus 0.197). The second and third columns show that, conditional on being past due, CU loans are are approximately 20% more likely to receive an accommodation (0.0410 vs 0.0339) and 10% less likely to experience a negative credit outcome (.2815 vs. 0.3159). Although there are other possible explanations for these differences, these results are suggestive of a post-origination channel by which CUs "treat" their borrowers with better outcomes through more accommodating and forgiving actions.

### 7.4 Mechanism: Mortgage Reselling

A natural next step to better understand what may be behind the improved credit outcomes is to ask what bank-related variables correlate with the improved outcomes. Because of how strikingly different CU and banks are in the likelihood of reselling mortgages, I further investigate how resell rates are correlated with outcomes.

To simplify the analysis, I focus on credit outcomes three years after origination and, in the case of credit profile outcomes, I compare them to three months prior. I segment loans based on the resell rates of their originating bank. I create 5 binary variables based on the percentage of loans they resell within the same calendar year: $Resell := \{< 10, 10 - 33, 34 - 66, 67 - 90, > 90\}$.

For mortgage-specific outcomes, I run the OLS specification in equation (11)[22]:

$$Y_{it} = \boldsymbol{\beta} Resell_i + \boldsymbol{\alpha} X_i + \epsilon_{it}. \tag{11}$$

For credit-profile outcomes, I run the OLS specification in equation (12):

$$Y_{it} = \boldsymbol{\alpha} Resell_i + Post_{it} + \boldsymbol{\beta} Resell_i \times Post_{it} + \boldsymbol{\alpha} X_i + \epsilon_{it}. \tag{12}$$

I exclude the 0-10% binary variables and estimate one coefficient for each category. For both mortgage-specific and credit-profile outcomes, the coefficients $\beta$ are of interest because they capture the potential heterogeneity among banks when classified by resell rates and their impact on credit outcomes. Figure 9 plots the estimated coefficients for the seven credit outcomes for small and banks.

The results show that for mortgage-specific outcomes lower resell rates are associated with better outcomes. But this does not seem to extend the credit-profile outcomes. Considering that CUs are much less likely to resell their mortgages, the differential impact on mortgage-specific outcomes is a suggestive channel of the kinds of bank-level behavior that lead to better credit outcomes. This evidence is consistent with the idea that a banking model based on relatively little reselling of mortgages more successfully internalizes the incentives to achieve good credit outcomes.

### 7.5 Heterogeneity over Time

As shown in Appendix Figure A6, CUs were less likely to charge high interest rates prior to 2010. The difference, though, is driven by bank behavior, because banks charged high interest rates on as many as one in four loans. The pre-crisis period displayed high demand for mortgages, and presumably the ex-ante opportunities for lenders to profit were higher than at other points in time.

[22] For notational parsimony, I include the intercept in $X$.

CUs did not follow the overall trend that banks did. One interpretation of this fact is that CUs were less prone to pursue the profit opportunities that appeared to exist prior to 2008.[23] This analysis is also interesting because it suggests the possibility that the "CU effect" was observed during the pre-crisis period and may not exist since then.

I segment my sample into three time periods, based on when mortgages were originated: pre-crisis 2004–2008, bust 2009–2011, and the post-Dodd-Frank period 2012–2017.[24] Table 7 shows the result of estimating the 2SLS equations (3)-(4) by time period (equivalent to column (3) of Table 4). Indeed, the CU effect on interest rates has declined over time. Additionally, Figure 10 shows the results from estimating equation (5) on the three data subsamples of each period. The symbols plot the coefficient $\beta$ corresponding to three years post origination. Although the estimates are noisy given the smaller sample sizes, the CU effect on credit outcomes relative to small banks seems to have been greatest from 2004 to 2008 – especially among the estimates with statistical significance. Altogether, this analysis provides some support for the idea that prior to the financial crisis, when underwriting standards were lowest, CUs differentiated themselves the most with improved credit outcomes.

## 8 Conclusion

This paper develops empirical evidence that, relative to comparably-sized banks, Credit Unions charge lower interest rates on mortgages and that their borrowers have fewer mortgage delinquencies, higher credit scores, and a lower risk of bankruptcy several years later. These results are consistent with the idea that CUs behave differently than banks. The empirical evidence on the mortgage market in this paper weighs against the hypothesis that CUs are for-profits in disguise. Important questions remain in need of better evidence, such as whether CUs transfer all the tax

[23] Although for a different time period, Cororaton (2019) argues CUs forwent profit opportunities in order to extend more loans than banks.

[24] The Dodd–Frank Wall Street Reform and Consumer Protection Act was passed by U.S. Congress in 2010. I begin the reform period in 2012 with a purposeful lag of approximately one and a half years.

exemption to their members or if CUs expand access to credit. That this research suggests at least some transfer of the tax exemption to customers stands in relatively optimistic contrast to the majority of the literature on non-profit hospitals, which, with important exceptions, suggests they behave like for-profit firms.

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# 9 Figures and Tables

Table 1.
Representativeness of Matched Sample

| | CU | | Small Bank | | Large Bank | |
|---|---|---|---|---|---|---|
| | Sample | HMDA | Sample | HMDA | Sample | HMDA |
| Loan Characteristics | | | | | | |
| – Loan Amount ($K) | 184 | 139 | 231 | 191 | 273 | 224 |
| – Applicant Income ($K) | 105 | 96 | 121 | 103 | 135 | 113 |
| Tract Characteristics | | | | | | |
| – Credit Score | 50 | 49 | 51 | 50 | 50 | 50 |
| – Reject Rate | 0.17 | 0.18 | 0.18 | 0.19 | 0.18 | 0.19 |
| – Fraction Urban | 0.80 | 0.81 | 0.75 | 0.78 | 0.84 | 0.86 |
| – Median Income ($K) | 70 | 67 | 71 | 67 | 78 | 73 |
| Bank Characteristics | | | | | | |
| – Loan Reject Rate | 0.19 | 0.17 | 0.16 | 0.17 | 0.19 | 0.19 |
| – Loan Resell Rate | 0.36 | 0.30 | 0.65 | 0.60 | 0.70 | 0.68 |
| – Assets ($M) | 4,975 | 4,629 | 7,228 | 6,539 | 870,779 | 612,748 |
| Lien Status | | | | | | |
| – First | 0.89 | 0.73 | 0.95 | 0.85 | 0.97 | 0.89 |
| – Subordinate | 0.11 | 0.21 | 0.04 | 0.12 | 0.03 | 0.10 |
| – Not Secured | 0.00 | 0.06 | 0.00 | 0.03 | 0.00 | 0.02 |
| Loan Purpose | | | | | | |
| – Home Purchase | 0.24 | 0.24 | 0.35 | 0.38 | 0.24 | 0.33 |
| – Home Improvement | 0.10 | 0.22 | 0.05 | 0.11 | 0.04 | 0.07 |
| – Refinance | 0.66 | 0.55 | 0.60 | 0.52 | 0.72 | 0.60 |
| Year | | | | | | |
| – Pre-2009 | 0.10 | 0.47 | 0.19 | 0.30 | 0.20 | 0.25 |
| – 2009 to 2011 | 0.21 | 0.33 | 0.24 | 0.52 | 0.28 | 0.56 |
| – Post-2011 | 0.69 | 0.20 | 0.57 | 0.18 | 0.52 | 0.19 |
| Borrower Age | | | | | | |
| – Under 35 | 0.17 | | 0.21 | | 0.16 | |
| – 35-60 | 0.65 | | 0.64 | | 0.66 | |
| – Over 60 | 0.18 | | 0.15 | | 0.18 | |
| Credit Score Percentile | | | | | | |
| – Below 50 | 0.13 | | 0.13 | | 0.13 | |
| – 50-75 | 0.40 | | 0.40 | | 0.38 | |
| – Above 75 | 0.47 | | 0.46 | | 0.49 | |
| Term (Years) | | | | | | |
| – 10 | 0.14 | | 0.06 | | 0.05 | |
| – 15 | 0.28 | | 0.22 | | 0.21 | |
| – 20 | 0.07 | | 0.06 | | 0.07 | |
| – 30 | 0.51 | | 0.66 | | 0.66 | |
| N | 284,696 | 7,639,394 | 868,671 | 27,608,599 | 1,163,459 | 33,234,647 |

Notes: Mortgage data are from HMDA, and credit records data are from TransUnion. The HMDA columns show means for the universe of conventional (i.e., non- FHA, VA, FSA, or RHS) mortgages with a first-lien on an owner-occupied, one-to-four family property in HMDA from 2004 to 2017. Means for tract- and bank-level characteristics are weighted by the number of originated mortgages.The Sample columns show means for the matched sample. Further details on the data match and variable constructions can be found in Section 4.

Table 2.
Stability of Instrument First Stage to Variations in Controls

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|
| | Instrument | 0.45 | 0.40 | 0.36 | 0.33 | 0.32 | 0.33 | 0.33 | 0.33 |
| | | (0.05) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| Loan Characteristics | log(Loan Amount) | | −0.04 | −0.06 | −0.04 | −0.04 | −0.00 | −0.00 | −0.00 |
| | | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| | Loan was Resold | | −0.24 | −0.25 | −0.06 | −0.06 | −0.05 | −0.05 | −0.05 |
| | | | (0.02) | (0.02) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| | log(Applicant Income) | | 0.00 | −0.01 | −0.01 | −0.02 | −0.04 | −0.04 | −0.04 |
| | | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Tract Characteristics | Credit Score | | | −0.03 | −0.05 | −0.03 | −0.03 | −0.03 | −0.03 |
| | | | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| | Reject Rate | | | −0.05 | −0.06 | −0.03 | −0.02 | −0.02 | −0.02 |
| | | | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| | Fraction Urban | | | 0.05 | 0.07 | 0.08 | 0.08 | 0.08 | 0.08 |
| | | | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| | Median Income | | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Bank Characteristics | Loan Resell Rate | | | | −0.39 | −0.39 | −0.39 | −0.39 | −0.39 |
| | | | | | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) |
| | Loan Reject Rate | | | | 0.09 | 0.10 | 0.07 | 0.07 | 0.07 |
| | | | | | (0.16) | (0.15) | (0.15) | (0.15) | (0.15) |
| | log(Assets) | | | | −0.03 | −0.03 | −0.03 | −0.03 | −0.03 |
| | | | | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Years | Pre-2009 | | | | | −0.12 | −0.11 | −0.11 | −0.10 |
| | | | | | | (0.02) | (0.01) | (0.01) | (0.01) |
| | Post-2011 | | | | | 0.04 | 0.05 | 0.05 | 0.05 |
| | | | | | | (0.01) | (0.01) | (0.01) | (0.01) |

Continued on next page

**Table 2 – continued from previous page**

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|
| Loan Purpose | Subordinate | | | | | | 0.11 | 0.11 | 0.11 |
| | | | | | | | (0.02) | (0.02) | (0.02) |
| | Not Secured | | | | | | −0.02 | −0.02 | −0.02 |
| | | | | | | | (0.08) | (0.08) | (0.08) |
| Lien Status | Home Improvement | | | | | | 0.05 | 0.04 | 0.04 |
| | | | | | | | (0.02) | (0.02) | (0.02) |
| | Refinance | | | | | | 0.07 | 0.07 | 0.07 |
| | | | | | | | (0.01) | (0.01) | (0.01) |
| Term (Years) | 10 | | | | | | 0.07 | 0.07 | 0.07 |
| | | | | | | | (0.02) | (0.02) | (0.02) |
| | 15 | | | | | | 0.02 | 0.02 | 0.02 |
| | | | | | | | (0.01) | (0.01) | (0.01) |
| | 20 | | | | | | −0.01 | −0.01 | −0.01 |
| | | | | | | | (0.01) | (0.01) | (0.01) |
| Borrower Age | Under 35 | | | | | | | −0.01 | −0.01 |
| | | | | | | | | (0.00) | (0.00) |
| | Over 60 | | | | | | | −0.00 | −0.00 |
| | | | | | | | | (0.00) | (0.00) |
| Credit Score | Below 50 | | | | | | | | −0.01 |
| | | | | | | | | | (0.00) |
| | Above 75 | | | | | | | | 0.00 |
| | | | | | | | | | (0.00) |
| | Constant | 0.17 | 0.53 | 0.82 | 1.48 | 1.42 | 1.27 | 1.28 | 1.29 |
| | | (0.02) | (0.04) | (0.06) | (0.18) | (0.18) | (0.18) | (0.18) | (0.18) |
| | N | 1,153,367 | 1,153,367 | 1,153,367 | 1,153,367 | 1,153,367 | 1,153,367 | 1,153,367 | 1,153,367 |
| | Adj. R2 | 0.02 | 0.11 | 0.12 | 0.18 | 0.19 | 0.2 | 0.2 | 0.2 |

Notes: The table reports first-stage OLS estimates of regressing a CU indicator dummy on $CuDensity$ and a varying set of controls. Data are from the matched sample described in Section 4 restricted to CUs and small banks.

Table 3.
Preditiveness of Controls on CU Indicator and Instrument

| | | (1) | (2) |
|---|---|---|---|
| Loan Characteristics | log(Loan Amount) | −1.106 | −0.704 |
| | | (0.025) | (0.078) |
| | Loan was Resold | −0.048 | −5.340 |
| | | (0.034) | (0.106) |
| | log(Applicant Income) | −0.299 | −4.066 |
| | | (0.025) | (0.078) |
| Tract Characteristics | Credit Score | −0.655 | −3.132 |
| | | (0.017) | (0.053) |
| | Reject Rate | −1.396 | −2.838 |
| | | (0.021) | (0.064) |
| | Fraction Urban | 6.361 | 9.911 |
| | | (0.035) | (0.110) |
| | Median Income | −0.058 | 0.077 |
| | | (0.001) | (0.002) |
| Bank Characteristics | Loan Resell Rate | −1.419 | −39.561 |
| | | (0.049) | (0.151) |
| | Loan Reject Rate | 0.035 | 6.873 |
| | | (0.105) | (0.327) |
| | log(Assets) | −0.166 | −3.135 |
| | | (0.007) | (0.021) |
| Years | Pre-2009 | −0.177 | −10.494 |
| | | (0.041) | (0.127) |
| | Post-2011 | 0.287 | 5.519 |
| | | (0.029) | (0.091) |
| Loan Purpose | Home Improvement | −0.790 | 10.804 |
| | | (0.063) | (0.195) |
| | Refinance | −1.428 | −2.540 |
| | | (0.237) | (0.735) |
| Lien Status | Subordinate | −0.556 | 4.246 |
| | | (0.055) | (0.171) |
| | Not Secured | −0.388 | 6.550 |
| | | (0.027) | (0.085) |
| Term (Years) | 10 | 0.604 | 6.884 |
| | | (0.051) | (0.157) |
| | 15 | 0.036 | 1.810 |
| | | (0.031) | (0.097) |
| | 20 | −0.304 | −1.461 |
| | | (0.050) | (0.155) |
| Borrower Age | Under 35 | 0.178 | −1.281 |
| | | (0.031) | (0.096) |
| | Over 60 | −0.481 | −0.285 |
| | | (0.034) | (0.104) |
| Credit Score | Below 50 | 0.006 | −1.412 |
| | | (0.038) | (0.118) |
| | Above 75 | −0.223 | 0.065 |
| | | (0.026) | (0.080) |
| | Constant | 33.038 | 139.461 |
| | | (0.201) | (0.623) |
| | Observations | 1,153,367 | 1,153,367 |
| | Adjusted $R^2$ | 0.066 | 0.195 |
| | F Statistic (df = 23; 1153343) | 3,561.916 | 12,184.350 |

Notes: The table reports OLS estimates of regressing a CU indicator dummy on $CuDensity$ and a varying set of controls. Data are from the matched sample described in Section 4 restricted to CUs and small banks.

Table 4.
Differential Interest Rates at CUs vs. Banks

**Relative to Small Banks**

| | Dependent variable: Interest Rate | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| CU | −0.189 | −0.107 | −0.295 |
| | (0.060) | (0.029) | (0.087) |
| Controls | No | Yes | Yes |
| IV | No | No | Yes |
| Adj. R2 | 0.0026 | 0.4497 | |
| 1st Stage F-Stat. | | | 8,482.48 |
| N | 767,991 | 767,991 | 767,991 |

**Relative to Large Banks**

| | Dependent variable: Interest Rate | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| CU | −0.152 | −0.046 | −0.434 |
| | (0.156) | (0.070) | (0.619) |
| Controls | No | Yes | Yes |
| IV | No | No | Yes |
| Adj. R2 | 0.0024 | 0.4171 | |
| 1st Stage F-Stat. | | | 508.04 |
| N | 1,024,516 | 1,024,516 | 1,024,516 |

Notes: Table reports estimates from the regressions detailed in equations (1)–(3), the CU effect on mortgage interest rates. Standard errors clustered at the bank level are reported in parentheses.

Table 5.
Auto Loans

**Loan Outcomes**

| | Interest Rate | 90+ Days Past Due | Amount Past Due | Charged-off or In Collections |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| CU | -0.460 | -0.002 | -0.153 | -0.011 |
| | (0.198) | (0.002) | (0.036) | (0.006) |
| Controls | Yes | Yes | Yes | Yes |
| IV | Yes | Yes | Yes | Yes |
| 1st Stage F-Stat. | 2,700.7 | 2,700.7 | 2,700.7 | 2,700.7 |
| N | 7,848,838 | 7,848,838 | 7,848,838 | 7,848,838 |

**Credit Outcomes**

| | Trades 90 Days Past Due | Amount Past Due | Score | Num. of Public Rec. Bankruptcies |
|---|---|---|---|---|
| | (5) | (6) | (7) | (8) |
| CU | 0.004 | -1.70 | 2.83 | -0.055 |
| | (0.017) | (0.431) | (1.03) | (0.017) |
| Controls | Yes | Yes | Yes | Yes |
| IV | Yes | Yes | Yes | Yes |
| 1st Stage F-Stat. | 2,656.0 | 2,656.0 | 2,656.0 | 2,656.0 |
| N | 7,775,323 | 7,775,323 | 7,775,323 | 7,775,323 |

Notes: Table reports estimates from the regressions detailed in equations (6) and (7) the CU effect on auto interest rates, loan outcomes, and credit outcomes. Standard errors are reported in parentheses.

Table 6.
Accommodations and Negative Outcomes on Loans Past Due

| | Ever 90+ Past Due | Conditional on Ever Being 90+ Days Past Due | |
|---|---|---|---|
| | | Accommodation | Negative Outcome |
| CU | 0.0114 | 0.0410 | 0.2815 |
| Small Bank | 0.0197 | 0.0339 | 0.3159 |
| Difference | -0.0083 | 0.0070 | -0.0344 |
| p-value: | 0.0000 | 0.0275 | 0.0000 |

Notes: The first column reports the fraction of loans that were 90+ days past due at least once during the loan's lifetime. The second column reports the fraction of loans that, conditional on ever being 90+ days past due, received an accommodation. A loan is considered to have received an accommodation it was in deferment or in forbearance. The third column reports the fraction of loans that, conditional on ever being 90+ days past due, ultimately experienced a negative outcome. A loan is considered to have experienced a negative outcome if it was ever in foreclosure, repossession, charged off, or in collections. Reported p-values are for tests of difference in proportions, based on one-sided alternative hypotheses (the alternative hypothesis is that the CU proportion is smaller, larger, and smaller, for each column respectively).

## Table 7.
## Differential Interest Rates at CUs vs. Banks by Time Period

| | Dependent variable: Interest Rate | | |
|---|---|---|---|
| | ’04-’08 | ’09-’11 | ’12-’17 |
| CU | −0.973 | −0.414 | −0.185 |
| | (0.271) | (0.151) | (0.090) |
| Controls | Yes | Yes | Yes |
| IV | Yes | Yes | Yes |
| 1st Stage F-Stat. | 801.6 | 1,331.73 | 6,635.85 |
| N | 111,297 | 187,225 | 469,469 |

Notes: Table reports estimates from the regressions detailed in equations (1)–(3), the CU effect on mortgage interest rates, broken out by time periods for the sample of CUs and small banks only. Standard errors clustered at the bank level are reported in parentheses.

Figure 1.
Characteristics of Originated Loans

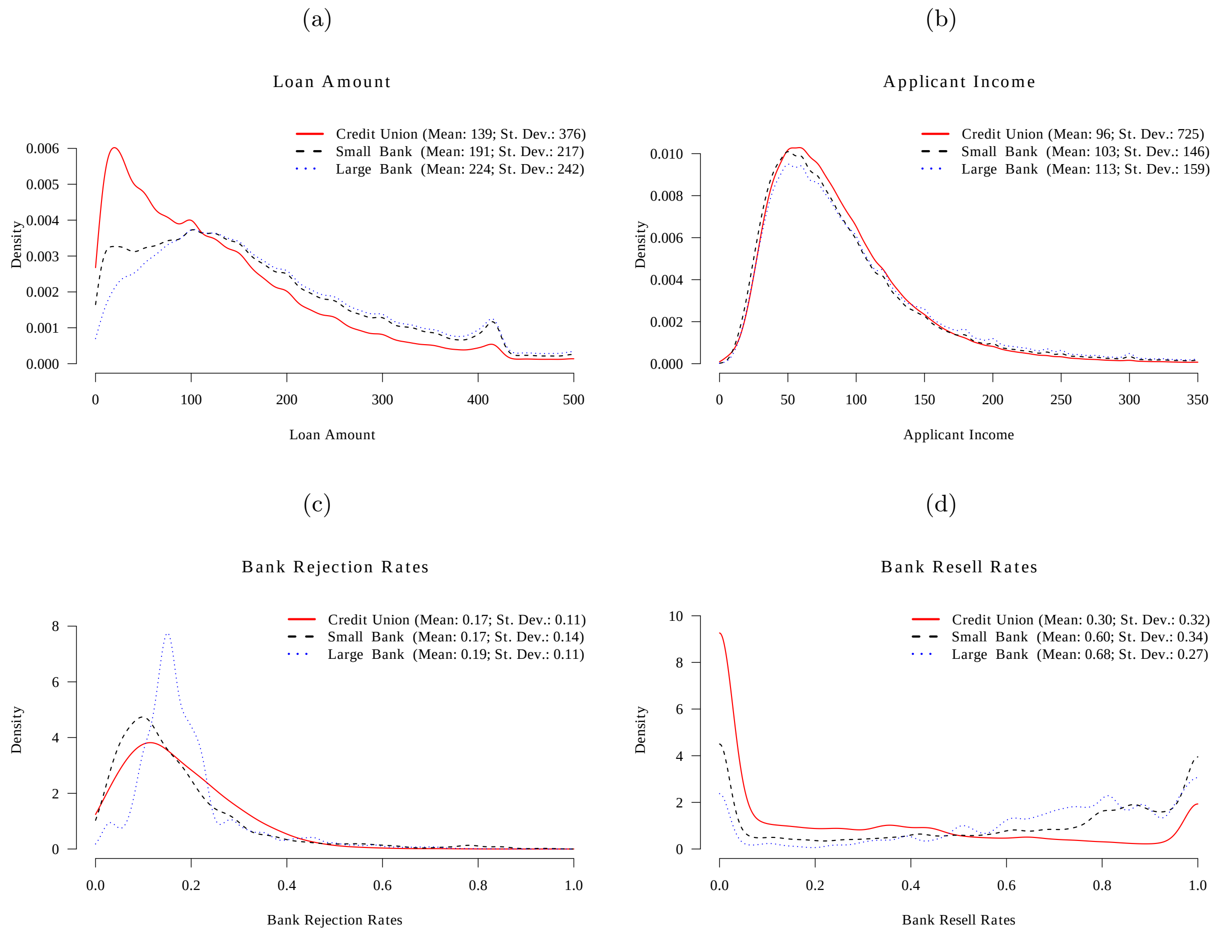
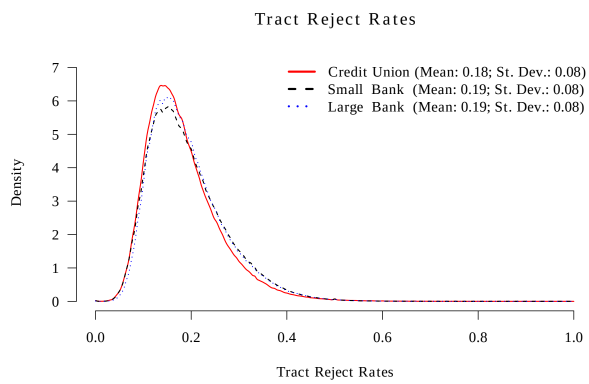
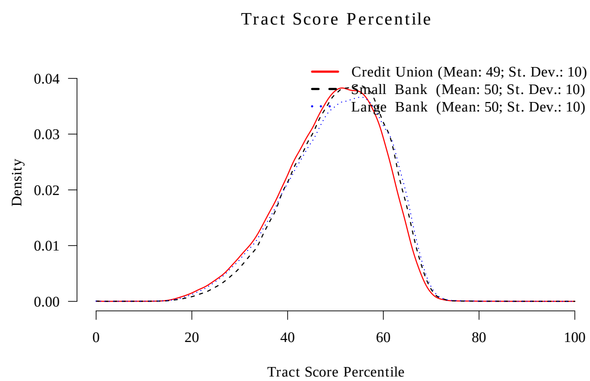


Figure 1. (continued)

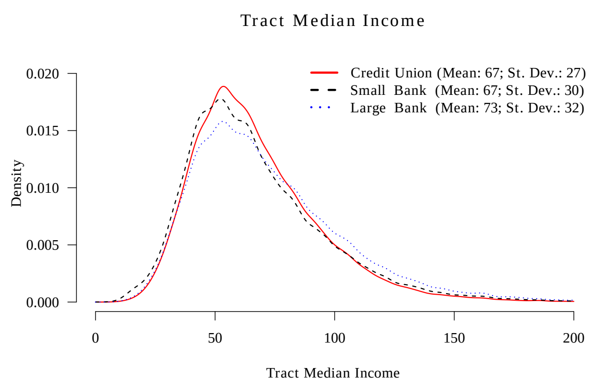
(e)



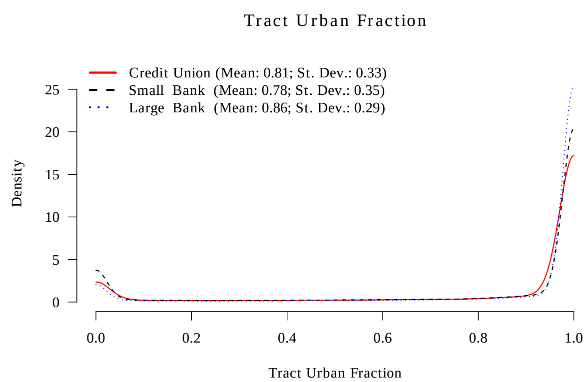

(f)




(g)




(h)



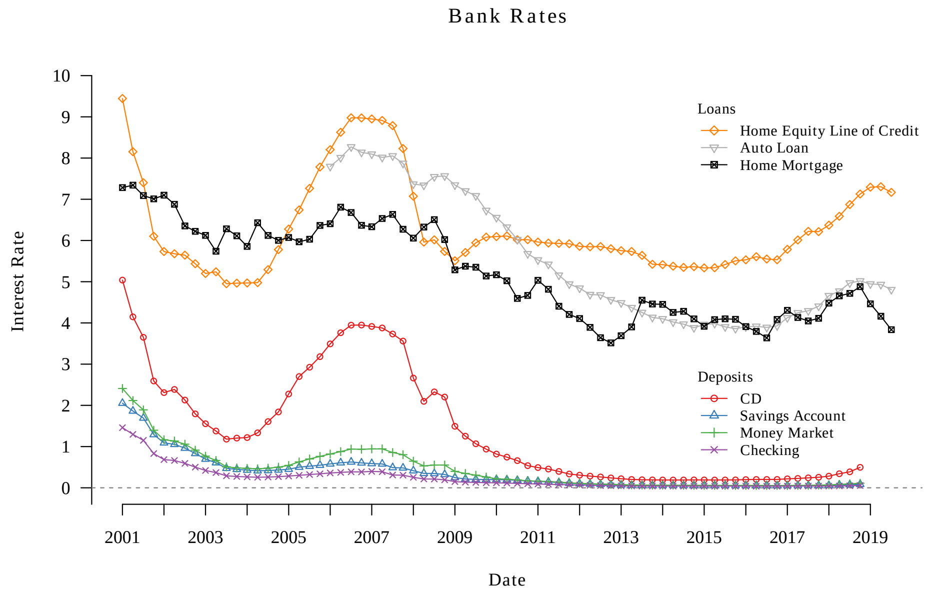

Notes: Mortgage data are from HMDA and credit records data are from TransUnion. Each subfigure plots kernel density estimates based on the universe of conventional (i.e., non- FHA, VA, FSA, or RHS) mortgages with a first-lien on an owner-occupied, one-to-four family property in HMDA from 2004 to 2017. Each plot shows the density of a given variable weighted by the number of originated mortgages. Each figure breaks out density estimates by the type of bank that originated the mortgage: Credit Unions, small banks, or large banks. A bank is defined as a small/large bank if its total assets reported to HMDA in the given year are less/more than 105% the total assets of the largest Credit Union in that year.

In Panels (a) and (b), amounts are presented in thousands of US Dollars. In Panel (c), bank rejection rates are calculated at the bank-year level and represent the fraction of applications that a bank reported to HMDA and were not originated due to a denial. In Panel (d), bank resell rates are calculated at the bank-year level and represent the fraction of loans that were originated by a lender and sold within the same calendar year. In Panel (e), tract reject rates are computed at the tract-year level, and the fraction of applications from a given tract that were reported to HMDA and were not originated due to a denial. In Panel (f), mean tract score percentiles are calculated at the tract-year level. Tract median income in Panel (g) is in thousands of constant 2012 US dollars and come from Census data. Panel (f) shows the distribution of tracts' urban fractions according the Census data.

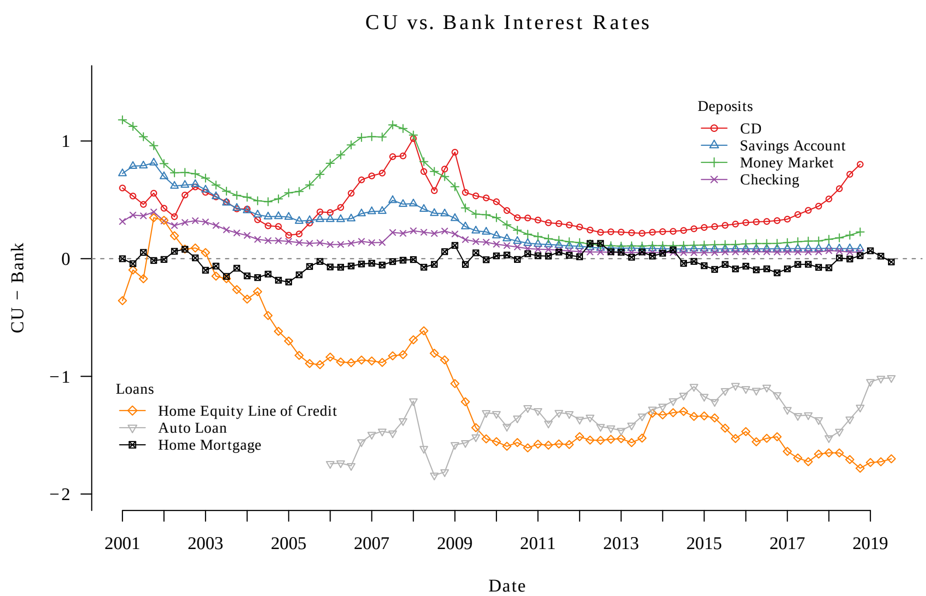
Densities are estimated using Gaussian kernels. Smoothing bandwidths are constant within each plot, although they differ across plots. To faithfully reflect the mass of data at the 0 and 1 bounds of the measure, Panels (d) and (h) "reflect" the data outside 0 and 1 boundaries and compute densities on the reflected vector limited to the [0,1] range. Let $X$ be a vector such that its elements $x_i \in [0, 1]$, the reflection $R$ of vector $X$ is defined as $R := \{-X, X, 2 - X\}$. Densities are computed on $R$ instead of $X$ and multiplied by three to account for the added data.

Figure 2.
List Prices at CUs and Banks

(a)



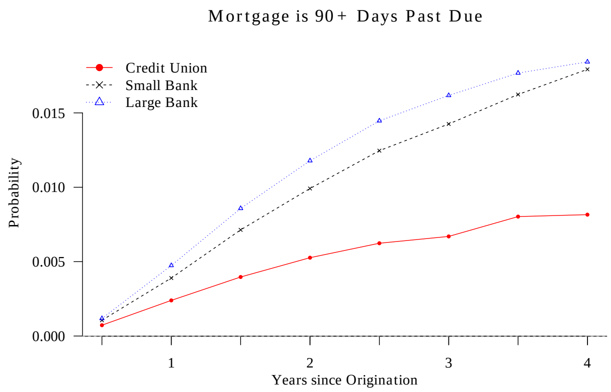

(b)



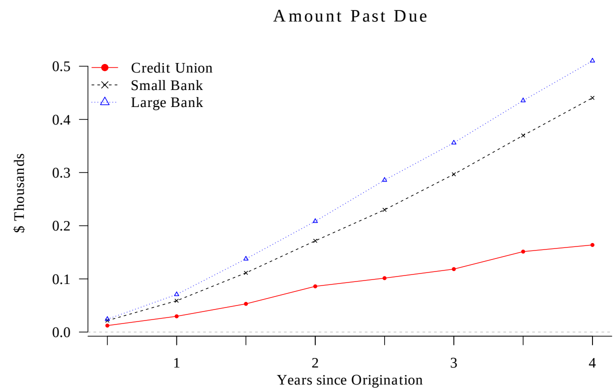

Notes: Data are from S&P RateWatch, which surveys bank and CU branches for loan and deposit prices. Panel (a) shows mean bank rates by month for various loan and deposit products. Panel (b) shows the difference in monthly mean prices for each loan or deposit product. Home Equity Line of Credit loans are tier 1 risk for loan-to-value ratio between 0-80 percent; Auto Loans are 48-month loan for a 2-year used automobile; Home Mortgage loans are 30-year fixed rate mortgage of US $175,000; CDs are 12-month Certificates of Deposit of US $10,000; Savings Accounts, Money Market accounts, and Checking Accounts that require a minimum balance of US $2,500.

Figure 3.
Mortgage Outcomes

(a)




(b)




(c)

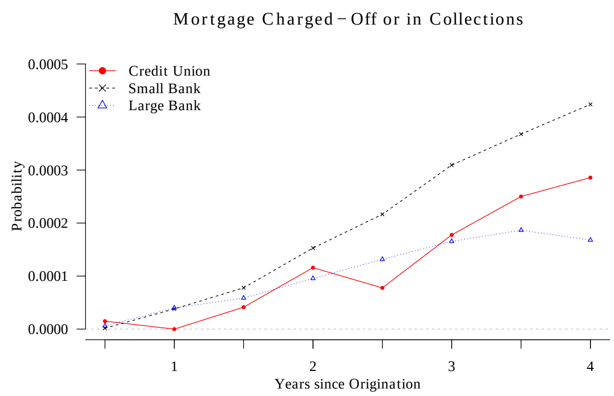
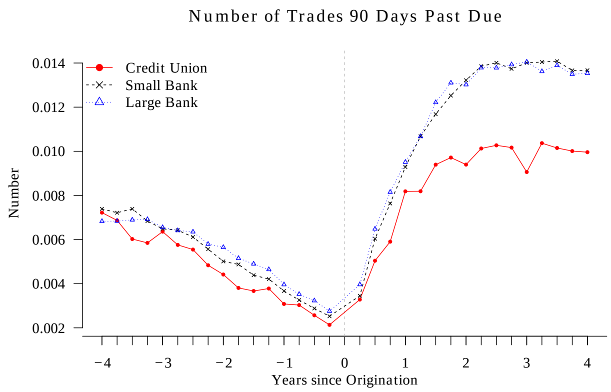
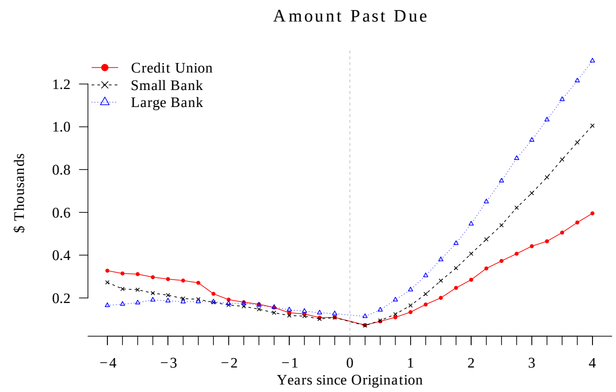


Figure 3. (continued)
Credit Profile Outcomes

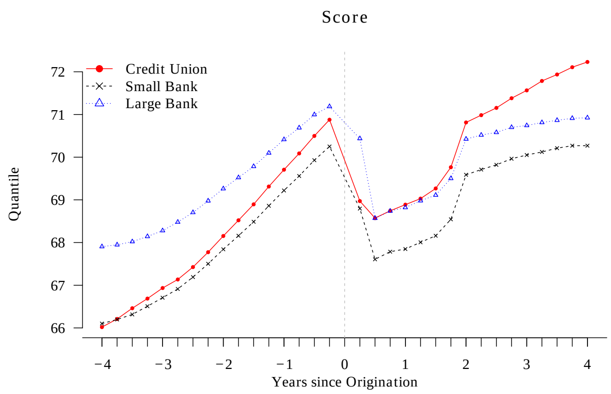
(d)



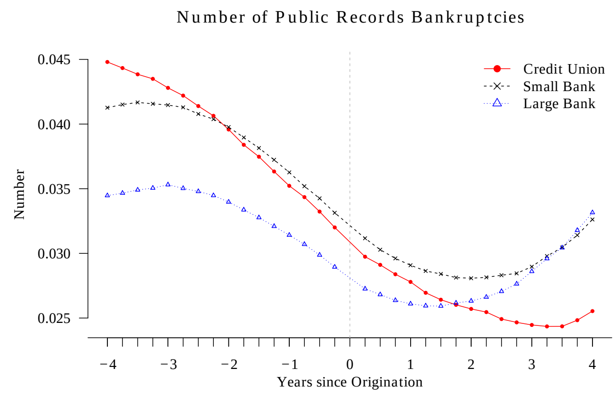

(e)




(f)

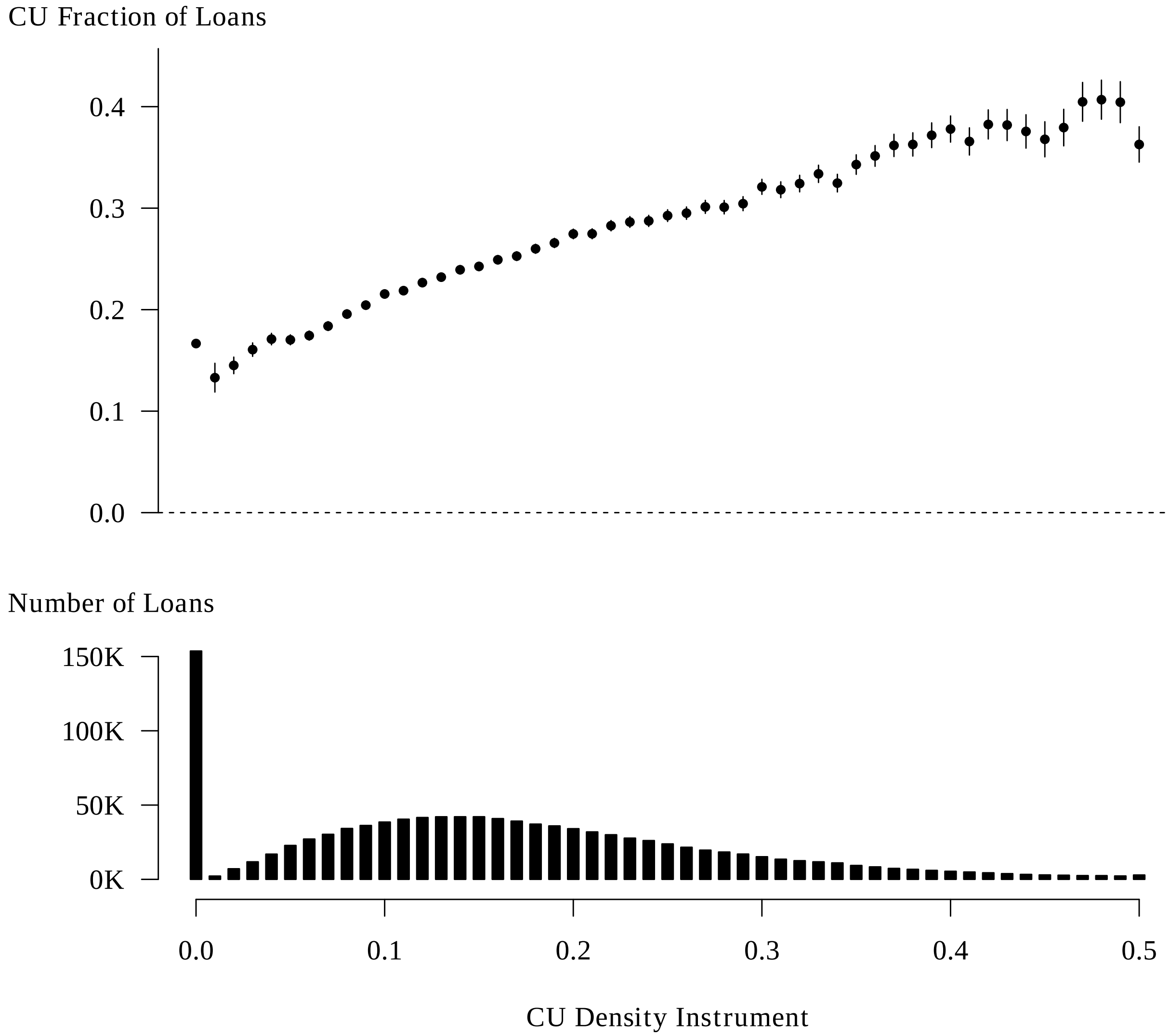



(g)




Notes: Data are from the matched sample described in Section 4 restricted to 30-year term mortgages. Plots show the mean value by bank type of each variable according to event time, defined from the month of mortgage origination.

Figure 4.
Unconditional Instrument First Stage




Notes: Data are from the matched sample described in Section 4 restricted to CUs and small banks. The top panel plots the fraction of individuals using a CU by 0.01 instrument point bins. The vertical lines represent confidence intervals of the fraction CU. The bottom panel plots a histogram of observations per bin. Figure excludes the 1.7% of observations with CU density above 0.5.

Figure 5.
CU Treatment Effect on Mortgage Outcomes

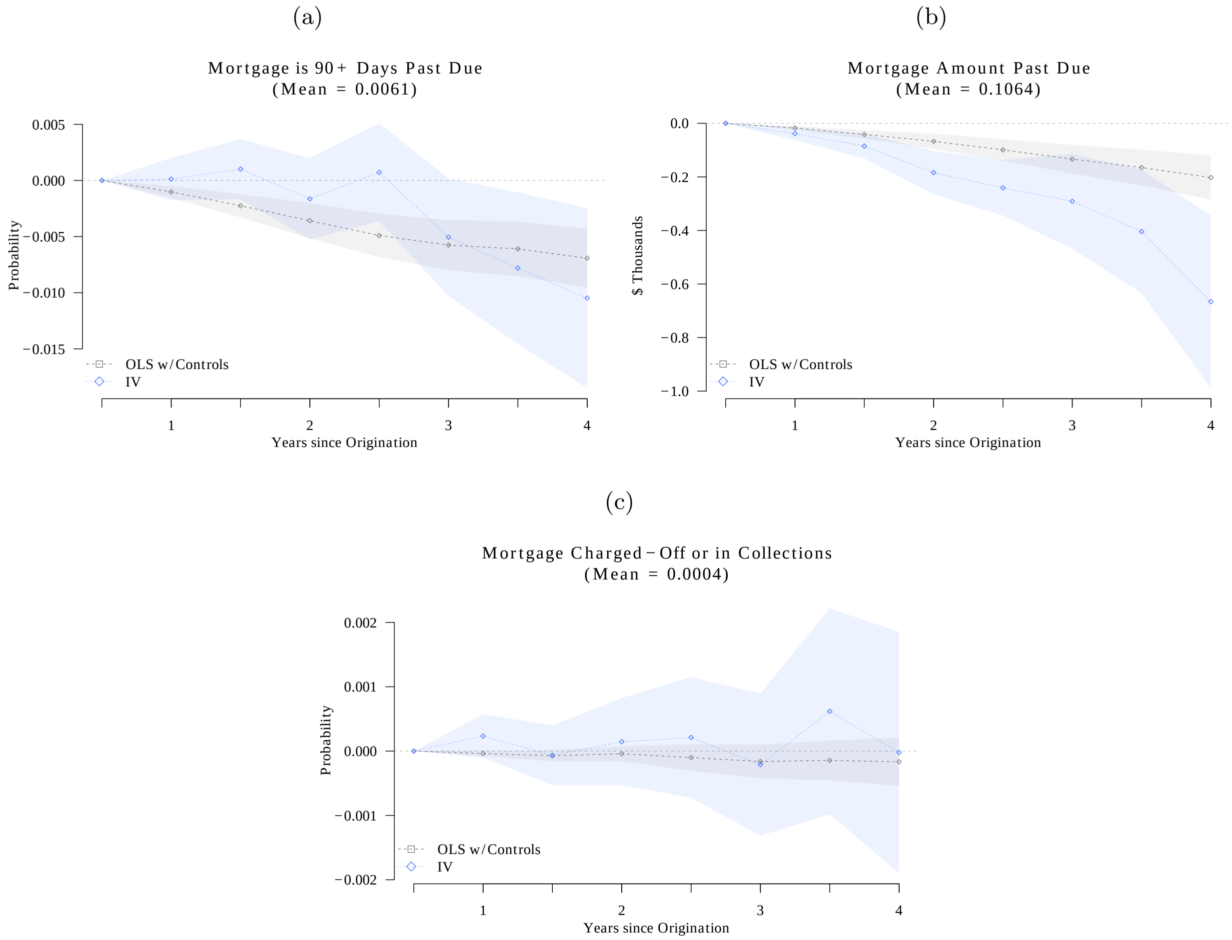
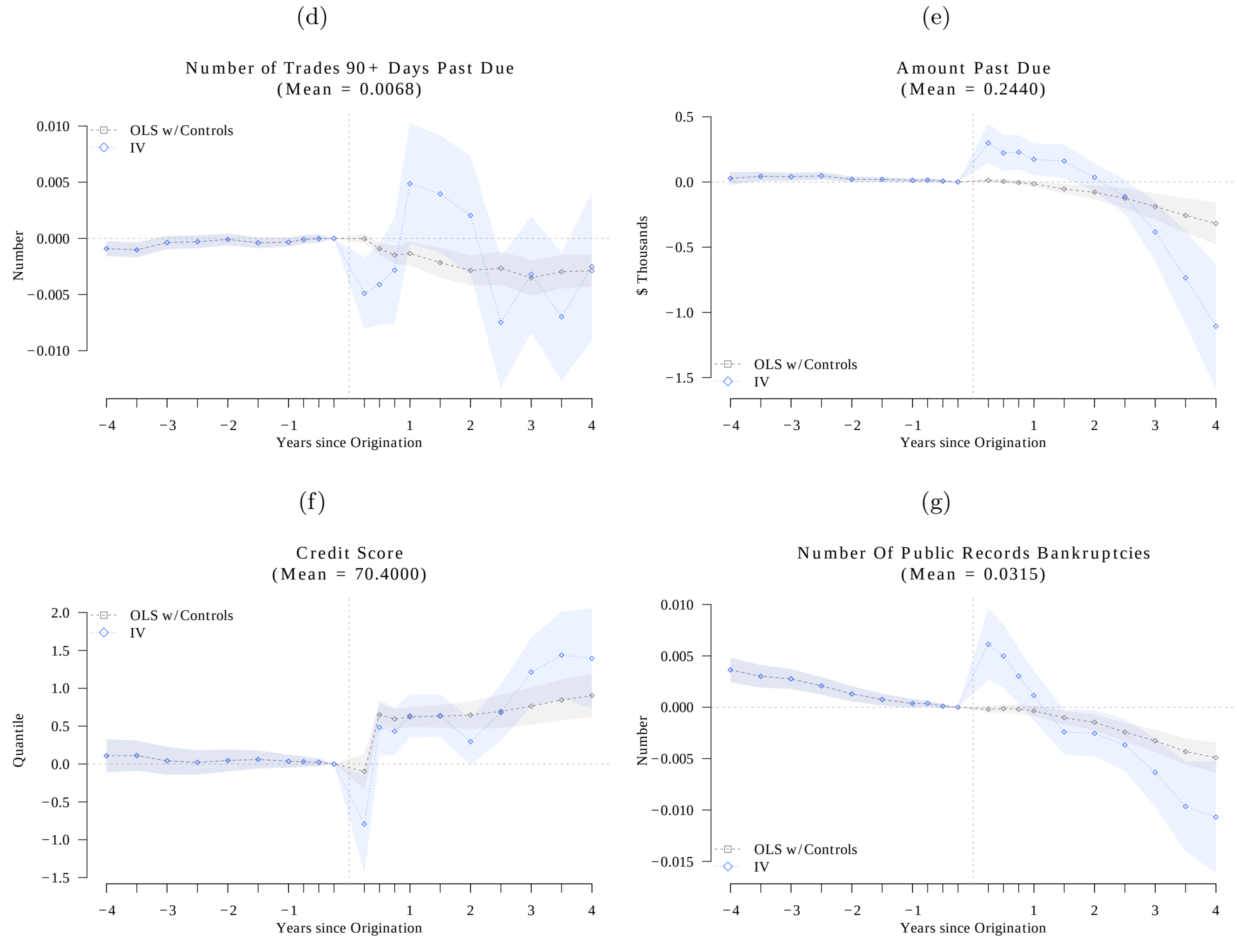
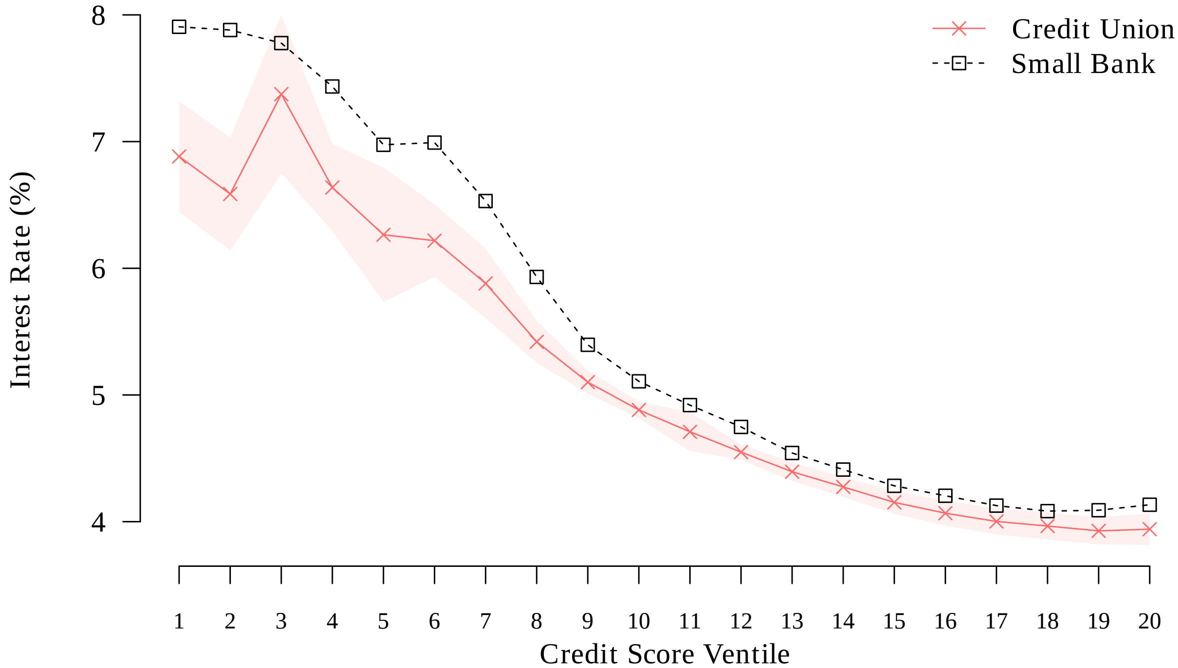


Figure 5. (continued)
CU Treatment Effect on Credit Profile Outcomes



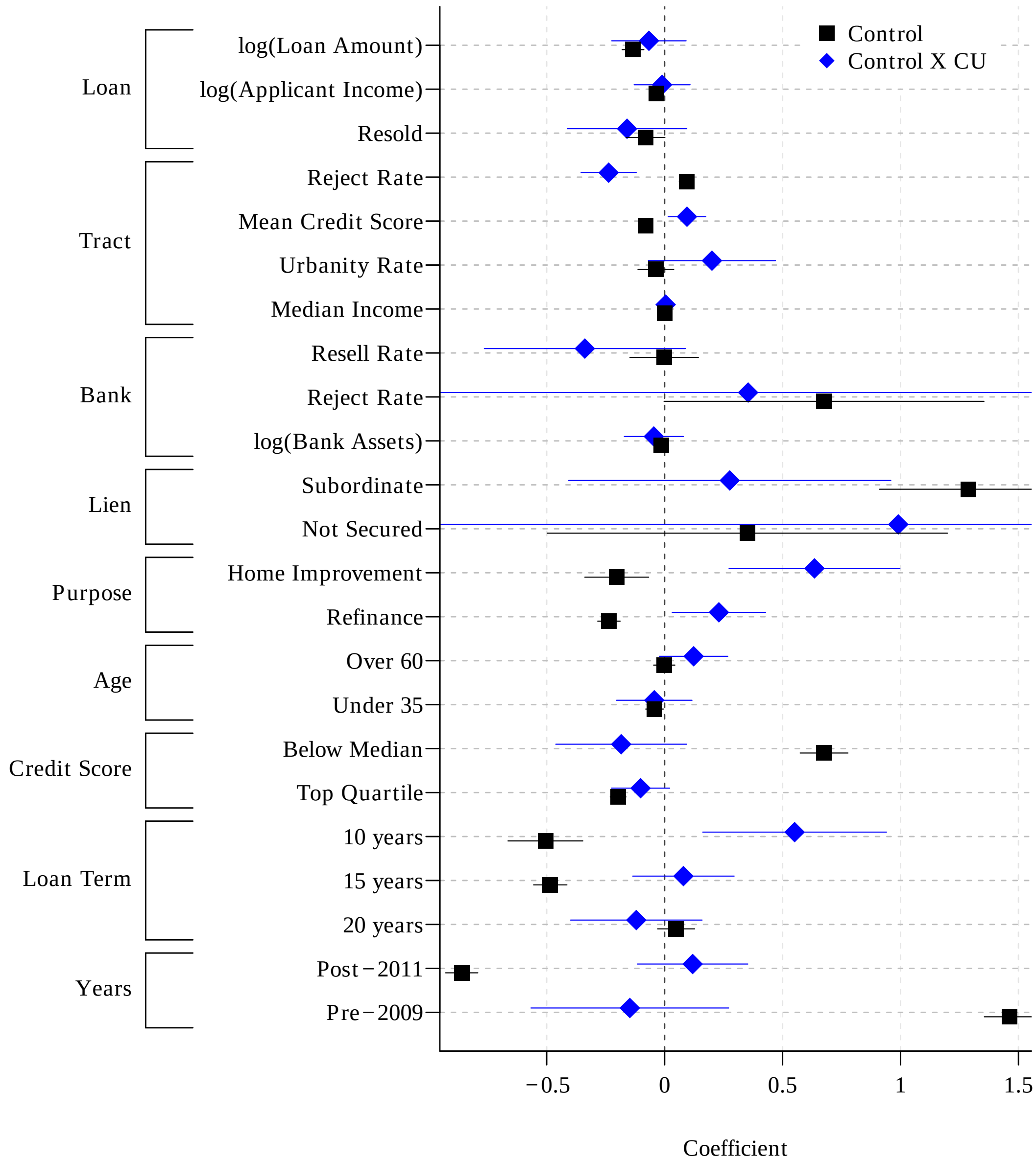

Notes: Data are from the matched sample described in Section 4. Plots show estimates of the $\boldsymbol{\beta}$ coefficients defined in equations (5) and (6), in black squares and blue diamonds, respectively. The $\boldsymbol{\beta}$ coefficients are interpreted as the differential effect that originating a mortgage with a CU has relative to originating a mortgage with a **small** bank. The shaded areas represent 95% confidence intervals based on standard errors clustered at the bank level. Appendix Figure A10 contains the equivalent results when the reference group is large banks.

Figure 6.
Interest Rates by Credit Score



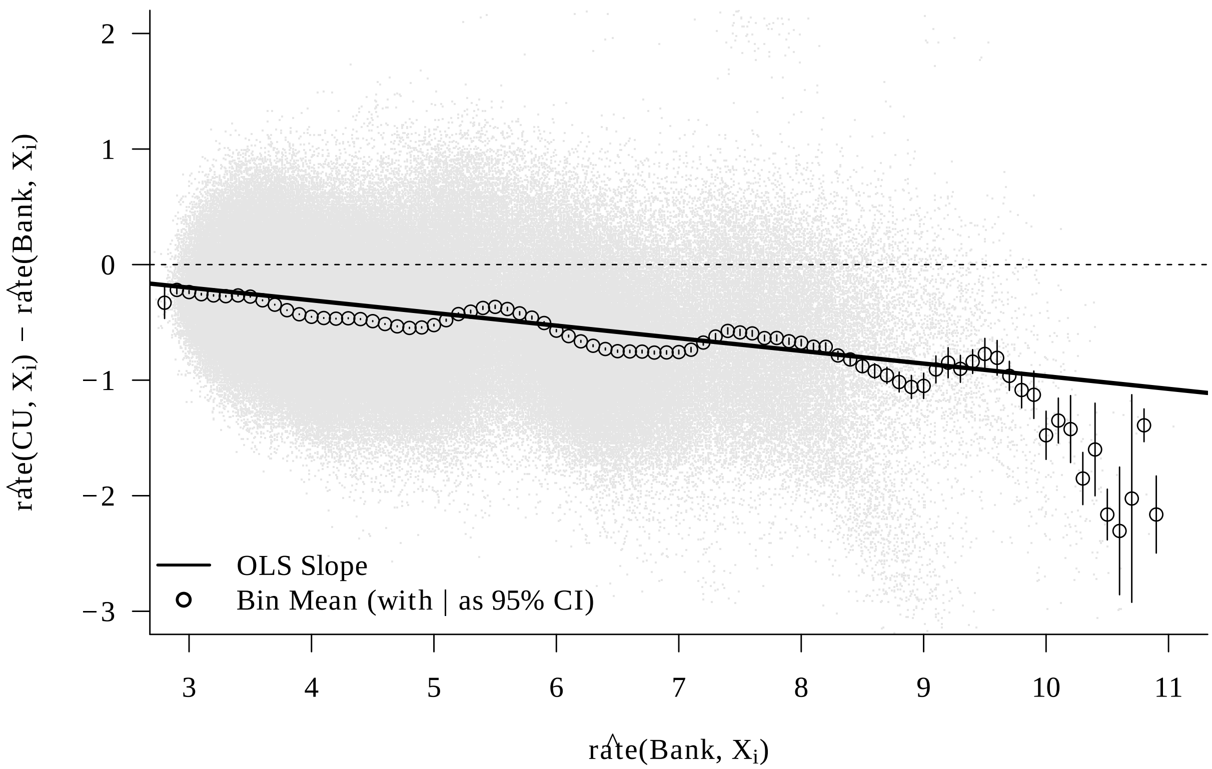

Notes: Data are from the matched sample described in Section 4 restricted to CUs and small banks. Plots coefficients from a regression of interest rates on credit score ventiles interacted with a CU dummy variable.

Figure 7.
Differentialy Priced Factors at CUs vs. Banks



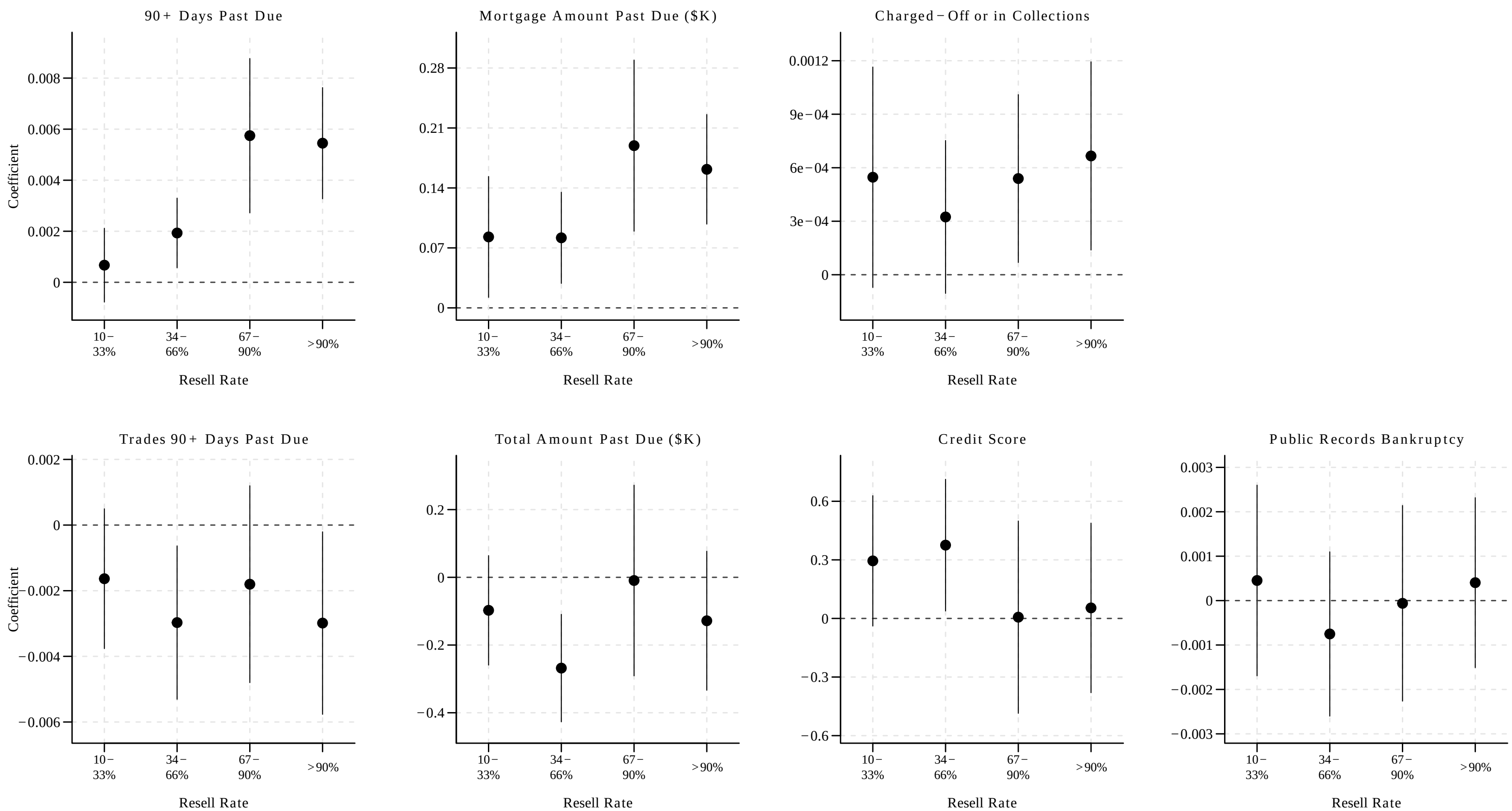

Notes: Data are from the matched sample described in Section 4. Plots show estimated coefficients of $\beta_1$ and $\beta_2$ defined in equation (8), in black squares and blue diamonds, respectively. The $\beta_1$ coefficient captures the coefficient of a given control variable on interest rates, and the $\beta_2$ coefficient captures the additive effect of the given variable on interest rates for CUs. The horizontal lines around squares and diamonds represent 95% confidence intervals based on standard errors clustered at the bank level. For loan, tract, and bank variables, each coefficient pair is derived from a separate regression. For the rest of the groups, the coefficients come from one regression per group because they are a variable being discretized into dummies or categorical variables treated as dummies. The excluded category for each group, in descending order, is: first lien, home purchase, between 35 and 60, third quartile, 30 years, and 2009–2011. Appendix Table A4 reports the coefficients for these excluded base categories in column "CU."

Figure 8.
Counterfactual Individual Prices at CUs vs. Banks



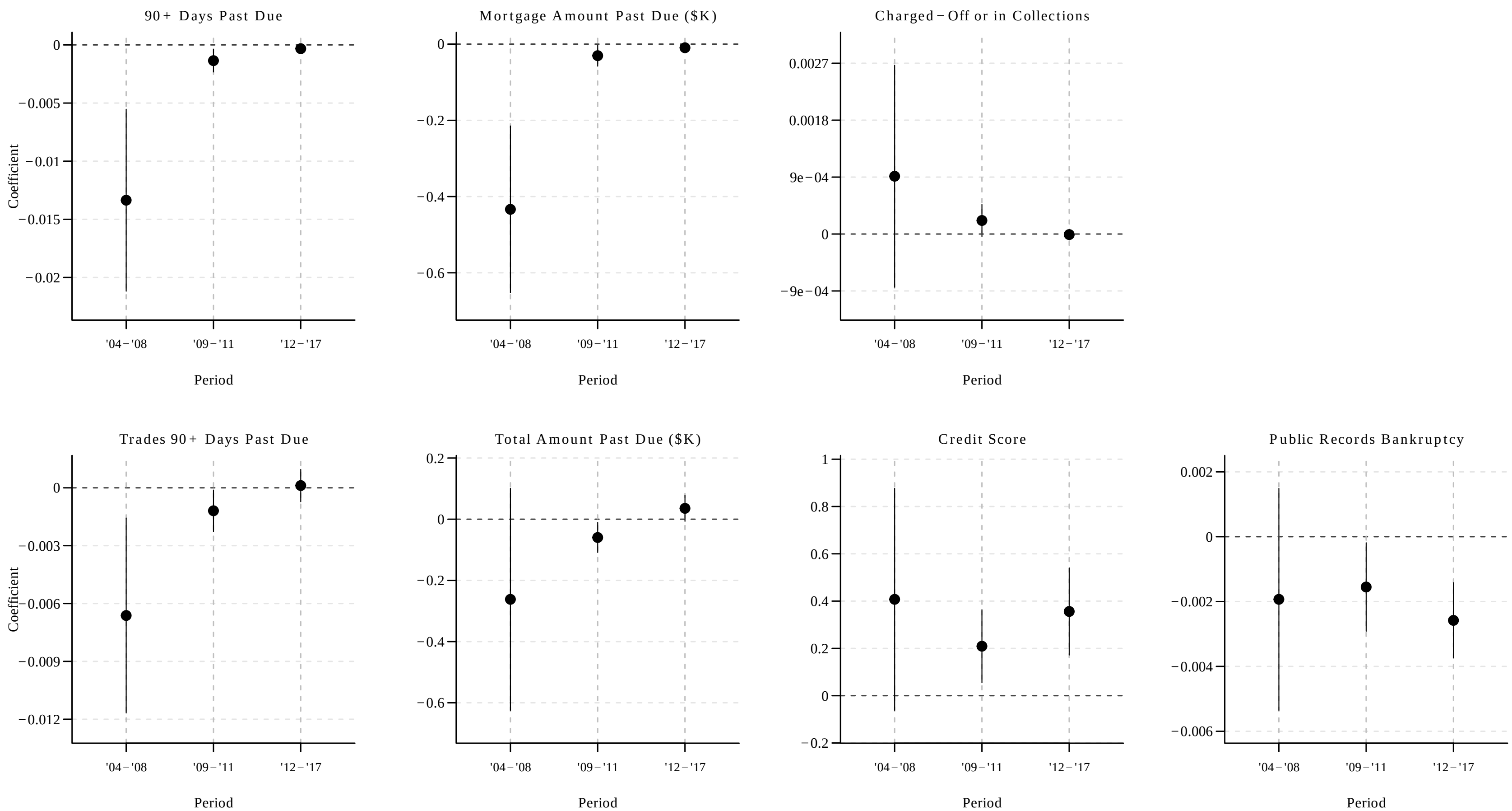

Notes: Data are from the matched sample described in Section 4 restricted to CUs and small banks. Plots counterfactual CU and bank interest rates for all individuals.

Figure 9.
Heterogeneity in Credit Outcomes by Secondary Market Resell Rates




Notes: Data are from the matched sample described in Section 4. Plots show estimated coefficients of $\beta_1$, $\beta_2$, and $\beta_3$ defined in OLS equations (11) and (12). The coefficients capture the association with changes in credit outcomes for CUs that have high, mid, and low rates of mortgage reselling. The horizontal lines around the symbols represent 95% confidence intervals based on standard errors clustered at the bank level.

Figure 10.
Heterogeneity in Credit Outcome Effects by Time Period




Notes: Data are from the matched sample described in Section 4. Black squares represent estimates of $\beta$ three years after origination from equation (5). An independent regression is run on three mutually exclusive data subsamples, one for each time period, and extracting the coefficient $\beta$ corresponding to three years post origination. The horizontal lines around the symbols represent 95% confidence intervals based on standard errors clustered at the bank level.

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# A Appendix Figures and Tables

Appendix Table A1.
Differential Likelihood of Identifying Interest Rates

| Category | Variable | Coefficient | St. Error |
|---|---|---|---|
| | CU | 0.034 | (0.008) |
| Loan Characteristics | log(Loan Amount) | 0.020 | (0.003) |
| | Loan was Resold | 0.017 | (0.004) |
| | log(Applicant Income) | −0.029 | (0.002) |
| Tract Characteristics | Reject Rate | 0.010 | (0.002) |
| | Credit Score | 0.001 | (0.002) |
| | Fraction Urban | 0.001 | (0.003) |
| | Median Income | −0.000 | (0.000) |
| Bank Characteristics | Loan Reject Rate | −0.059 | (0.013) |
| | Loan Resell Rate | 0.106 | (0.031) |
| | log(Assets) | −0.002 | (0.002) |
| Years | Pre-2009 | −0.166 | (0.009) |
| | Post-2011 | −0.031 | (0.008) |
| Loan Purpose | Home Improvement | −0.001 | (0.008) |
| | Refinance | −0.136 | (0.015) |
| Lien Status | Subordinate | 0.015 | (0.005) |
| | Not Secured | −0.004 | (0.003) |
| Term (Years) | 10 | −0.130 | (0.007) |
| | 15 | −0.124 | (0.003) |
| | 20 | −0.040 | (0.003) |
| Borrower Age | Under 35 | 0.003 | (0.001) |
| | Over 60 | 0.014 | (0.002) |
| Credit Score | Below 50 | −0.004 | (0.003) |
| | Above 75 | −0.023 | (0.002) |
| | Constant | 0.798 | (0.057) |
| | N | 1,153,367 | |
| | Adj. R2 | 0.03 | |

Notes: Data are from the matched sample described in Section 4, limited to CUs and small banks. Table reports results from regressing an indicator variable for whether the observation has a successfully estimated interest rate or not. Standard errors calculated at the lender-level are reported in parentheses. Section 4.4 details the calculation of implied interest rates

## Appendix Table A2.
## Complier Characteristics

| Variable | Percent Compliers |
|---|---|
| Loan Characteristics | |
| – log(Loan Amount) | 6.0 |
| – Loan was Resold | 6.5 |
| – log(Applicant Income) | 7.9 |
| Tract Characteristics | |
| – Credit Score | 8.6 |
| – Reject Rate | 9.7 |
| – Fraction Urban | 9.4 |
| – Median Income | 8.2 |
| Bank Characteristics | |
| – Loan Resell Rate | 4.3 |
| – Loan Reject Rate | 10.6 |
| – log(Assets) | 5.9 |
| Lien Status | |
| – First | 9.7 |
| – Subordinate | 11.7 |
| – Not Secured | 19.5 |
| Loan Purpose | |
| – Home Purchase | 7.9 |
| – Home Improvement | 14.7 |
| – Refinance | 10.8 |
| Years | |
| – Pre-2009 | 6.7 |
| – 2009 to 2011 | 8.4 |
| – Post-2011 | 11.1 |
| Age | |
| – Under 35 | 9.6 |
| – 35-60 | 9.8 |
| – Over 60 | 11.8 |
| Credit Score Percentile | |
| – Below 50 | 11.3 |
| – 50-75 | 10.3 |
| – Above 75 | 9.4 |
| Term (Years) | |
| – 10 | 17.1 |
| – 15 | 11.6 |
| – 20 | 11.0 |
| – 30 | 7.7 |
| Overall Percent Compliers | 10.0 |
| Percent Compliers of Treated | 20.2 |

Notes: Data are from the matched sample described in Section 4, limited to CUs and small banks. Complier percentages are calculated using the methodology in Angrist and Pischke (2009) after discretizing the instrument into a binary variable based on the median value of the instrument. For binary control variables $B$, table reports the percent of compliers among those for whom $B = 1$. For continuous control variables $C$, table reports the percent of compliers among those for whom $C >= median(C)$.

## Appendix Table A3.
## Sensitivity of CU Effect on Interest Rate to Instrument Choice

| | Within 10km | | |
|---|---|---|---|
| | Inverse Distance | Negative Exponential | Branch Count |
| Credit Union | −0.295 | −0.305 | −0.305 |
| | (0.087) | (0.090) | (0.092) |
| N | 767,991 | 767,991 | 767,991 |
| First-Stage F-Statistic | 8,482.48 | 8,786.85 | 8,454.17 |

| | Nearest 20 Branches | | |
|---|---|---|---|
| | Inverse Distance | Negative Exponential | Branch Count |
| Credit Union | −0.291 | −0.303 | −0.294 |
| | (0.081) | (0.083) | (0.082) |
| N | 767,991 | 767,991 | 767,991 |
| First-Stage F-Statistic | 9,370.63 | 10,536.06 | 10,631.99 |

| | Within 10km or Nearest 20 Branches | | |
|---|---|---|---|
| | Inverse Distance | Negative Exponential | Branch Count |
| Credit Union | −0.308 | −0.319 | −0.311 |
| | (0.085) | (0.089) | (0.089) |
| N | 767,991 | 767,991 | 767,991 |
| First-Stage F-Statistic | 11,356.87 | 12,189.42 | 12,148.86 |

Notes: Data are from the matched sample described in Section 4. Table reports estimates of the $\beta_1$ coefficient from equation (3) for nine different instrumental variable specifications. The instrument and its alternative specifications are defined in Section 6.1. The coefficient for "Within 10km" and "Inverse Distance" corresponds to the estimate reported in column (3) of the top panel of Table 4.

Appendix Table A4.
Differential Interest Rates at CUs vs Small Banks: Complete Results

| | | OLS | IV | 1st Stage | CU | Control | CU×Control |
|---|---|---|---|---|---|---|---|
| | Credit Union | −0.107 | −0.295 | | | | |
| | | (0.029) | (0.087) | | | | |
| | Instrument CU Density | | | 0.003 | | | |
| | | | | (0.000) | | | |
| Loan | log(Loan Amount) | −0.152 | −0.152 | −0.003 | 0.019 | −0.134 | −0.067 |
| | | (0.010) | (0.010) | (0.007) | (0.415) | (0.024) | (0.081) |
| | Resold | −0.120 | −0.129 | −0.053 | −0.225 | −0.081 | −0.159 |
| | | (0.016) | (0.017) | (0.012) | (0.118) | (0.042) | (0.129) |
| | log(Applicant Income) | −0.030 | −0.038 | −0.040 | −0.250 | −0.036 | −0.011 |
| | | (0.007) | (0.007) | (0.005) | (0.272) | (0.015) | (0.061) |
| Tract | Mean Credit Score | −0.049 | −0.056 | −0.029 | −0.755 | −0.081 | 0.095 |
| | | (0.006) | (0.006) | (0.008) | (0.228) | (0.013) | (0.041) |
| | Reject Rate | 0.038 | 0.033 | −0.024 | 0.118 | 0.093 | −0.237 |
| | | (0.007) | (0.006) | (0.010) | (0.110) | (0.016) | (0.060) |
| | Fraction Urban | −0.008 | 0.010 | 0.078 | −0.435 | −0.037 | 0.201 |
| | | (0.012) | (0.016) | (0.014) | (0.130) | (0.039) | (0.137) |
| | Median Income | 0.001 | 0.001 | 0.001 | −0.551 | 0.000 | 0.004 |
| | | (0.000) | (0.000) | (0.000) | (0.141) | (0.000) | (0.002) |
| Bank | Resell Rate | −0.003 | −0.080 | −0.391 | −0.163 | −0.002 | −0.338 |
| | | (0.038) | (0.055) | (0.033) | (0.115) | (0.074) | (0.217) |
| | Reject Rate | 0.750 | 0.757 | 0.069 | −0.350 | 0.676 | 0.354 |
| | | (0.194) | (0.180) | (0.147) | (0.145) | (0.346) | (0.949) |
| | log(Bank Assets) | −0.017 | −0.022 | −0.031 | 0.648 | −0.014 | −0.046 |
| | | (0.007) | (0.008) | (0.010) | (1.256) | (0.010) | (0.064) |
| Lien | Subordinate | 1.393 | 1.419 | 0.111 | −0.315 | 1.288 | 0.276 |
| | | (0.056) | (0.057) | (0.025) | (0.083) | (0.192) | (0.348) |
| | Not Secured | 0.749 | 0.753 | −0.021 | −0.315 | 0.351 | 0.991 |
| | | (0.081) | (0.087) | (0.076) | (0.083) | (0.433) | (0.991) |

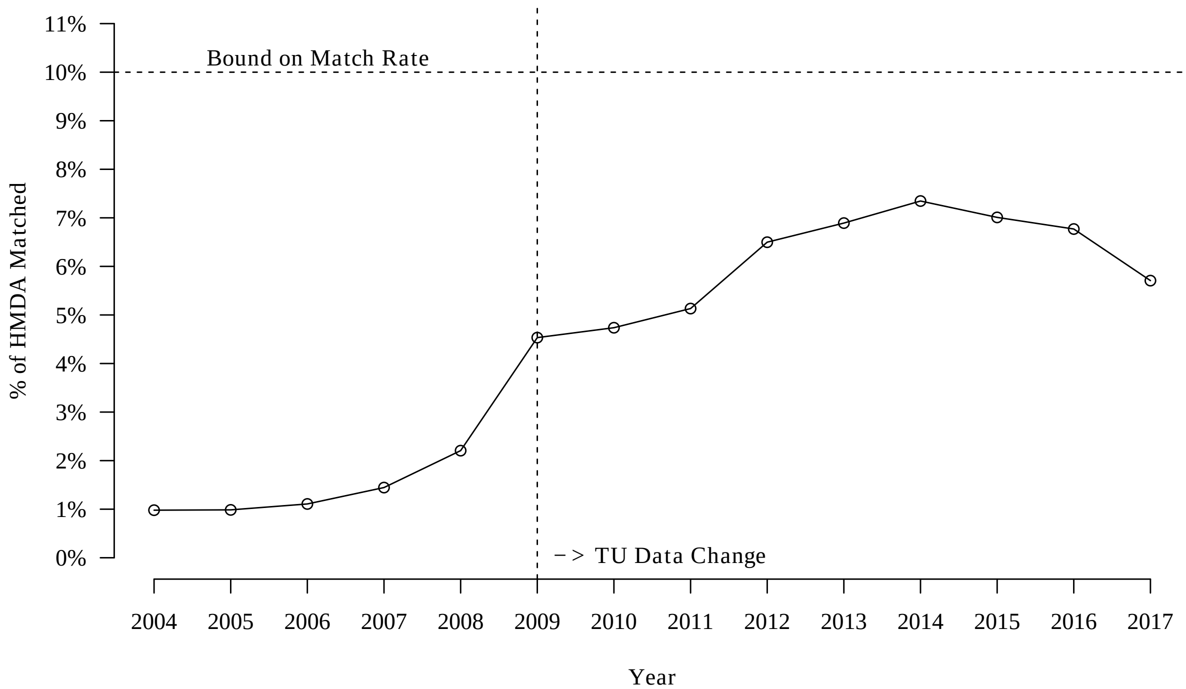
Continued on next page

**Appendix Table A4 – continued from previous page**

| | | OLS | IV | 1st Stage | CU | Control | CU×Control |
|---|---|---|---|---|---|---|---|
| Purpose | Home Improvement | −0.010 | −0.003 | 0.044 | −0.488 | −0.203 | 0.635 |
| | | (0.028) | (0.026) | (0.016) | (0.119) | (0.069) | (0.185) |
| | Refinance | −0.200 | −0.188 | 0.067 | −0.488 | −0.236 | 0.230 |
| | | (0.012) | (0.015) | (0.008) | (0.119) | (0.024) | (0.101) |
| Year | Pre-2009 | 1.465 | 1.445 | −0.104 | −0.365 | 1.461 | −0.147 |
| | | (0.030) | (0.030) | (0.014) | (0.136) | (0.054) | (0.214) |
| | Post-2011 | −0.841 | −0.829 | 0.054 | −0.365 | −0.860 | 0.119 |
| | | (0.017) | (0.018) | (0.011) | (0.136) | (0.035) | (0.119) |
| Age | Under 35 | −0.049 | −0.052 | −0.013 | −0.308 | −0.043 | −0.044 |
| | | (0.006) | (0.006) | (0.003) | (0.093) | (0.019) | (0.082) |
| | Over 60 | 0.035 | 0.034 | −0.001 | −0.308 | −0.002 | 0.123 |
| | | (0.006) | (0.006) | (0.004) | (0.093) | (0.023) | (0.074) |
| Score | Below Median | 0.630 | 0.628 | −0.014 | −0.225 | 0.676 | −0.184 |
| | | (0.025) | (0.025) | (0.005) | (0.091) | (0.052) | (0.142) |
| | Top Quartile | −0.223 | −0.223 | 0.001 | −0.225 | −0.197 | −0.102 |
| | | (0.006) | (0.006) | (0.003) | (0.091) | (0.017) | (0.063) |
| Term | 10 years | −0.288 | −0.276 | 0.067 | −0.386 | −0.505 | 0.551 |
| | | (0.028) | (0.030) | (0.018) | (0.085) | (0.081) | (0.199) |
| | 15 years | −0.470 | −0.467 | 0.018 | −0.386 | −0.485 | 0.080 |
| | | (0.016) | (0.016) | (0.005) | (0.085) | (0.036) | (0.110) |
| | 20 years | 0.016 | 0.012 | −0.014 | −0.386 | 0.049 | −0.120 |
| | | (0.017) | (0.018) | (0.009) | (0.085) | (0.040) | (0.142) |
| | N | 767,991 | 767,991 | 1,153,367 | | | |
| | Adj. R2 | 0.45 | | 0.204 | | | |
| | F-stat. | | 8,482.48 | | | | |

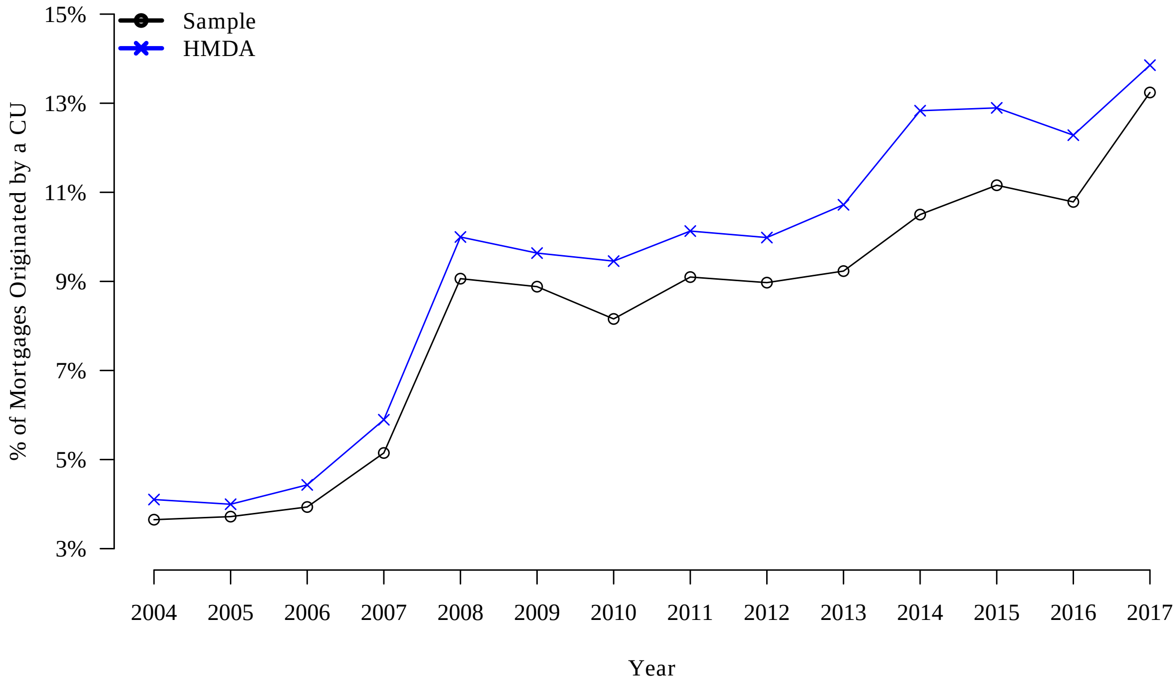
Notes: Data are from the matched sample described in Section 4. Table reports regression coefficients for equations (2), (3) and (8). The column OLS and IV correspond to equations (2) and (3), respectively. Each triple of coefficients in the last three columns reports the estimates $\beta_1$, $\beta_2$, and $\alpha^x$ for each of the regressions specified in equation (8). For loan, tract, and bank variables, each coefficient triple is derived from a separate regression. For the rest of the groups, the coefficients come from one regression per group as they are a variable being discretized into dummies or categorical variables treated as dummies. The excluded category for each group, in descending order, is: first lien, home purchase, between 5–60, third quartile, 30 years, and 2009–2011.

Appendix Figure A1.
TU-HMDA Match Rate



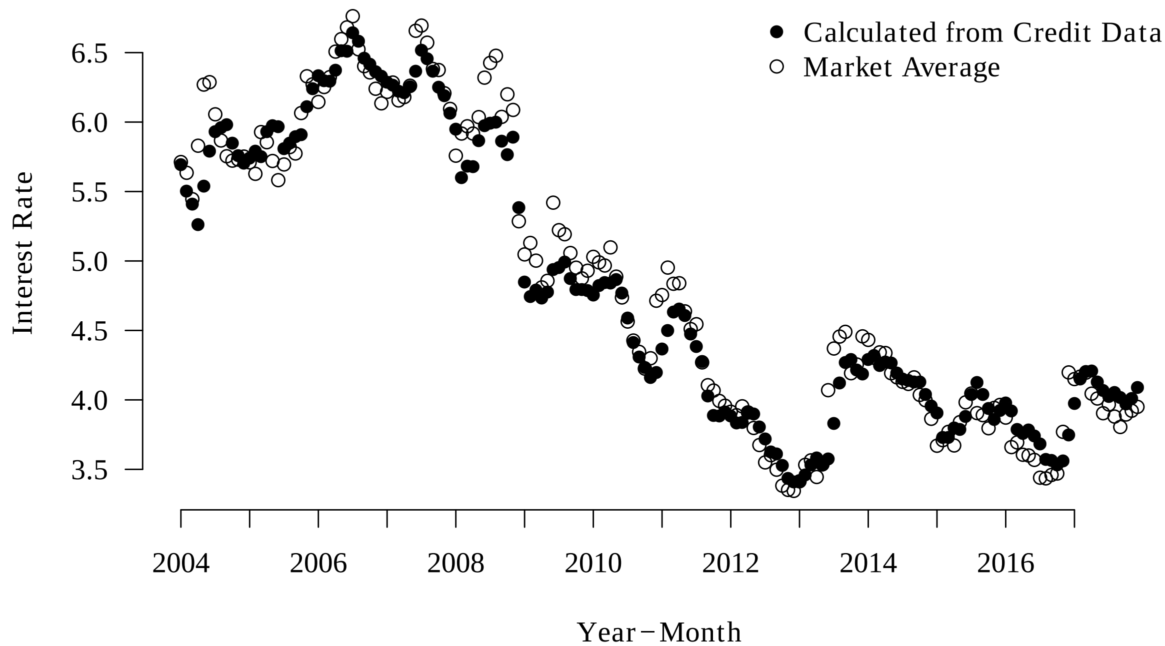

Notes: Figure plots the number of mortgages in the matched sample (including non-bank originations) as a fraction of total originations in the HMDA data. The bound on the match rate is set at 10% because the credit records data are a 10% sample.

Appendix Figure A2.
CU Representation in Population vs. Matched Sample



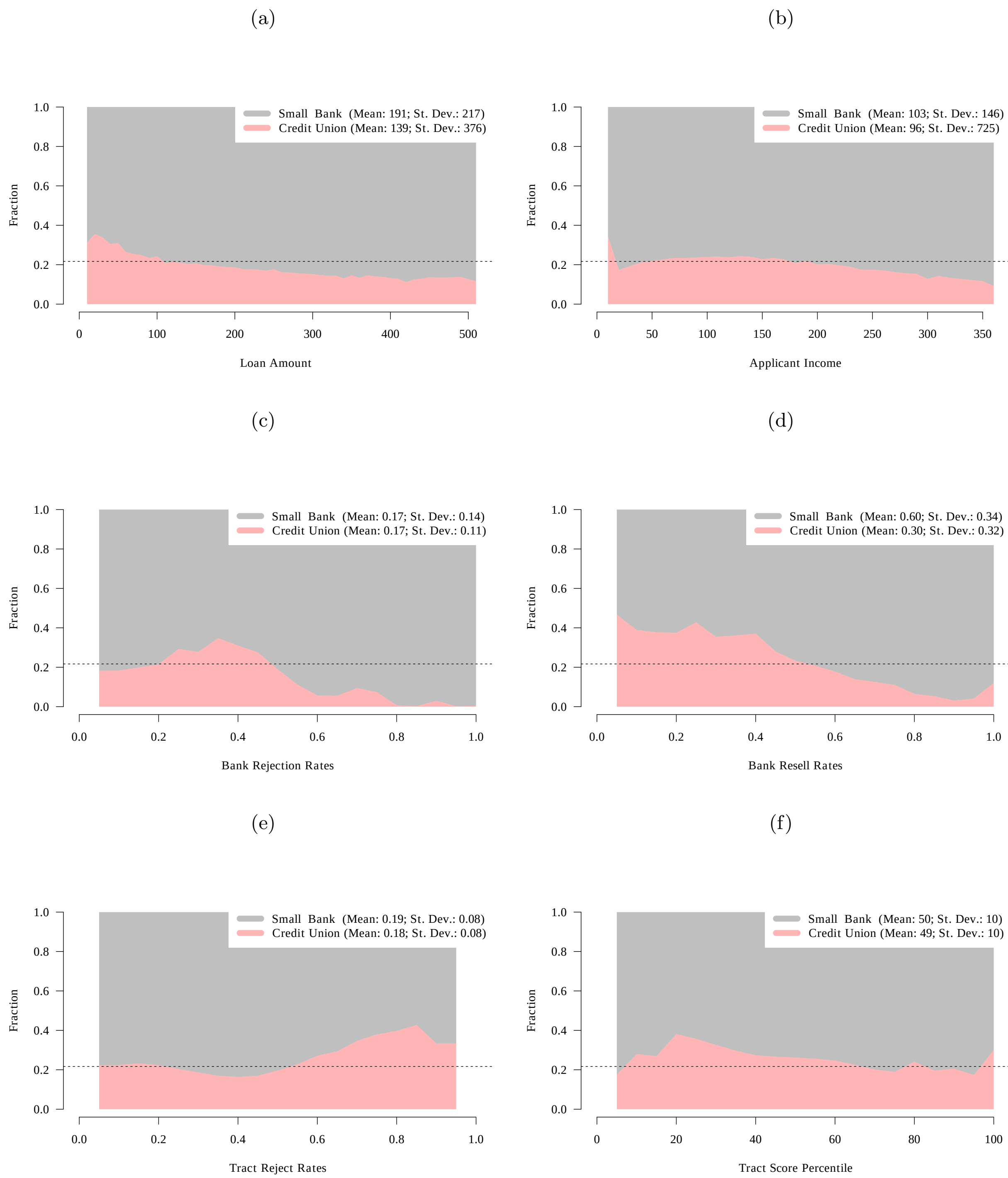

Notes: Figure plots the number of CU-originated mortgages as a fraction of total originations in two samples: the HMDA universe and in the matched sample.

Appendix Figure A3.
Derived vs. Actual Interest Rates



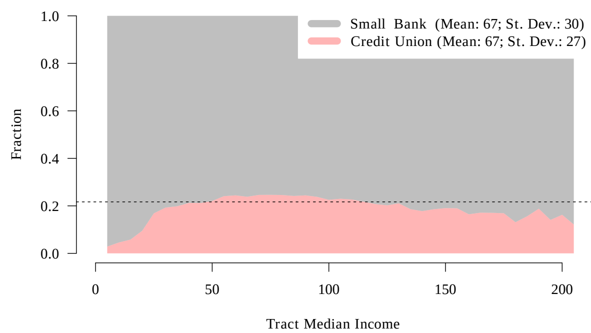

Notes: Data are from the matched sample described in Section 4 and averages of 30-year fixed rate mortgages from FRED. Plot shows the mean of originations and market averages by month. Section 4.4 details the calculation of implied interest rates.

Appendix Figure A4.
CU Fraction of Loans Across Distribution of Loan Characteristics

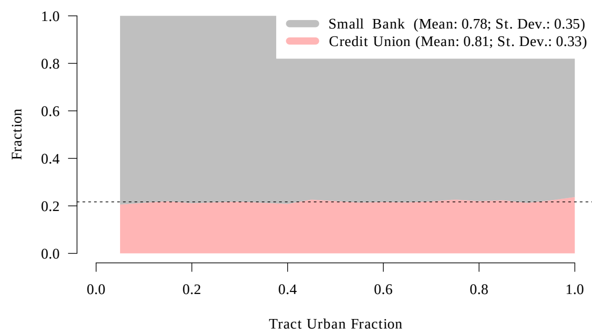


Appendix Figure A4. (continued)

(g)




(h)

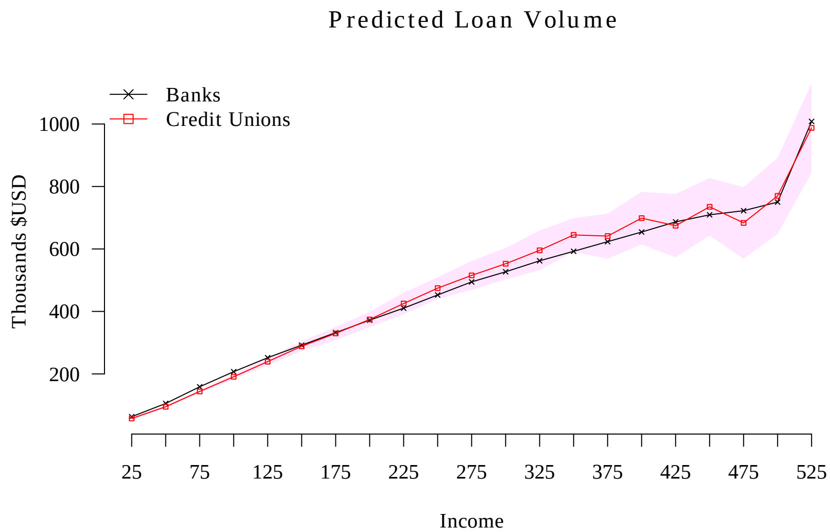



Notes: Mortgage data are from HMDA and credit records data are from TransUnion. Each plot is based on the universe of conventional (i.e., non-FHA, VA, FSA, or RHS) mortgages with a first-lien on an owner-occupied, one-to-four family property in HMDA from 2004 to 2017. A bank is defined as a small bank if its total assets reported to HMDA on the given year are less/more than 105% the total assets of the largest Credit Union in that year.

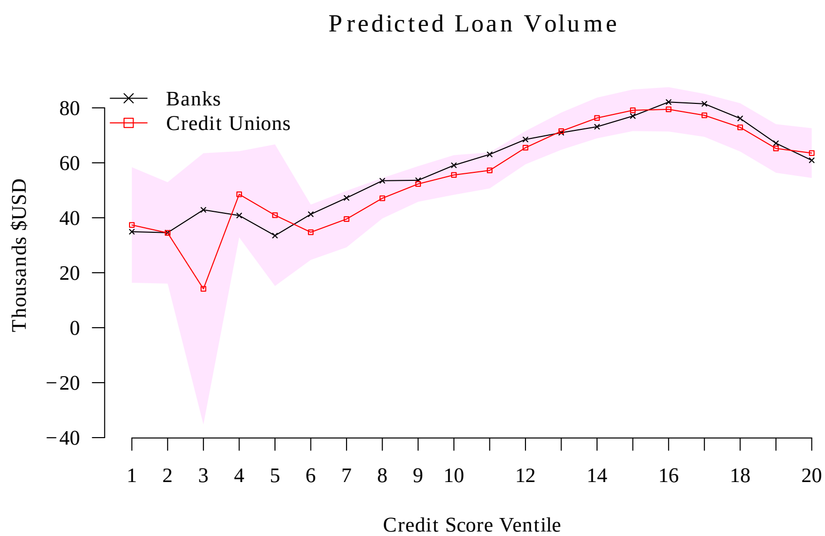
In Panels (a) and (b), amounts are presented in thousands of US Dollars. In Panel (c) bank rejection rates are calculated at the bank-year level and represent the fraction of applications that a bank reported to HMDA and were not originated due to a denial. In Panel (d) bank resell rates are calculated at the bank-year level and represent the fraction of loans that were originated by a lender and sold within the same calendar year. In Panel (e) tract reject rates are computed at the tract-year level, and fraction of applications from a given tract that were reported to HMDA and were not originated due to a denial. In Panel (f) mean tract score percentiles are calculated at the tract-year level. Tract median income in Panel (g) is in thousands of constant 2012 US Dollars and comes from Census data. Panel (f) shows the distribution of tracts' urban fractions according to Census data.

Appendix Figure A5

(a)




(b)

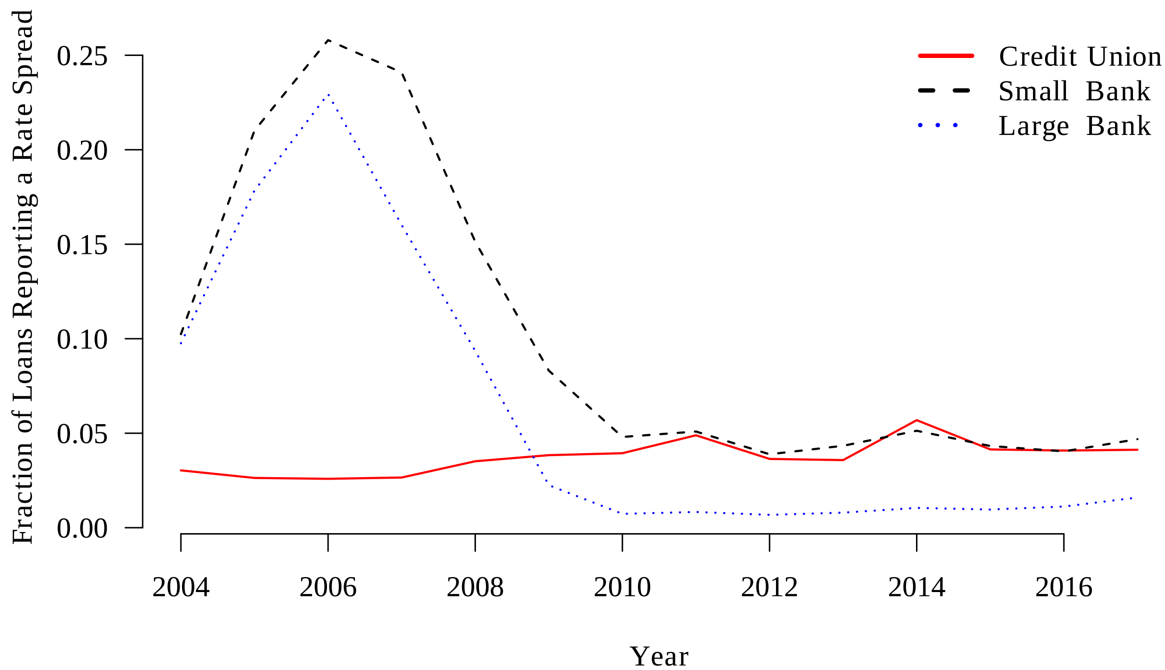



Notes: Data are from the matched sample described in Section 4 restricted to loans for a home purchase with a first lien, comparing CUs to small banks. The figures plot the predicted loan amount based on the following regression

$$LoanAmount = CU + IncomeGroup \times CU + ScoreVentile \times CU.$$

Panel (a) usese the 11 credit score ventile to set the intercept level and panel (b) uses the $75K to $100K group to set the intercept level.

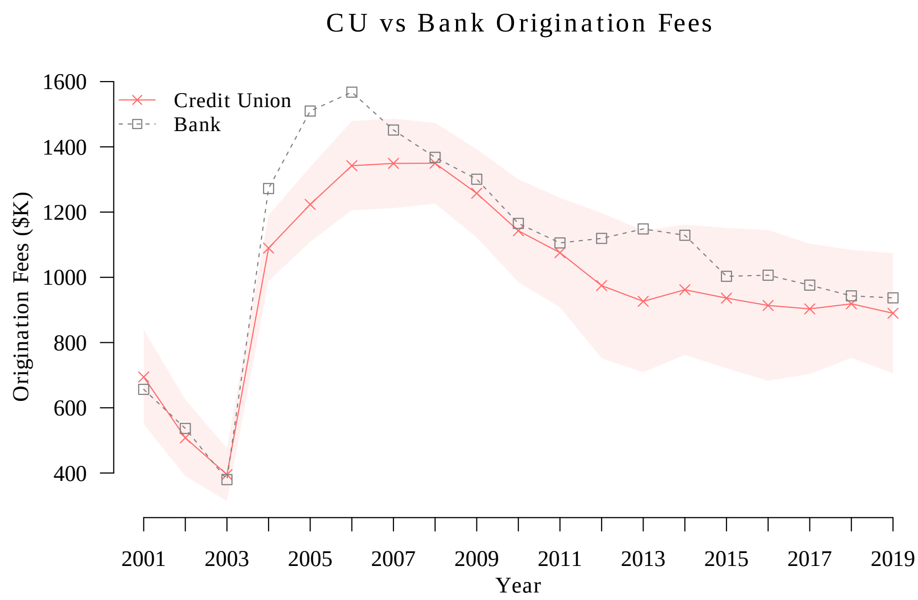
Appendix Figure A6.
Loans Reporting a "High" Interest Rate in HMDA



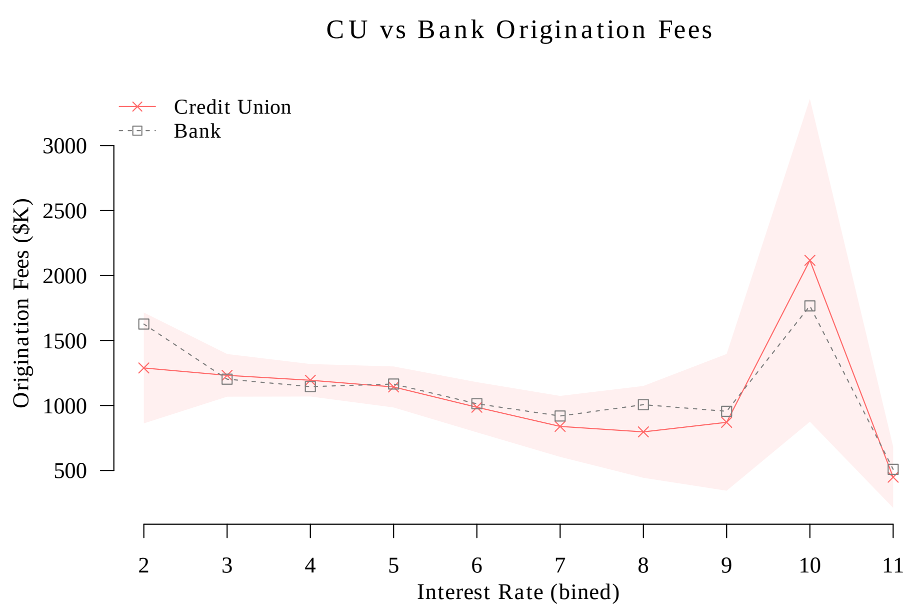

Notes: Data are from the HMDA, restricted to originated loans. The HMDA requires lenders to report a "rate spread" on loans with an interest rate that is 3% (or 1.5%, depending on the year) points above the Treasury yield. Plot shows the fraction of loans by lender type and year that report a rate spread.

Appendix Figure A7

(a)

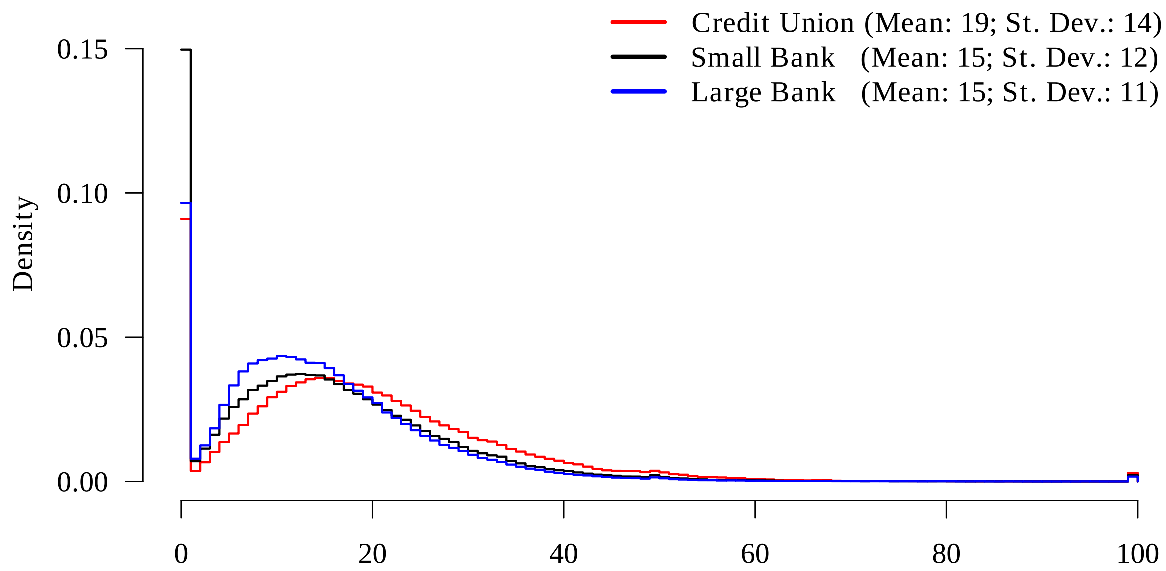



(b)



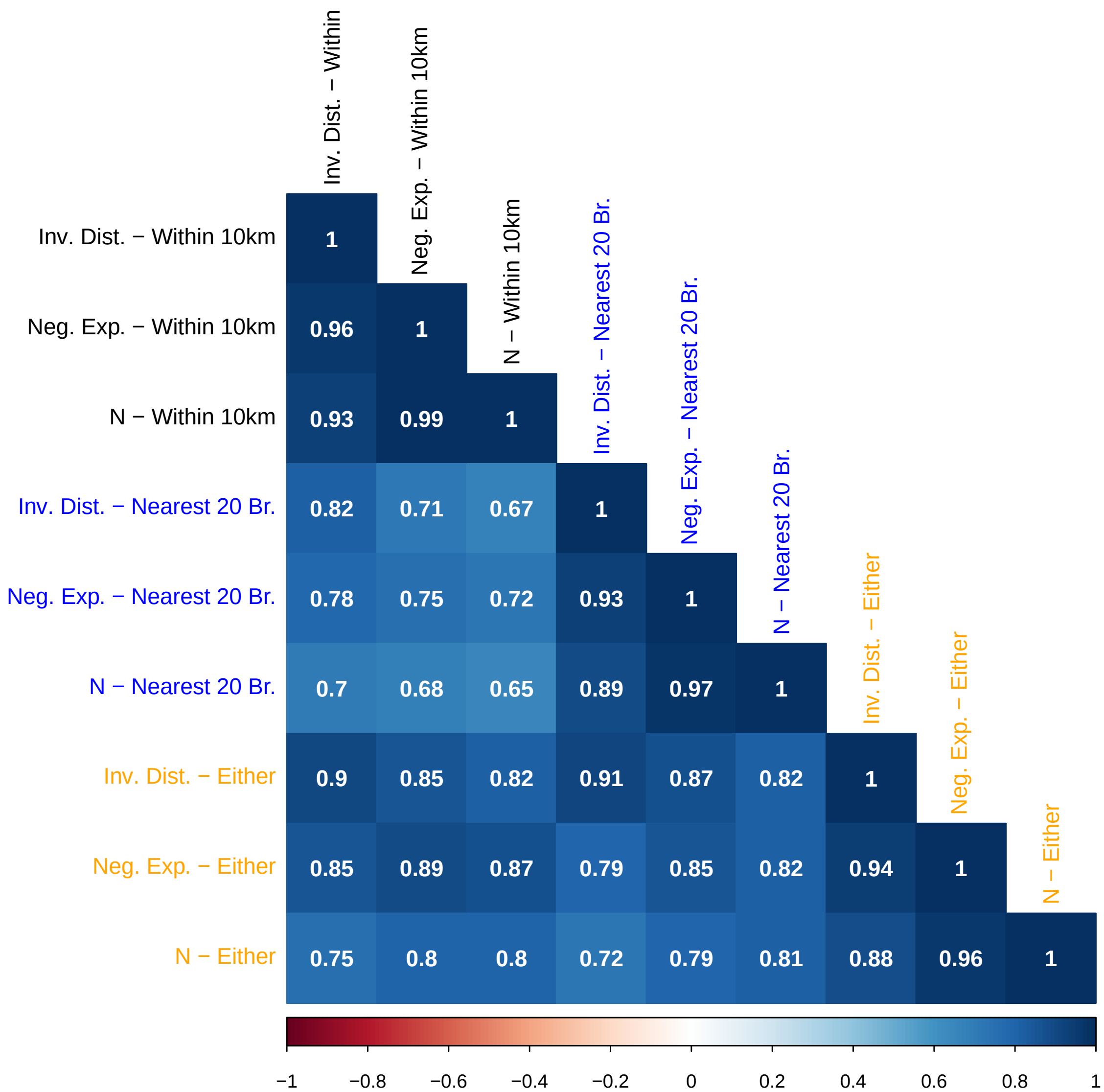

Notes: Data are from S&P Ratewatch. Panel (a) and (b) plot the coefficients from the following regression $OriginationFees = CU + Year + InterestRate + CU \times Year + CU \times InterestRate$, where $CU$ is a dummy for whether the bank branch is a Credit Union, as opposed to a bank. Interest rates are grouped by rounding down to their nearest integer. Panel (a) shows the predicted origination fees for banks and CUs by year, and panel (b) shows the predicted origination fees by banks and CUs by interest rate level.

Appendix Figure A8.
Distribution of Instrument Values by Lender



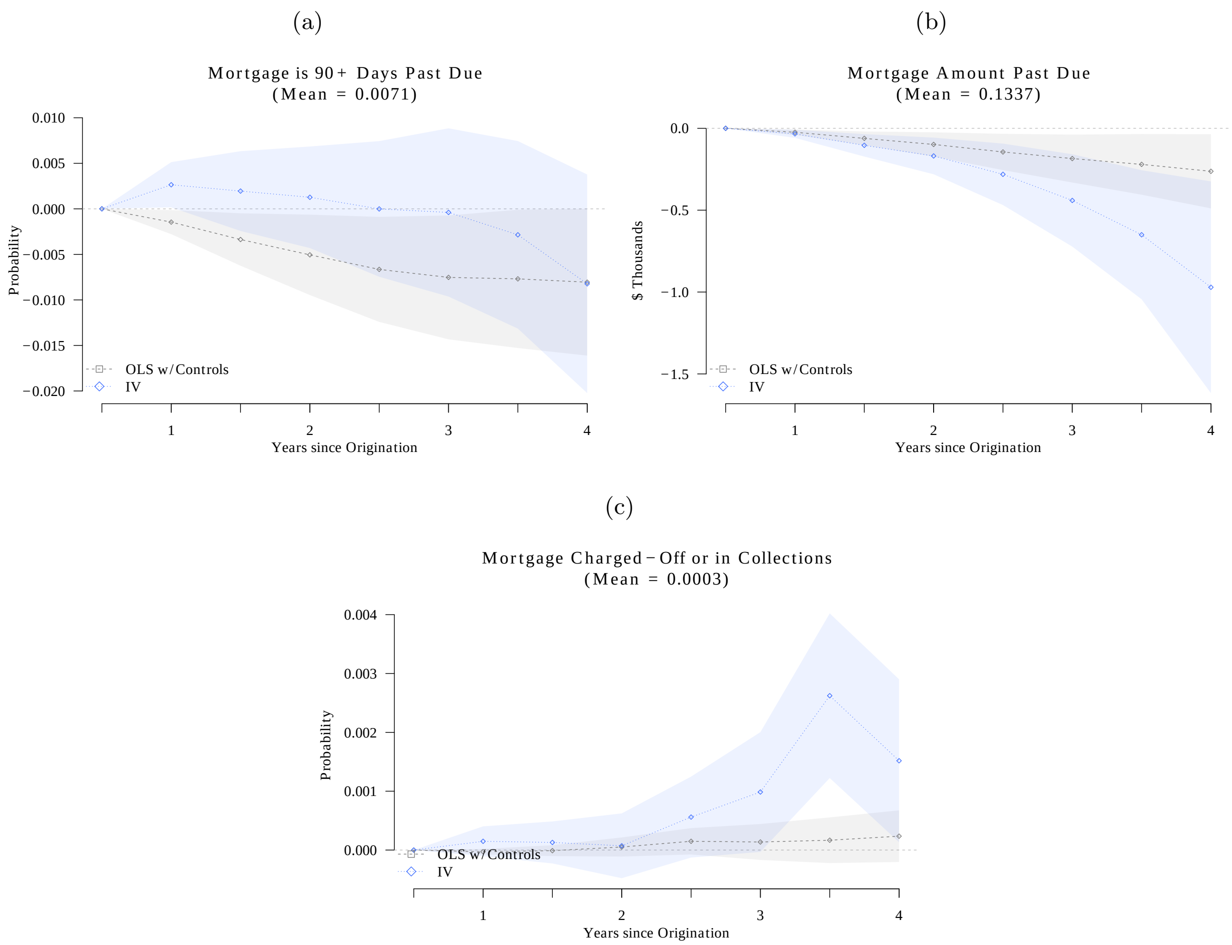

Notes: Data are from the matched sample described in Section 4 and plot a histogram of the instrument values for mortgages by bank type. The instrument is defined in Section 6.1. All three histograms use a bin width of one.

Appendix Figure A9.
Correlation Between Instrument Specifications



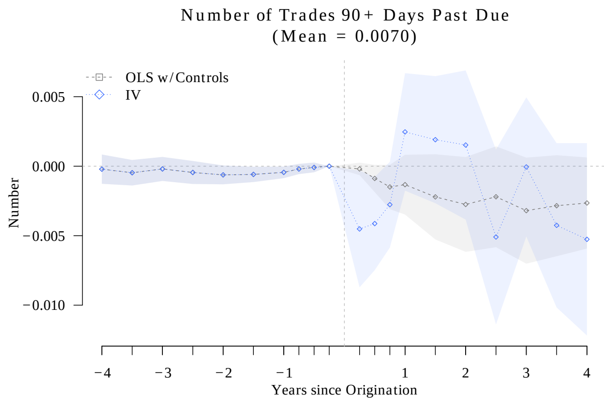

Notes: Data are from the matched sample described in Section 4 and present a correlation matrix of the nine instrument specifications considered. The instrument and its alternative specifications are defined in Section 6.1.

Appendix Figure A10.
CU Treatment Effect on Mortgage Outcomes, to Large Banks

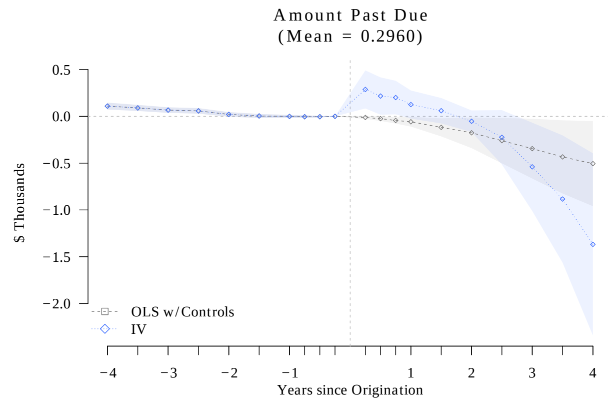


Appendix Figure A10. (continued)
CU Treatment Effect on Credit Profile, Relative to Large Banks

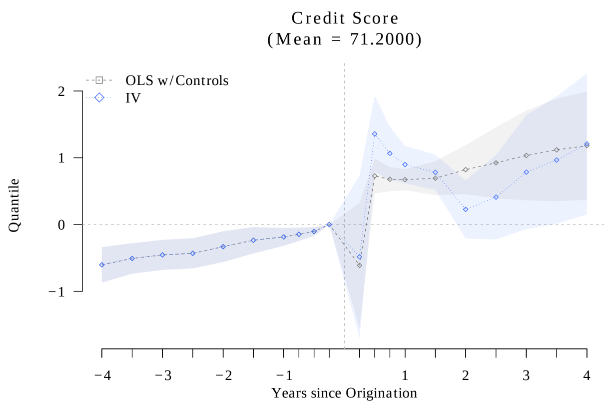
(d)



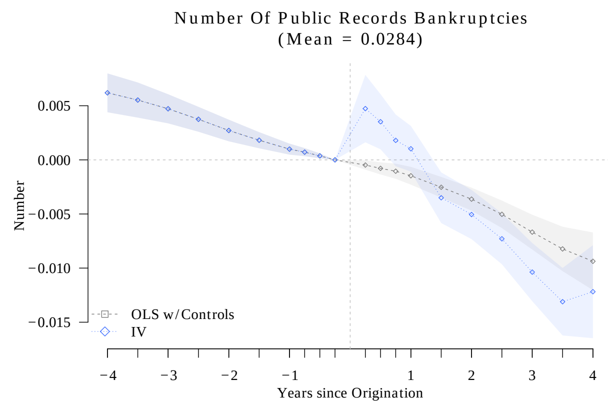

(e)




(f)



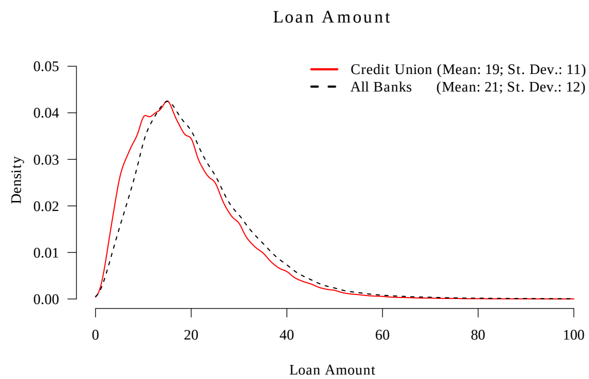

(g)



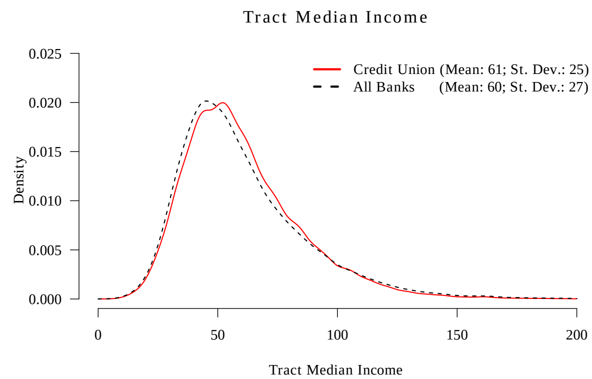

Notes: Data are from the matched sample described in Section 4. Plots show estimates of the $\boldsymbol{\beta}$ coefficients defined in equations (5) and (6), in black squares and blue diamonds respectively. The $\boldsymbol{\beta}$ coefficients are interpreted as the differential effect that originating a mortgage with a CU has relative to originating a mortgage with a **large** bank. The shaded areas represent 95% confidence intervals based on standard errors clustered at the bank level. Figure 5 contains the equivalent results when the reference group is small banks.

Appendix Figure A11.
Characteristics of Auto Loans

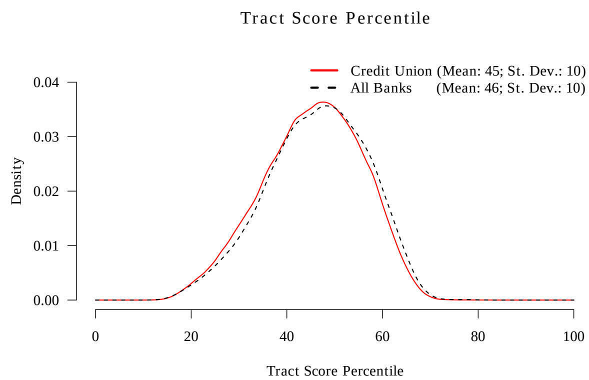
(a)



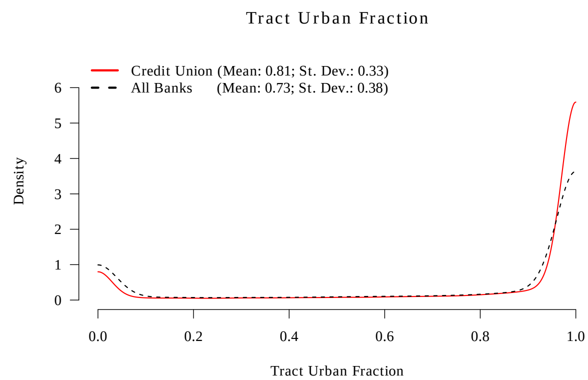

(b)



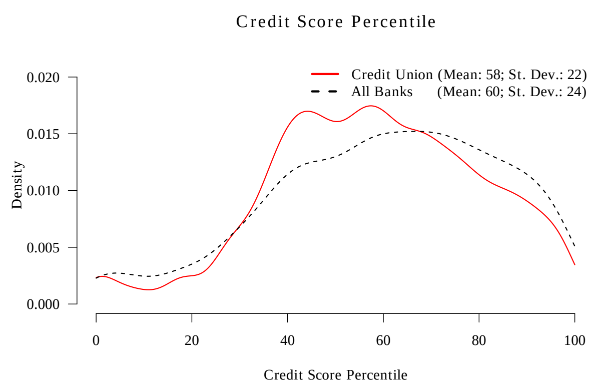

(c)




(d)




(e)




Notes: Data are from TransUnion and Census. Each subfigure plots kernel density estimates based on the originated by banks and CUs 2004 to 2017 in the TransUnion sample. Densities of a given variable are weighted by the number of originated loans. Panels (a) and (b) show amounts in thousands of US Dollars. Panel (b) is in constant 2012 US dollars and is derived from Census data. Panel (c)'s mean tract score percentiles are calculated at the tract-year level. Panel (d)'s tract urban fractions are derived from Census data. Panel (e) shows borrower credit score percentile at origination. See further details in Figure 1.

## B Derivation of Probability of CU Choice in Bounded Search Model

As in Section 6.1.1, let the probability that a borrower samples a CU be given by:

$$\rho = \frac{\sum_{l \in C} \frac{1}{d(i,l)}}{\sum_{l \in C} \frac{1}{d(i,l)} + \sum_{l \in B} \frac{1}{d(i,l)}}.$$

Further, the probability that a borrower chooses a CU conditional on it being in among the quoted lenders is given by $\frac{c}{n}\delta$, where $\delta$ is a multiplicative adjustment factor.

I derive the unconditional probability that a borrower chooses a CU as a function of $n, B, C$, let $c = y + 1$ and $n = m + 1$, then

$$\begin{aligned}
\mathbf{Pr}\left[i \longrightarrow c | n, B, C\right] &= \sum_{c=1}^{n} \frac{n!}{(c-1)!(n-c)!} \rho^{c} (1-\rho)^{n-c} \frac{c}{n} \delta. \\
&= \frac{\delta}{n} \sum_{y=0}^{m} \frac{(m+1)!}{y!(m-y)!} \rho^{y+1} (1-\rho)^{m-y}. \\
&= \frac{\delta}{n} (m+1) \rho \sum_{y=0}^{m} \frac{m!}{y!(m-y)!} \rho^{y} (1-\rho)^{m-y}. \\
&= \delta \rho.
\end{aligned}$$

The last equality follows from the binomial theorem. By setting $\delta = 1$, $\delta = \frac{1}{\pi}$, and $\delta = (1 - \mu)$, we obtain the results in the three choice regimes outlined at the end of Section 6.1.1.