BANKING SOCIALLY*

Francesco D'Acunto† Quentin Dupont‡ Agustin Hurtado§ Joonsung Won¶

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Abstract

We ask whether borrowers' social preferences may create non-pecuniary repayment incentives (*social monitoring*). To study this question, we use credit unions as a setting because, unlike banks, they link owner-borrowers through social ties that may generate social monitoring through altruism, social pressure, or both. Comparing lending outcomes at credit unions and banks of similar size, three findings suggest social monitoring is economically meaningful and point to social pressure as the dominant channel. First, credit unions face lower default rates on loans whose defaults are visible to peers (mortgages), but higher default rates on those whose defaults are not visible (credit cards). Second, these differences are strongest at one- and two-branch institutions, where peers' default visibility is highest. Third, mortgage default differences are strongest for professional bonds and muted for religious bonds, where altruism is likely strongest. Observable risk or contract terms in borrower-level data cannot account for these results.

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†Georgetown University.

‡Georgetown University.

§University of Maryland.

¶University of Virginia.

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Abstract

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I. Introduction

Financial intermediation is profitable when lenders can effectively monitor borrowers, who have an incentive to strategically default whenever the pecuniary benefits of non-repayment exceed the expected costs of default. Yet monitoring is costly and subject to agency problems, creating scope for inefficiencies in intermediation (Diamond, 1984; Gale and Hellwig, 1985; Townsend, 1979). A large literature on social preferences suggests a potentially costless substitute to bank monitoring: borrowers' default can be tempered by non-pecuniary costs of default, such as stigma arising from peers' awareness of one's default or disutility from violating ingrained moral norms (Akerlof and Kranton, 2000; Bursztyn et al., 2019; Fay et al., 2002; Guiso et al., 2013; Diep-Nguyen and Dang, 2022). If agents have social preferences, they might face higher subjective costs of default than standard economic agents and hence be less likely to default. We term this mechanism *social monitoring:* borrowers' moral hazard is sobered by non-pecuniary costs of default arising from social peers' awareness of delinquency and/or disutility from violating moral norms.

In this paper, we aim to test whether social monitoring arises endogenously in the field and, if so, through which mechanisms. Empirically, this test faces two main challenges. First, the econometrician must observe default behavior among comparable borrowers who face similar strategic incentives to default and bank with institutions that supply similar products, but differ in the likelihood of being endowed with social preferences or in the salience of social preferences when making repayment decisions. Second, the setting should allow assessing alternative theoretical mechanisms behind social monitoring.

To tackle these challenges, we use novel and unique institution-product-quarter data on repayment outcomes for two types of local financial institutions, commercial banks and credit unions. It is important to stress from the onset that none of our tests or empirical results compare large commercial banks with smaller credit unions. As discussed below, we compare institutions that are similar in size and geographic coverage, offer broadly similar loan products, and whose borrowers and depositors have similar observable demographic characteristics (Li and van Rijn, 2022; Shahidinejad, 2025), suggesting comparable strategic incentives to default and monitoring costs.

Credit unions, however, differ in two key aspects, which provide us with the variation needed to tackle our question. First, they are organized around an explicit common bond, which is typically based on professional, geographic, or religious social groups. Second, borrowers are also owners, so defaulting imposes direct losses on social peers within the group. While the financial incentives of default are comparable across credit unions and commercial banks, we argue that credit unions' institutional design generates systematic variation in the scope for social monitoring across institutions. On the one hand, credit unions might be more likely to attract borrowers who are endowed with social preferences and value being part of a network of peer borrower-owners. On the other hand, social preferences might be more salient to credit unions' borrowers when making

repayment choices, because the visibility and negative consequences of their default on other peer borrower-owners are high.

A simple comparison of default rates between credit unions and otherwise similar commercial banks is uninformative, as any differences could reflect systematic variation in lending policies or other supply-side features across the two types of institutions rather than borrowers' social preferences (Li and van Rijn, 2022; Shahidinejad, 2025). We therefore design empirical tests that exploit variation in the potential channels behind social monitoring that is unlikely to be driven by differences lending policies.

Theoretically, social preferences could influence credit union borrowers' debt repayment decisions through two non-mutually-exclusive channels: altruism and social pressure. Because all credit union borrowers are also owners, a defaulting borrower imposes a loss on fellow credit union members. If borrowers have altruistic preferences, imposing a cost on social peers reduces their utility and hence their willingness to default above and beyond strategic default motives, *ceteris paribus*. Altruistic preferences and the socialization of default-related losses can thus sustain social monitoring. Social monitoring can also be sustained through social pressure: if borrowers' utility is affected by how others view them, knowing that peers might learn about the default would produce an incremental non-pecuniary cost of defaulting, stigma, which, *ceteris paribus*, would reduce borrowers' willingness to default (Bhutta et al., 2017; Fay et al., 2002; Guiso et al., 2013; Gross and Souleles, 2002).

Our empirical tests exploit variation in the scope of these potential drivers of social monitoring. If credit unions faced lower default rates than similar-sized banks when the scope for altruism is high but not when it is low, we would conclude that social preferences can sustain social monitoring in the field and that the altruism channel is relevant. In contrast, if credit unions had lower default rates than similar-sized banks in instances in which stigma is high but not in instances in which stigma is low, we would conclude that social preferences can sustain social monitoring, and that the social pressure channel is relevant.

To obtain variation in the extent of stigma from defaulting, we use the fact that we can compute default rates across starkly different loan types, whose default visibility to others varies substantially: mortgages, vehicle loans, and credit card debt. Whereas houses are collateral for mortgages and vehicles for vehicle loans, credit card debt is uncollateralized. Crucially for our aims, the public visibility of defaults, which is triggered by actions for collateral recovery, provide a highly visible signal that the borrower defaulted to his social peers.[1] Defaulting on mortgages leads to a set of procedures, ranging from formal and public foreclosure notices to actual foreclosures, as well as,

[1] As we elaborate more when discussing alternative interpretations, these loan types differ also in other dimensions. For instance, credit card issuance might be more sensitive to a lender's ability to extract soft information about the potential borrower, given the lack of collateral. If credit unions, as seems plausible, faced lower costs of extracting soft information about applicants (because of observing additional non-credit-related information), we should observe relatively lower defaults of credit card loans at credit unions than banks, *ceteris paribus*. The soft-information advantage should matter less for mortgage outcomes, where collateral reduces the relevance of soft information. None of our results align with these predictions.

in many cases, auctioning of the foreclosed property. This set of public signals makes default on mortgages highly visible and hence the most sensitive to stigma, given that a borrower's social peers would know very vividly that the borrower defaulted. Vehicles are a loan category in which the consequences of default in terms of visibility are ambiguous. On the one hand, vehicles can also be repossessed in the event of default. On the other hand, borrowers facing vehicle repossession can use cash to replace it, and argue that they intentionally changed it, or sold it. For these reasons, borrowers whose utility is affected by their perceived image by social peers can easily conceal the consequences of default and avoid its stigma. In the case of credit card debt, because no collateral exists, default is virtually invisible to social peers. Defaulting borrowers could face consequences such as income garnishment or seizure of other financial wealth, but none of those consequences would be visible to social peers. Importantly, in terms of the altruism channel, defaulting on any of these loan types imposes a loss against peer credit union members, irrespective of the visibility of this default to peers. Altruistic borrowers thus face a similar utility cost for defaulting on either loan type.

Our baseline empirical evidence is consistent with a role of social monitoring sustained by social pressure. We find that credit union's default rates relative to commercial banks flip around based on loan types ranked on the public visibility of default consequences. Indeed, as Panel A of Figure I shows, credit unions' mortgage default rates are lower than otherwise similar commercial banks. In contrast, we detect barely any economic or statistical difference on vehicle loan default rates across lender types. Finally, we find that credit unions have *higher* default rates for credit cards, whose consequences are socially invisible. This last result is inconsistent with a dominant role for altruism in social monitoring, based on which credit union borrowers should never be more willing to default on any loan types than commercial bank borrowers.[2] Instead, it is consistent with otherwise utilitarian borrowers who react to social pressure: credit union default rates are lower relative to commercial banks when default is more likely to generate stigma, but higher when the consequences of default are socially invisible.[3]

We design two additional sets of tests to corroborate a role of social pressure in social monitoring. First, we augment our baseline empirical test by exploiting variation in the tightness of social connections among borrowers. To capture this variation, we split institutions into groups based on their number of branches. Intuitively, institutions with one or two branches, whether credit unions or commercial banks, are likely to serve small local communities in which the scope for an effect of social preferences is higher. By contrast, institutions with dozens of branches are likely to serve pools of depositors and borrowers that are spread in space and have diverse social backgrounds,

[2]Incidentally, it is also inconsistent with potential systematic differences in policies towards default by credit unions and commercial banks, such as credit unions being more lenient toward their borrowers, or harsher, both of which are often raised as potential alternative interpretations.

[3]Utilitarian borrowers would find it optimal to partially offset their sobering of default in visible categories, which is costly to them, with greater default in non-visible categories. Because our data do not link repayment behavior across products for the same borrower, though, we cannot test this prediction directly.

whose social connections are likely weaker than those of smaller and tighter communities. If social preferences are economically relevant, we would thus expect that the baseline effects are stronger when comparing default rates across loan types between credit unions and banks that have fewer branches relative to those that have more branches. And, indeed, as Panel B of Figure I shows, we find that the economic magnitudes of the effects in either direction are largest when comparing few-branch institutions; they decrease monotonically as the number of branches of both credit unions and banks increases. The fact that our effects, as predicted by social preferences, are largest when comparing small credit unions with small commercial banks also dismisses many concerns related to systematic differences in banking policies, management, and products across institutions. For instance, a one-branch credit union in a rural location will be run similarly to a one-branch commercial bank in a rural location, extract similar soft information about customers, and provide similar products.

Second, we consider variation in the scope for the altruism channel of social monitoring. To do so, we use another unique feature of our setting that we can measure in our data: the types of common bonds that define credit unions. Common bonds range across three broad categories: religious, geographic, and professional. Credit unions based on a religious bond bring together members of a religious community, which, by definition, share the same deep values and charitable sense of fraternal community, thus producing a high scope for altruism among members. Geographic common bonds include local groups of borrowers, who though do not necessarily share any common values or social connections. Finally, professional common bonds, which bring together borrowers who work in the same professional category or for the same public institution, intuitively provide the least scope for altruism, given that many of these members are likely to not interact outside their professional activities and, crucially, do not necessarily share any common fraternal or community values with each other. As illustrated in Panel C of Figure I, our baseline effects are weaker or even reverted for religious common bonds, in which the scope for altruism should be highest. By contrast, they are stronger for professional common bonds, where altruism is unlikely to be a defining feature of relationships. Ultimately, these results are consistent with the interpretation of our previous tests that social monitoring is sustainable in the field and that the social pressure channel appears to prevail.

As discussed above, credit unions and banks might differ across several dimensions, such as borrower types, and hence potentially borrower risk, information production, loan terms and product design, and others. Before testing empirically if some of these differences arise in our setting, it is important to stress that many such potential systematic differences would not be able to explain our results, even if they existed. For instance, suppose that one type of institution had systematically riskier borrowers, or was systematically more lenient when dealing with defaulting borrowers. These difference would lead to higher default rates across all loan categories at that type of institution. Instead, our main result is the reversal in the credit union default differential across loan types. Moreover, many of these systematic differences are likely to arise when comparing the average

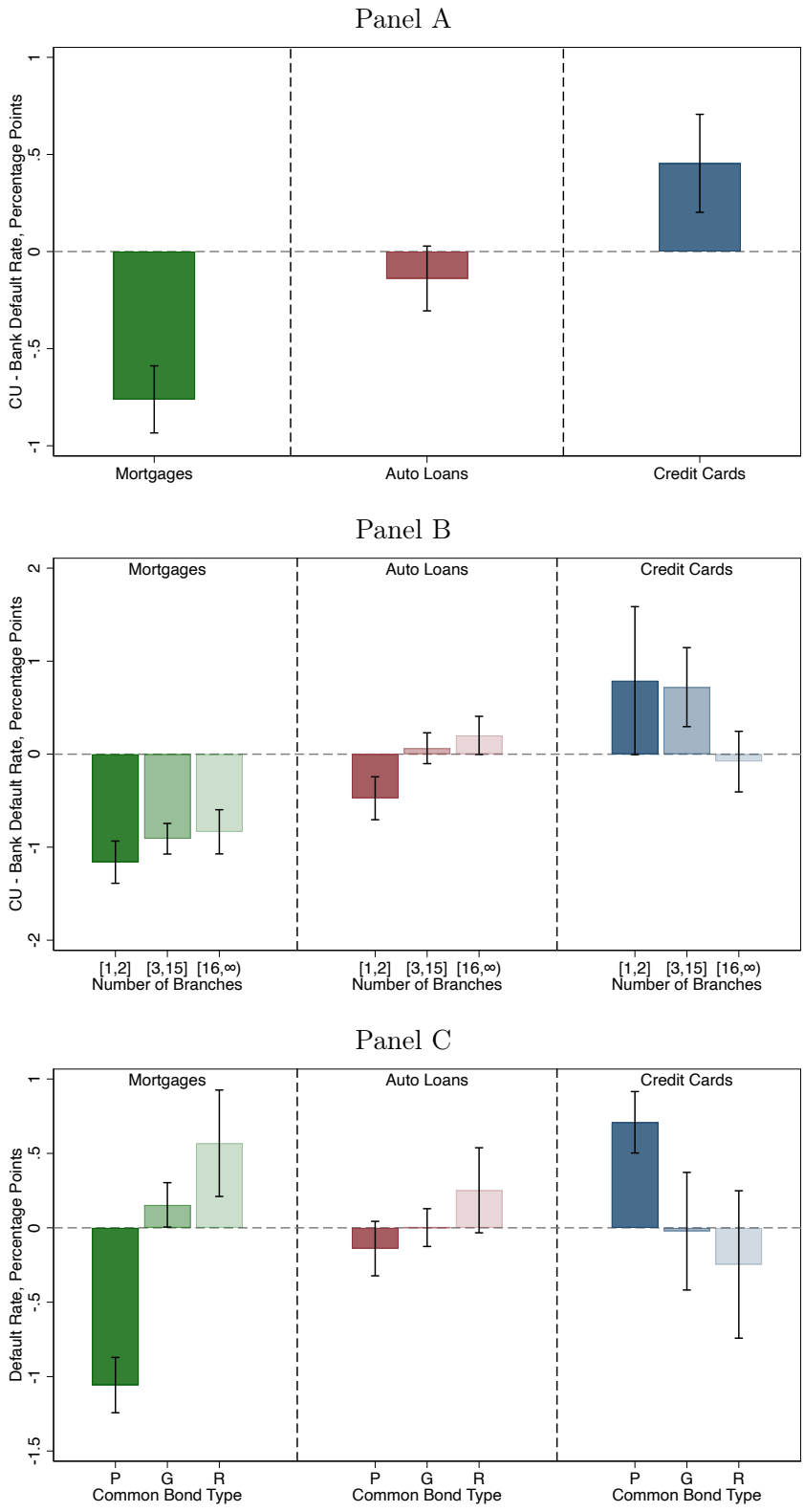

Figure I: **Loan Default Rates.** This figure reports estimated differences in loan default rates between credit unions and otherwise similar commercial banks, using the controls in equation (1). Negative values indicate lower default rates at credit unions. Panel A shows average differences, Panel B separates by branch size, and Panel C by common bond type. P, G, and R denote professional, geographic, and religious common bonds. Vertical axes report percentage point differences, with bars as point estimates and lines as 95% confidence intervals.

commercial bank with the average credit union, which have different sizes and geographic diffusion. But not only are all our results are obtained when including full sets of branch-number fixed effects, thus only comparing institutions of similar size and diffusion, but they are even stronger when comparing one- and two-branch credit unions with one- and two-branch commercial banks, for which many of the differences in demand and supply are likely to be minimal, if they arise at all.

To provide more direct empirical evidence, we complement our setting with public HMDA data, which allow us to compare observable mortgage borrower risk and contract terms across lender types. We find no systematic differences in borrower debt burdens or leverage, while differences in introductory rates and interest-only features are mixed and do not consistently point toward safer mortgage lending by credit unions. These conclusions are similar when we focus on the branch-size and common-bond groups for which our main effects are strongest. Overall, using these mortgage-level data, we find no evidence that systematic differences in borrower risk or loan terms can account for our results.

In the last part of the paper, we study how social monitoring emerges and diffuses in space. To provide clean and reliable comparisons, all our analyses so far were based on comparing credit unions and commercial banks operating in the same locations and having the same size, which is important to reduce concerns about systematic differences on the supply-side of lending across institutions. However, if credit unions' common bonds truly provide scope for social monitoring that does not arise in commercial banks, we should expect that credit union activities relative to traditional bank activities vary endogenously across space based on whether social monitoring is more or less valuable. To capture the value of social monitoring, we need a proxy for the extent to which borrowers would strategically default under standard moral hazard. We propose social capital: where social capital is high, moral norms are stronger, which sobers borrowers' willingness to default above and beyond the formal monitoring institutions designed by their lenders. Endogenously, we would thus expect a higher activity and presence of credit unions relative to local commercial banks in low-social-capital locations, in which the value of social monitoring to restrain default is higher, relative to locations in which social capital is high. Consistently, across a broad range of social capital proxies, we find that the presence of credit unions relative to commercial banks is systematically higher in locations that display lower levels of social capital, and vice versa.

As was mentioned above, our results can be consistent with two non-mutually-exclusive ways in which social preferences are more relevant to the debt repayment decisions of credit union borrowers relative to otherwise similar bank borrowers. On the one hand, credit unions might attract borrowers with stronger social preferences, who value the social nature of common bonds, relative to borrowers who do not have social preferences, who would be indifferent between banking with credit unions or commercial banks. Such potential sorting does not seem reflected in observable demographic characteristics, which earlier research finds to be similar across borrowers of same-sized credit unions and commercial banks (Li and van Rijn, 2022; Shahidinejad, 2025). On the other hand, credit

unions might increase the salience of borrowers' underlying social preferences when they make debt repayment choices, due to their peculiar institutional features. Even if all borrowers in the same location were similarly endowed with social preferences, those who bank with credit unions would be more aware and ponder more the social consequences of their debt repayment choices relative to others, given that the tighter social community of peer borrower-owners would be more likely to learn about a default and would face a direct financial loss due to a default.

Literature. Our work contributes to three strands of research in economics and finance. First, we add to the literature on the determinants and effects of monitoring by financial intermediaries. Foundational theories study the trade off between the costs and benefits of monitoring (Diamond, 1984; Gale and Hellwig, 1985; Townsend, 1979). We build on this literature by proposing an empirical setting to study social monitoring, whereby the standard utilitarian framework to assess borrowers' incentives to default is complemented by the effects of default choices on social peers for borrowers who hold social preferences, that is, whose utility also depends on the utility of others.

Second, we connect to work on the role of social norms in economic choices, and especially debt choices (Bursztyn et al., 2019; Guiso et al., 2013). Our results are, in particular, consistent with the impact of stigma associated with debt default on borrowers' choices (Skiba and Tobacman, 2008; Diep-Nguyen and Dang, 2022). More broadly, we contribute to the extensive applied microeconomics literature on the drivers and consequences of agents' social preferences. Foundational work in this area has studied two broad forms of social preferences: altruism, whereby agents' utility is determined by their own consumption as well as others' consumption (Andreoni, 1989, 1990; Becker, 1981; Becker and Barro, 1986; DellaVigna et al., 2022; Fehr and Schmidt, 1999; Charness and Rabin, 2002; Andreoni and Miller, 2002; Bénabou and Tirole, 2006), and social pressure, whereby agents' utility is affected by how they believe others perceive them (Ash, 1953; Milgram, 1963; Akerlof, 1991; Garicano et al., 2005; Falk and Ichino, 2006; Mas and Moretti, 2009; D'Acunto et al., 2024). Related work emphasizes social comparisons as a form of peer pressure, where agents adjust behavior toward their group's norm (Allcott, 2011; Allcott and Rogers, 2014; Blader et al., 2020). Inspired by research on charitable giving (DellaVigna et al., 2012), we test empirically predictions that aim to disentangle these two alternative microfoundations of social preferences in the context of debt choices. Our contribution is to document a pattern of default rates consistent with stigma avoidance rather than altruism or social comparison.

Finally, we advance a small but growing literature on the economics of credit unions (Chatterji et al., 2021; Cororaton, 2019; Shahidinejad, 2025; Li and van Rijn, 2022). This work emphasizes organizational form, membership, and consumer outcomes; we provide a mechanism that links these features to repayment. Specifically, our evidence suggest that common-bond membership and denser social ties amplify the role of peer observability and the social incidence of losses, which lowers default through a social-monitoring channel. In this way, our setting clarifies how organizational design interacts with non-pecuniary enforcement.

II. Institutional Setting and Data

A. Setting

The U.S. depository institution sector includes two organizational forms that provide the key variation necessary for our study. The first is commercial banks, which extend loans to a broad set of customers and are generally owned by third-party shareholders with no social connection to borrowers. The second is credit unions, which differ from commercial banks along two institutional dimensions that are central to our setting.

First, credit unions only lend to members of a specific social group, united by a "common bond," whereby borrowers are members of the credit union. This common bond can be of three main types: (i) professional (members of the credit union are required to work for a given company); (ii) religious (members must belong to the same church or charitable organization); or (iii) geographic (members live in the same geographic area, e.g., a given county). Credit unions' common bond creates the *social* context between borrowers: borrowers belong to the same professional, geographic or religious network.

The second aspect of interest of credit unions for our study is that, by construction, credit unions' borrowers are owners of the financial institution to whom they have a financial obligation. This link between users of the institution's service and owners of the institution is part of the very definition of credit unions. Therefore, defaulting on a loan to a credit union imposes a cost to the other borrowers who are also owners of the institution.

These two features create the possibility of social monitoring. Previous work on banks and credit union emphasizesPD the fact that borrowers from both types of institutions are similar on observable characteristics (Li and van Rijn, 2022; Shahidinejad, 2025). Where they potentially differ is in the relevance of social preferences for repayment decisions. Credit unions may attract borrowers with stronger social preferences, or their common bond and shared ownership may make those preferences more salient when borrowers decide whether to repay. Therefore, our setting offers a laboratory to study the possible impact of social monitoring on loan default.

B. Data

B.1. Call Report and Common Bond Data

We build a new institution-product-quarter panel that makes lending and repayment outcomes comparable across commercial banks and credit unions. Our primary sources are the FFIEC 031/041 Call Reports for commercial banks and the NCUA 5300 Call Reports for credit unions. Although the Call Reports do not identify individual borrowers or individual default events, they report outstanding and delinquent balances for major consumer credit products. A key challenge is that

product definitions and delinquency categories differ across the two reporting systems and change over time. We harmonize the two systems at the institution, product, and quarter level, requiring an exact correspondence between outstanding and delinquent balances for each product. This exercise allows us to construct consistent repayment outcomes for mortgages, vehicle loans, and credit card debt at both types of institutions over common sample periods.

Our main outcome is the default rate for each institution, product, and quarter. Throughout the paper, we use "default" as shorthand for delinquency of at least 30 days. We construct the default rate as the dollar amount of loans at least 30 days delinquent divided by the corresponding dollar amount of loans outstanding, expressed in percentage points. Constructing a comparable measure requires reconciling different delinquency reporting conventions across banks and credit unions. In particular, credit unions report delinquency using finer categories that change in 2022, and a separate 90+ day delinquency measure is only available for credit unions beginning in 2022. By contrast, 30+ day delinquency can be constructed consistently for both institution types over our harmonized sample periods. We therefore use the 30+ day default rate throughout the analysis. Appendix Table A.3.1 reports the availability of the underlying series, and the Online Appendix provides the exact delinquency buckets and additional construction details.

For mortgages, we match loans and lines of credit secured by first liens on residential properties with one to four families across the two reporting systems. For vehicle lending, we combine new and used vehicle loans reported by credit unions and match them to automobile loans reported by commercial banks. For credit cards, no product mapping is necessary because both banks and credit unions report credit card loans as a distinct category, allowing us to directly match outstanding and delinquent balances. The resulting harmonized mortgage and credit card samples cover 2003q1 through 2024q4, while the harmonized vehicle loan sample covers 2013q2 through 2024q4.

A distinctive feature of our data is that we also observe the type of common bond linking credit union members. We obtained Type of Membership (TOM) codes and their official descriptions from the National Credit Union Administration through a Freedom of Information Act request covering 2003 through 2024. We combine these newly collected data with quarterly NCUA filings and classify credit unions into three economically meaningful common bond groups: professional or occupational, geographic or community, and religious or associational. These classifications allow us to exploit variation in the nature of the social connections among credit union members in our mechanism tests. The Online Appendix reports the complete classification of TOM codes, discusses the classification choices, and documents the evolution of common bond types over time.

We augment the panel with assets, employment, branch counts, and headquarters location from the call reports, which allow us to compare credit unions and commercial banks of similar size and geographic scope.

We devote particular attention to maintaining comparability across institution types when constructing the final sample. For credit unions, we merge repayment outcomes, common bond

classifications, institution characteristics, and branch information using NCUA charter identifiers. For commercial banks, we combine the corresponding regulatory and branch data using RSSD identifiers. These procedures retain approximately 99.9% of the institutions in the underlying samples. We exclude observations without the identifiers or information required to construct the relevant repayment outcome and institutions that report no lending activity over their observed history. The Online Appendix describes each merge and screen in detail.

B.2. Other Data

Branch and Social Capital Data. For the analysis in Section V, we combine branch data from 2013 to 2015 from the NCUA Credit Union Branch Information files and the FDIC Summary of Deposits with four measures of social capital at the county level. We use the 2014 Putnam Index, constructed following Rupasingha et al. (2006), the county Protestant share from ARDA (2010), the negative of the soil heterogeneity index in Raz (2025), and an income adjusted measure based on itemized deductions from the IRS Statistics of Income data. The four measures capture different dimensions and determinants of local social connectedness. Their construction and underlying sources are described in the Online Appendix.

HMDA Data. For the analysis in Section IV, we use public Home Mortgage Disclosure Act (HMDA) data. HMDA provide information at the loan level on mortgage applications and originations, including lender identity, application outcomes, loan and property characteristics, property location, applicant income, and borrower demographics. HMDA do not contain subsequent repayment outcomes and therefore do not enter the construction of our default measures. Instead, we use them to characterize the mortgage borrowers served by credit unions and commercial banks and to assess the comparability of their observable borrower pools. This evidence complements the call reports, which provide consistent repayment measures across institutions and products but comparatively little information about the underlying borrowers. The Online Appendix describes the HMDA sample, lender matching, and variables used in these comparisons.

C. Summary Statistics

Table I reports summary statistics for the repayment panel at the institution, product, and quarter level. Default rates are right-skewed, with medians near zero and 90th percentiles between 4 and 6 percent across loan types. Unconditionally, mortgage default rates average 1.4 percent at credit unions and 2.6 percent at commercial banks, vehicle loan default rates average 1.1 and 1.8 percent, respectively, and credit card default rates average 1.7 and 1.8 percent.

Credit unions account for roughly half of the institutions in the sample and are smaller on average than commercial banks. Importantly, however, the distributions overlap substantially among small institutions. Figure II makes this comparison directly by plotting total assets and employment for

banks and credit unions with one or two branches.

Figure III provides descriptive evidence on geographic overlap by aggregating institutions by headquarters county and mapping mortgage default rates separately for credit unions and commercial banks. Although credit unions are headquartered in fewer counties, the two institution types are headquartered in many of the same counties. In counties where both institution types are headquartered, the maps also show differences in mortgage default rates across credit unions and commercial banks.

III. Social Monitoring: Scope and Economic Mechanisms

A. Altruism and Social Pressure: Predictions

As discussed in the introduction, we then move on to consider the economic channels through which social monitoring might be sustained in the field by considering two non-mutually-exclusive mechanisms: altruism and social pressure.

Under altruistic preferences, social monitoring is sustained by the fact that others' outcomes enter directly into borrowers' utility. Since all members of a credit union hold fractional ownership, a default on credit union-issued debt effectively imposes a financial burden on fellow members, thus resulting in a socialized loss. If borrowers exhibit altruistic preferences, the utility loss from harming peers would be internalized, leading to a decreased propensity to default, all else equal.

Social pressure, instead, arises when borrowers' utility is influenced by how others perceive their self-image. In this case, the decision to default would account not only for the consumption costs but also for the reputational costs borrowers face from others' obtaining information about their default, which would reduce borrowers' utility by lowering others' perception of their self-image. In this case, heightened visibility of default to social peers increases the reputational costs associated with default, thereby discouraging default behavior above and beyond an otherwise standard cost/benefit analysis, ceteris paribus.

To disentangle these two channels, one needs variation in either the size of the loss others face when the borrower defaults keeping constant the reputational costs or, conversely, variation in the reputational costs keeping constant the size of the loss others face. Our setting allows us to design a test that exploits the second direction, that is, using variation in the social stigma associated with default, while holding constant the extent to which altruism might affect borrower behavior. This design aims to compare default rates on credit union loans versus loans issued by same-sized local commercial banks, across contexts where the degree of stigma varies but the size of the loss imposed on the financial institution under default can be controlled for. In this design, commercial banks serve as a benchmark group. Should we observe consistently lower default rates at credit unions relative to banks, regardless of stigma intensity, we would conclude that the social pressure

mechanism is empirically negligible in explaining social monitoring. Conversely, if differential default choices appear in high-stigma settings and vanish in low-stigma ones, the evidence would suggest that social pressure is an empirically important mechanism to implement social monitoring.

A key challenge in implementing this test lies in capturing meaningful variation in the degree of social stigma attached to default choices. To address this, we leverage data on institution-level default rates across three loan types, each secured by distinct forms of collateral: mortgages, vehicle loans, and credit card debt. Importantly, while defaulting on any of these obligations generates a comparable financial externality for the credit union, i.e., keeping the altruistic incentive barely changed, the degree of public visibility of default outcomes across these types of loans differs dramatically across categories.

This variation in visibility, and consequently in the social stigma associated with default, is central to our empirical strategy. We argue that mortgage defaults generate the most conspicuous public signals among the three loan types: formal eviction notices, property foreclosures, and public auctions, all of which make the borrower's default widely observable among their social network. As a result, mortgage default carries a high stigma and therefore provides substantial scope for social pressure affecting the decision to default, ceteris paribus. In turn, vehicle loan defaults present ambiguous visibility. Although vehicles may be repossessed, borrowers often have the option to replace the vehicle with cash or claim to have sold it voluntarily, thereby masking the default event. Finally, credit card debt defaults entail barely any repossession or visible public consequence, given that this form of debt is unsecured. While financial penalties such as wage garnishment or credit-score drops may follow, these are largely hidden from public view and do not generate observable stigma.

B. **Altruism and Social Pressure: Evidence**

To implement our main test to disentangle the potential economic mechanisms that sustain social monitoring, we estimate a linear specification of the following form by OLS:

$$Default\ Rate_{i,l,s,t} = \alpha + \beta Credit\ Union_{i,l,s,t} + \gamma X_{i,s,t} + \phi_{s,t} + \varepsilon_{i,l,s,t}, \tag{1}$$

where $Default\ Rate_{i,l,s,t}$ is the percentage of outstanding loan balances for loan-type l at institution i that are at least 30 days delinquent in quarter t; $Credit\ Union_{i,s,t}$ is an indicator for whether institution i is a credit union; $X_{i,s,t}$ is the vector of institution-quarter level characteristics we observe, which include the logarithm of employees and total assets as proxies for size, and the total number of branches of the institution across any locations in which it operates to proxy for the size of the potential pool of borrowers the institution serves; $\phi_{s,t}$ are a full set of state-by-quarter fixed effects, which aim to capture local business cycle fluctuations that might drive the demand and supply of credit, as well as affect default behavior. In all specifications, for the purpose of

statistical inference, we cluster standard errors at the state level to account for spatial correlation of unknown form across the outcomes of financial institutions operating in the same states as well as autocorrelation in within-institution outcomes.

We estimate the specification in equation (1) separately across the three types of consumer credit loans that vary by the visibility of their default to others, that is, mortgages, vehicle loans, and credit card debt:

$$Default\ Rate\ Mortgages_{i,s,t} = \alpha + \beta_M Credit\ Union_{i,s,t} + \gamma X_{i,s,t} + \phi_{s,t} + \varepsilon_{i,s,t}$$

$$Default\ Rate\ Vehicle\ Loans_{i,s,t} = \alpha + \beta_V Credit\ Union_{i,s,t} + \gamma X_{i,s,t} + \phi_{s,t} + \varepsilon_{i,s,t}$$

$$Default\ Rate\ Credit\ Cards_{i,s,t} = \alpha + \beta_C Credit\ Union_{i,s,t} + \gamma X_{i,s,t} + \phi_{s,t} + \varepsilon_{i,s,t}$$

Based on whether altruism or social pressure are empirically more relevant mechanisms to sustain social monitoring, we would expect different signs attached to the three main coefficients of interest, that is, β_M, β_V, and β_C.

If altruism is an empirically more relevant mechanism to sustain social monitoring, we would expect negative estimated coefficients across all three loan types, that is, $\beta_M < 0$, $\beta_V < 0$, and $\beta_C < 0$. The intuition is that defaulting on either loan type produces a loss for social peers who are also members of the credit union for credit-union borrowers, whereas it would produce a loss for the unknown shareholders of commercial banks for commercial-bank borrowers. The social monitoring channel would therefore be stronger in credit unions and similarly so across loan types because of both credit unions potentially attracting more altruistic borrowers among their customers as well as the fact that credit union member-owners are part of borrowers' social network through the shared common bond but commercial-bank shareholders generally are not.

By contrast if social pressure is an empirically more important mechanism, the predictions about the signs and relative sizes of the estimates differ across loan types. Indeed, credit-union borrowers should be less likely to default, ceteris paribus, on mortgages relative to borrowers of commercial banks of the same size, number of branches, and operating in the same locations and at the same time ($\beta_M < 0$); for vehicle loans, given the ambiguity of their visibility, we do not have clearcut predictions regarding the sign of the coefficient, but we have a clearcut prediction regarding the order of magnitudes across the three types of loans, that is, we expect that $\beta_M < \beta_V < \beta_C$. Finally, under social pressure, we expect that $\beta_C \geq 0$, that is, there is no mechanism lowering borrowers willingness to default on credit card debt when banking with credit unions relative to otherwise similar standard commercial bank. If anything, if altruism had no role, credit union borrowers could be more likely to default on credit card debt in order to recoup the additional costs faced by restraining their default choices on mortgages relative to commercial-bank borrowers, because they

would not care about imposing a loss on the institution's owners through defaulting but only about the stigma costs arising to them from visible defaults.

Table II report the results for estimating the specifications implied by variations of equation (1), whereby Panel A reports coefficients estimates for mortgages (β_M), Panel B for vehicle loans (β_V), and Panel C for credit cards (β_C). For each loan type, we assess the robustness of our estimates by proposing specifications that compare the outcomes of credit unions and commercial banks that have similar size in terms of employees (column (1)), account for time-varing local business cycle fluctuations (column (2)), additional restrictions to compare similar-sized banks by assets (column (3)), and, finally, our most restrictive specification that restricts the variation within institutions with the same number of branches.

Across all specifications, our estimates are consistent with the social monitoring channel's predictions, but not with what we would predict if altruism was a relevant channel. Specifically, across all specifications, in Panel A, we find that mortgage default rates are systematically lower at credit unions relative to otherwise similar commercial banks in the same locations and at the same point in time. In stark contrast, Panel C shows that credit-card default rates are, on average, higher at credit unions relative to similar commercial banks. Importantly, these results are not due to differences in size between banks and credit unions, as the results hold when controlling for asset size percentile fixed effects (Table II Columns (3) and (4)) and number of branches fixed effects (Column (4)). And, again consistent with the predictions of the social monitoring channel, we find that the estimated sizes of the coefficients on the credit union indicator for default rates on vehicle loans lie consistently within those we estimate for mortgages and credit card debt: $\hat{\beta_M} < \hat{\beta_V} < \hat{\beta_C}$. While being consistent with social pressure, these estimates are not consistent with altruism playing a relevant role, which would imply that $\hat{\beta_C} > 0$, which is the opposite of what we find.

C. Intensive Margin: Variation in the Scope for Social Monitoring

After having provided evidence according to which, on average, the social pressure channel of social monitoring prevails over the altruism channel, we move on to further assess the relevance of the main channel by considering cross-sectional variation in the scope for social monitoring.

Using the banking outcomes of commercial banks with similar characteristics as the control group, we exploit variation in the scope for each potential channel sustaining social monitoring across credit unions, so that we keep constant the overall incentives credit-union borrowers might have to implement social monitoring, which are likely systematically different from commercial-bank borrowers due to the selection into credit-union banking we discussed above, but we vary the intensive margin of the scope for social monitoring across different groups of credit-union borrowers.

To capture the scope for social monitoring, we use the size of borrower pools served by each financial institution, which captures the tightness of the social peer groups to which borrowers

belong. Intuitively, the smaller is the size of the social group, the higher is the likelihood that each member knows a higher fraction of the other members, and hence knows that more social peers would be aware of their default outcomes, when visible. We proxy for the variation in the size of social groups that bank with the same institution with the number of branches of each institution. The rationale is that institutions with fewer branches serve smaller and hence, presumably, tighter communities..

For instance, consider a single-branch institution. Such institution would serve members that are presumably all located in geographic proximity. The scope for social monitoring in this setting is at its highest, because the default outcomes of each borrower can easily be observed and known quickly by social peers. And, due to credit unions' common bonds, credit-union borrowers are further connected to each other based on a similar associational, religious, or professional purpose. In contrast, the higher is the number of branches, the broader are the communities the institutions serves, and hence the weaker is the average tightness of the connections among any two borrowers within the served community. The scope for social monitoring should thus be lower in such communities.

Based on these arguments, we estimate versions of equation (1), in which we add a full set of interactions between the credit union dummies and dummies capturing two groups by number of branches—between 3 and 15 branches and more than 15 branches. We report the results for estimating these specifications in Table III, where each column uses our most restrictive specification for each of the three loan types in the baseline analysis—mortgages, vehicle loans, and credit cards. In these specifications, the omitted category is the group of credit unions that only have one or two branches, that is, the ones for which the scope for social monitoring should be highest relative to otherwise similar commercial banks. Therefore, the *Credit Union* coefficient captures the difference in default rates between one/two-branch credit unions and otherwise similar commercial banks, whereas the two interactions capture the differential between these banks and credit unions with a higher number of branches.

For each loan type, we find results that are consistent with our conjecture regarding the scope for social monitoring. Starting with mortgages, we can see that, indeed, the baseline mortgage default-rate differential between credit unions and commercial banks is lowest at one/two-branch credit unions. Although default rates remain lower at credit unions, the differential becomes smaller as the number of branches increases. Specifically, the effect is about 22% smaller for mid-sized credit unions (between 3 and 15 branches) and about 28% lower larger credit unions (more than 15 branches). The results for credit-card debt are fully symmetric: the baseline default-rate differential between credit unions and commercial banks is highest at one/two-branch credit unions.[4] Instead, this effect declines at credit unions with more branches—so much so that the effect is completely

[4]This is consistent with the notion that, once default outcomes are not conspicuous, credit union borrowers, if anything, may partially offset the costs of suboptimal defaulting on visible loan collateral, such as mortgages. However, our data do not link repayment behavior across products for the same borrower.

reversed for credit unions with most branches.

The results for vehicle loans (column (2)) are also consistent with our conjecture. In this case, we also note a switch in the sign of the effects: vehicle-loan default rates are systematically lower for one/two-branch credit unions, relative to one/two-branch commercial banks. This difference disappears for mid-sized financial institutions, and reverts for larger financial institutions, to the extent that, on average, large credit unions exhibit higher vehicle-loan default rates than large commercial banks. This switch in sign is not inconsistent with our interpretation of the baseline effects, given that, as discussed above, the expected sign of the effects is ambiguous for vehicle loans. This test highlights that the variation we document aligns with the intuition we discussed above: for tighter communities in which borrowers are more likely to know and interact with each other, borrowers are less likely to default on vehicle loans, for which asset repossession is likely to be more visible. As, instead, we move to larger credit unions that serve different communities, the default of each individual vehicle loan borrower is less visible to the average other credit union member, and such borrower is more likely to default on vehicle loans.

Moving to credit card debt (column (3)), we see that, once again consistent with our interpretation, the higher credit-card default rate at credit unions is strongest in tighter communities in which the scope for social monitoring is higher. In contrast, the effect declines as the scope for social monitoring is reduced in larger communities—so much so that the effect disappears when we compare large credit unions and large commercial banks.

Overall, our empirical results are consistent with the possibility that credit unions are better able than otherwise similar commercial banks to sustain social monitoring, but also that the most relevant channel is social pressure. Because of this channel, social monitoring does not lead credit unions to face unconditionally lower default rates on all forms of consumer debt they issue, but rather to have a performance advantage in forms of debt whose defaults lead to visible consequences for borrowers' social peers, and a performance disadvantage in forms of debt whose defaults are not visible to social peers.

D. Variation in the Scope for Altruism: Types of Common Bond

The last cross-sectional test we implement aims at better characterizing the relative roles of the two channels that might sustain social monitoring. So far, we found that, on average, social pressure is the prevalent channel. At the same time, our results so far cannot exclude that altruism might still be an existing channel of social monitoring, albeit less economically relevant than social pressure.

Testing for the existence of an altruism channel above and beyond the prevalent social pressure channel requires cross-sectional variation in the scope for altruism across the credit unions we observe. If we could exploit such cross-sectional variation, we would be able to compare the default

rates across credit unions within loan types keeping constant the scope for social pressure, but across credit unions whose borrowers should be more or less exposed to altruistic motives towards their social peers. If we observe no differences in default rates between credit unions and commercial banks across loan types as the scope for altruism changes, we would conclude that the altruism channel is not just less economically relevant than the social pressure channel, but economically irrelevant whatsoever. If, instead, we detect variation in default rates within loan types across credit unions with a higher scope for altruism, we would conclude that, despite being less economically important, the altruism channel also contributes to sustaining social monitoring.

The main challenge in implementing this test is obtaining a viable empirical source of variation in the extent to which borrowers of different credit unions might face different scopes of altruistic motives toward other borrowers, but which, at the same time, does not capture variation in the scope for social pressure. To tackle this challenge, we take advantage of a unique institutional feature of credit unions, which we can observe in our data: the types of common bonds around which credit unions are established, which capture the nature of the connection among borrowers who decide to bank with different credit unions.

Specifically, common bonds can be categorized into three types: religious, geographic, and professional common bonds. Religious common bonds relate to social groups that are defined by their sharing of a common religious and associational motive, which goes beyond simple social interactions, and involves sharing a life purpose, moral and ethical values, and/or life objectives. Because of the deep sharing of life perspectives and values within religious communities, we argue that this category of common bonds might provide the highest scope for altruistic motives among its members, who are deeply and intimately connected to each other. Geographic common bonds bring together individuals whose commonality is defined by residing in the same location. Relative to religious bonds, geographic bonds are likely to provide a slimmer scope for altruistic motives among borrowers given the lack of such a deep and intense moral connection among the members. At the same time, because members of the same local community are likely to interact with each other relatively frequently and are exposed to the same common local shocks, the scope for altruistic motives might be moderate. Of the three types of common bonds, we interpret professional bonds as the ones that involve the weakest altruistic motives. Professional common bonds pool together individuals who work in the same sector or industry, such as teachers, engineers, or automotive workers. Although this is also a legitimate source of commonality that results in a shared bond among borrowers, in this case, borrowers might not even know each other, they might live in different locations, and they might not share any deeper trait, belief, or moral conviction.

Based on these arguments, in Table IV, we report the estimates of specifications that augment equation (1) with interactions between the credit union dummy and the types of common bonds. The omitted category is professional common bonds, which, as discussed above, should be the one with a low scope for altruistic motives among borrowers. Note that common bonds are only defined

for credit unions and hence, in these tests, the full set of commercial banks acts as the control group for each of the types of credit unions, while at the same time, the types of common bonds allow for heterogeneous effects within credit unions.

Overall, our evidence is not consistent with a significant role for the altruism channel in social monitoring. In column (1), we can see that the baseline lower (visible) mortgage default rate at credit unions is, in fact, stronger for professional credit unions—the common bond for which the scope for altruism among members is lower. In contrast, the lower mortgage default rate at credit unions is most muted for religious common bonds, whose scope for altruism is higher. A similar pattern arises for vehicle loans. For credit cards, also inconsistent with altruism, we detect the opposite pattern, even though, statistically, we cannot reject the null of no differences between the higher likelihoods of defaulting across all three types of common bonds.

IV. Alternative Interpretations

On average, banks and credit unions differ along a number of dimensions, in terms of both the demand side (types and characteristics of borrowers) and the supply side (organizational structures, policies, relationship with borrowers, etc.). In this section, we discuss why many potential systematic differences across these types of institutions, which we fully acknowledge, generally deliver predictions that differ from those of social monitoring and are inconsistent with the set of results we described above.

A. Theoretical Considerations

First of all, we would like to stress that all our empirical tests consider default behavior by borrowers at the two types of institutions by comparing institutions that have similar sizes, captured with full sets of fixed effects for each institution's number of branches and direct controls for proxies of size (assets and number of employees). Therefore, none of our results is based on a simplistic comparison of large commercial banks with local and small credit unions, which would obviously confound many potentially unobservable differences across institution types. In fact, we find that our results are strongest when comparing one-two branch credit unions with one-two branch banks. Many of the stark differences that are stereotypically associated with commercial banks relative to credit unions (impersonal service, lack of direct loan officer-borrower relationship, difficulty in collecting and interpreting soft information due to more complex hierarchy and organizational layers, etc.) are, in fact, related to institutions' size and hence are absorbed away in our tests and have no scope where our results are stronger, that is, settings in which commercial banks' structure, organization, and policies are very similar to those of the average credit union. Neither our sample nor earlier published research that reports systematic information about borrower characteristics across credit unions and similar-sized banks detects systematic differences across the borrower pools

of the two institution types, whether using bank-level of borrower-level data (Li and van Rijn, 2022; Shahidinejad, 2025).

Moreover, on the demand side, our tests based on the predictions of social monitoring restrict the scope for borrower heterogeneity to explain the empirical results. Recall that we never propose a simple comparison of default behavior across the two types of institutions, for which social monitoring has no prediction, and which could instead be a test of systematic differences in the creditworthiness of the two borrower pools (e.g., credit union borrowers are systematically more or less likely to default on loans than commercial bank borrowers). Instead, our tests are based on opposite predictions about default choices at credit unions and banks across different loan types. For systematic differences across borrowers to explain our results, credit unions and banks should not simply have different borrower pools, but borrower pools whose characteristics differ in opposite ways across different types of loans. Specifically, mortgage borrowers at credit unions should be substantially more creditworthy, while credit card borrowers at the same credit unions should be substantially less creditworthy, than borrowers accessing the corresponding loan types from commercial banks of similar size in the same locations. Last, on the demand side, note that our results are stronger for institutions that serve tighter social communities, i.e. those with one-two branches, a setting in which borrower characteristics heterogeneity is likely to be lower relative to comparing institutions that serve varied borrowers across many geographies, economies, and industries.

Moving on to systematic differences on the supply side, several potential candidates appear plausible. For instance, credit unions are likely to find it cheaper/easier to extract soft information from borrowers, even relative to same-sized banks. This is because, by construction, they observe at least one set of characteristics that banks cannot perfectly observe: professional conduct in the case of professional common-bond credit unions, religious behavior in the case of religious common-bond unions, etc. Note, though, that credit union's potential advantage in extracting soft information predicts different patterns than what social monitoring predicts, which instead can explain our results. Specifically, soft information is a substitute of collateral: it matters more for loan types with low/no collateral. Based on this channel, we should not observe relevant differences in the default behavior of mortgage borrowers across the two types of institutions. In contrast, we should observe one of two outcomes for credit-card borrowers: either credit-union borrowers default systematically less than bank borrowers, because credit unions, keeping constant hard observable characteristics, use their advantage in extracting soft information to cater to better borrowers for their soft-information-sensitive loans; or, average defaults are similar, but credit unions provide credit card loans to an average pool that looks worse based on hard information, again exploiting their soft-information extraction advantage. None of these predictions overlaps with the predictions of social monitoring and/or is at all consistent with our empirical evidence.

One might wonder whether the same loan types, in fact, capture different product types across

credit unions and small commercial banks. For instance, credit unions might tend to issue mortgages and credit cards that are systematically different from those of same-sized banks. While we do not find systematic differences in mortgage sizes or credit-card loan characteristics based on the features we can observe in call report data, and we are not aware of such differences from the literature, unobserved differences might arise. For instance, credit unions might be more/less likely to issue conforming loans they sell to federal agencies, or might issue mortgages charging systematically higher/lower rates and fees. They might also issue credit cards that include less generous loyalty programs in terms of cash back, rewards, and other perks. While these features certainly differ when comparing the average credit union to the average commercial bank, which is substantially larger, we are not aware of these differences when comparing institutions of similar size. Indeed, many of these features of loan products depend on institutions' size rather than type. Even if these differences existed, an alternative interpretation of this type should entail that credit unions propose safer mortgages but riskier credit cards to their borrowers, and that this difference is especially strong between one-two branch credit unions and one-two branch banks, and it is true for professional-bond credit unions but not for religious-bond credit unions.

B. Empirical Tests Using HMDA Data

We move on to assess more directly empirical data at the loan and borrower levels, so as to assess empirically whether systematic differences across similar-sized credit unions and commercial banks arise at all. To do so, we zoom in on the mortgage market, where publicly available borrower-level data let us observe key borrower and contract characteristics for 2018-2025.

On the demand side, we focus on debt-burden and leverage measures. Higher debt burdens reduce the room households have to absorb shocks, increasing the likelihood of default (Campbell and Cocco, 2015), while higher leverage implies a smaller equity cushion and greater exposure to house-price declines, and is also tightly linked to default (Gupta and Hansman, 2022). We proxy for debt burden using a dummy variable equal to one if a borrower has a debt-to-income (DTI) ratio of at least 50 percent, and zero otherwise.[5] We call this variable high-DTI dummy We proxy for leverage using combined loan-to-value (CLTV) in levels.[6]

On the supply side, we focus on two mortgage contract features that affect repayment timing and increase the likelihood of default: introductory rates and interest-only payments. Introductory-rate loans can raise default risk because the later payment reset tightens borrowing constraints and increases payment stress (Campbell and Cocco, 2015; Gupta and Hansman, 2022), while interest-only mortgages defer principal repayment and have been associated with higher default risk both theoretically and empirically (Campbell and Cocco, 2015; Brueckner et al., 2016). We use

[5]Public HMDA data do not report DTI as a continuous variable. Instead, the data provide the following buckets: <20%, 20%-<30%, 30%-<36%, 36%, 37%, 38%, 39%, 40%, 41%, 42%, 43%, 44%, 45%, 46%, 47%, 48%, 49%, 50%-60%, >60%.

[6]Public HMDA reports CLTV as a continuous variable rather than in brackets.

a dummy variable equal to one for loans with an introductory rate, and zero otherwise, as a proxy for this alternative explanation. Likewise, we use a dummy variable equal to one for loans with an interest-only payment feature, and zero otherwise, to test the prevalence of interest-only loans in credit unions relative to banks.

We use each of those proxies as an outcome variable in equation (1) in the paper and estimate the following:

$$Proxy_{i,j,s,t} = \alpha + \beta Credit\ Union_{i,j,s,t} + \gamma X_{j,s,t} + \phi_{s,t} + \varepsilon_{i,j,s,t} \tag{2}$$

where $Credit\ Union_{i,j,s,t}$ is an indicator for whether a borrower i got a mortgage from a credit union j; $X_{i,s,t}$ is the vector of institution-quarter level characteristics we observe, which include the logarithm of employees and total assets as proxies for size, and the total number of branches of the institution across any locations in which it operates to proxy for the size of the potential pool of borrowers the institution serves; $\phi_{s,t}$ are a full set of state-by-year fixed effects, which aim to capture local business cycle fluctuations that might drive the demand and supply of credit, as well as affect default behavior. In all specifications, we two-way cluster standard errors at the lender and state levels. [7]

Table V summarizes the results of our tests, using a similar fixed effects structure as the tests for our main results. On the demand side (Columns (1) and (2)), the coefficient of interest for both proxies are insignificant, indicating that credit union loans are no different than bank loans regarding the demand-side concerns. For the supply-side proxies (Columns (3) and (4)), the coefficients are significant but of opposite signs. To be consistent with the concern that credit unions' mortgages are systematically structured in ways than systematically mitigate default than banks' mortgages, the results would need to go in the same direction (both negative). This is not the case, hence we do not find conclusive evidence toward that concern.

Our earlier analysis reveals that our results are concentrated in (i) credit unions with 1 or 2 branches and (ii) professional common bond credit unions. We use the analysis above on HMDA data along those lines to see if we find any evidence of those alternative stories along the two cross sectional characteristics where are results are strongest.

Table VI breaks down the sample by the size (number of branches) of the financial institution. As per the results in Table III, the coefficient of interest is that on the *Credit Union* variable: if the alternative stories can explain our results, they should be significant for the smallest subset of credit unions. All but one of these coefficients are insignificant, and the marginally significant coefficient on the interest-only payment (Column (4)) goes against the concern proxies for in the test.

[7] Clustering at both levels is important because lenders may operate in multiple states, so this choice allows for correlation of unkonwn form of the residuals across borrowers residing in the same locations as well as borrowers banking with the same institution.

Table VII presents results across the cross section of credit unions split by common bonds. Again, to explain away our earlier results, the coefficients of interest are those on the *Credit Union* variable which captures professional common bond credit unions–while the interacted terms capture the effect on the other types. Like for the results in Table V, the coefficients for the demand side proxies are insignificant, while the results for the supply-side proxies are mixed and thus do not offer a consistent alternative to our interpretation.

V. Does Social Monitoring Emerge Where it is More Valuable?

All our evidence so far has compared similar borrower pools demanding credit in the same locations from two different types of financial institutions: credit unions embed the scope for social monitoring by creating an institutional social bond among borrowers, whereas standard local commercial banks do not. Comparing default decisions by similar consumers in similar locations is important to minimize the concern that unobservable borrower characteristics beyond their social preferences might explain our results. These comparisons keep constant the costs of standard monitoring by comparing decisions within the same borrower pools, who have a given likelihood of engaging in strategic defaults, and hence where the need for social monitoring as a substitute for standard monitoring is given.

At the same time, if social monitoring is relevant to financial intermediation, we should expect it to arise more prominently where it is more valuable, and hence that credit union activity is higher relative to similar-sized local commercial banks in locations in which social monitoring is more valuable.

To assess this possibility, we need to compare locations based on the relative value for social monitoring as a substitute for standard monitoring. To do so, we consider variation in social capital across U.S. locations. Social capital captures the extent to which local communities value and abide by ingrained social and moral norms, such as, for instance, the need to repay a debt when contracted. Whereas a standard agent would engage in strategic default, i.e. default on a debt whenever the costs of repaying are higher than the benefits of not repaying, agents who value adhering to moral norms would also consider the costs of behaving against such norms when considering a default choice. For this reason, social capital is a substitute for institutions that generate social monitoring: in communities in which social capital is higher, even absent any institutionally-induced social monitoring, local borrowers' default decisions will be tempered by their higher adherence to the morality of debt repayment. In contrast, in communities in which social capital is lower, debt repayment behavior is not sustained by borrowers' adherence to moral norms, and hence financial institutions whose features induce social monitoring have a relatively higher comparative advantage to standard commercial banks. We would thus expect that, if credit unions truly induce social monitoring while standard commercial banks do not, credit unions endogenously locate their

activities more in locations in which social capital is lower.

For this test, we estimate the following linear specification by OLS:

$$Credit\ Union\ Share_{c,t} = \mu + \zeta_s + \zeta_t + \delta Social\ Capital_{c,t} + \varepsilon_{c,t} \tag{3}$$

for county c in year t with both state and year fixed effects (ζ_s and ζ_t, respectively), for each of the three social capital proxies described in section II.B. In each regression, standard errors are clustered at the state level. Under the social pressure mechanism, we expect the coefficient of interest δ to be negative.

Figure IV presents the results for the δ coefficient of each of the social capital proxies in these regressions. In each case, social capital is negatively related to the local share of credit unions. These results are consistent with the emergence of social monitoring through credit unions' common bonds as a substitute to social capital in areas where it is lower, and hence social monitoring more valuable to financial intermediaries. In the context of financial intermediation, the credit unions' common bond offers a social monitoring mechanism in areas where social bonds do not provide this form of monitoring.

VI. Conclusion

To test whether and how financial institutions can support monitoring by leveraging borrowers' social preferences (*social monitoring* instead of standard contracts based on pecuniary incentives, we compare the debt choices of similar borrowers in the same locations who bank with commercial banks or credit unions. The scope for social monitoring is higher in credit unions. Intuitively, two channels might be at work: an altruism channel—a borrower's default imposes a loss on all other credit union members, who jointly own the institution—and a social pressure channel—the stigma attached to a borrower's default is higher for defaults whose consequences are more visible to one's social peers, who coincide with the credit union's owners.

We find evidence consistent with an economically and statistically significant effect of social monitoring on borrowers' debt repayment decisions. Moreover, tests that exploit the visibility of the consequences of default choices support the social pressure channel. Instead, we find no evidence that the altruism channel is relevant empirically in our setting, because credit union borrowers are more likely to default on credit card debt relative to commercial bank borrowers, and our baseline effects are not stronger for credit union types that bring together communities in which the scope for altruism is higher.

Our results inspire advances in financial intermediation theory, and especially on how social monitoring can be incorporated through borrowers' non-standard preferences . Moreover, our results beget follow-up empirical work to understand how social monitoring could be extended to financial

institutions that do not have a formal common bond and shared ownership among their members. The results also have implications for regulators and policy-makers, such as providing an economic justification for the differential regulatory treatment of credit unions and commercial banks.

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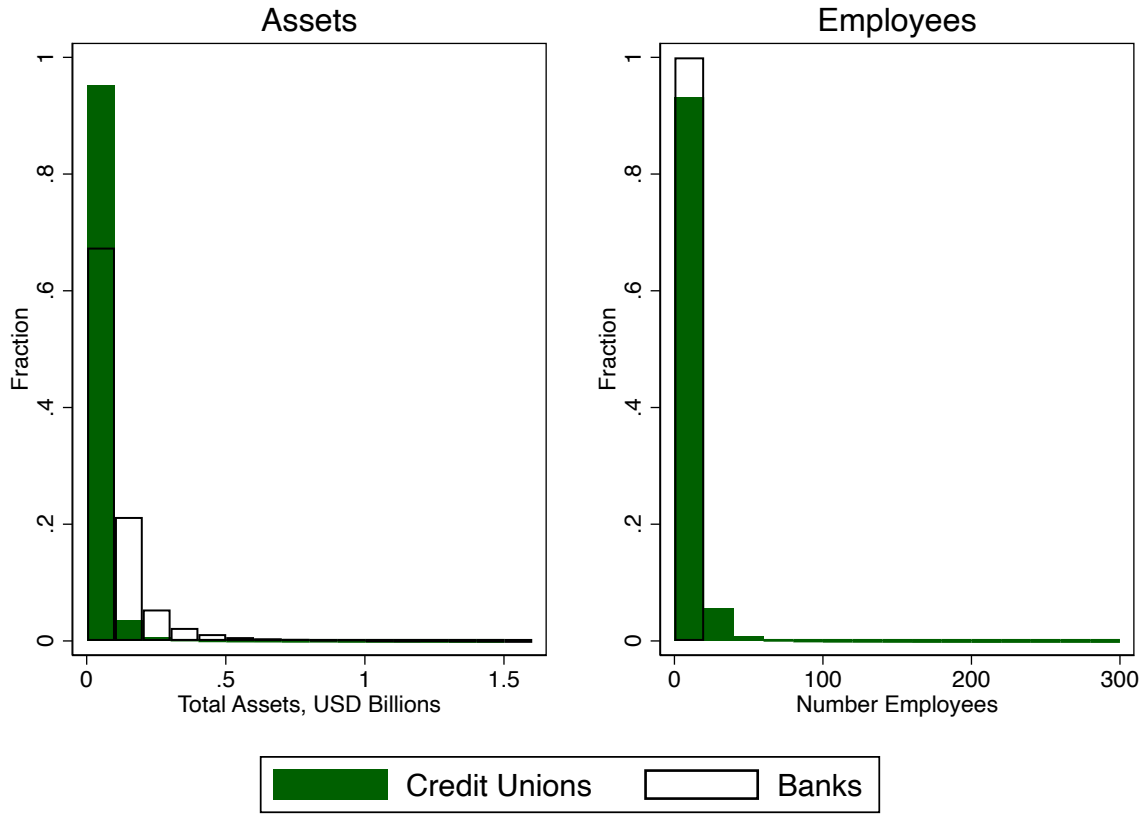

Figure II: **Asset and Employee Distributions.** This figure compares the distributions of total assets (left) and number of employees (right) across banks and credit unions from 2003q1-2024q4. Each panel overlays the distributions for institutions with one to two branches. The vertical axis shows the fraction of institutions in each bin. All distributions are trimmed at the 5th and 95th percentiles.

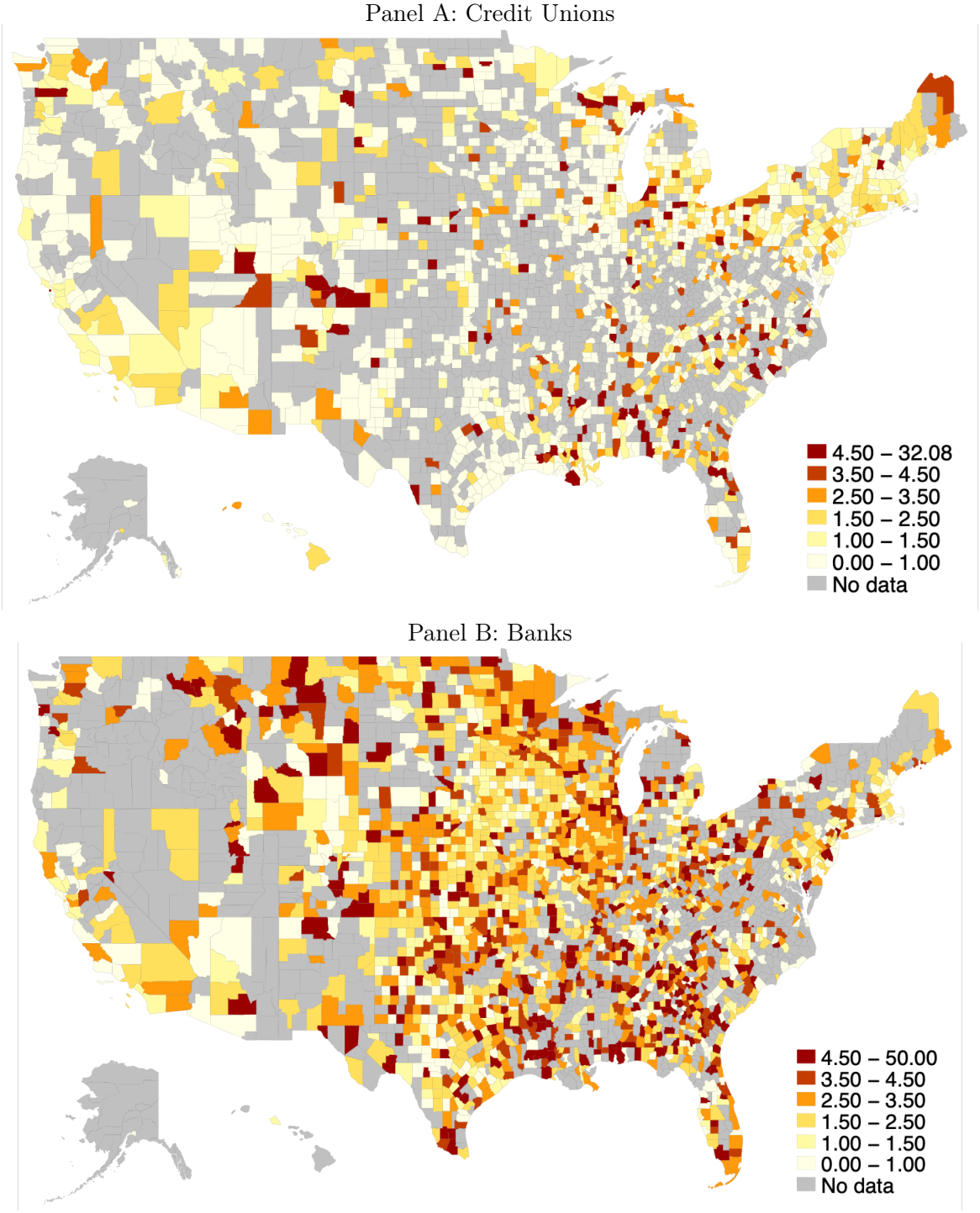

Figure III: **County-Level Mortgage Default Rates.** This figure maps average mortgage default rates across U.S. counties in 2024q4, separately for credit unions (Panel A) and banks (Panel B). Counties shaded gray indicate no data for that institution type.

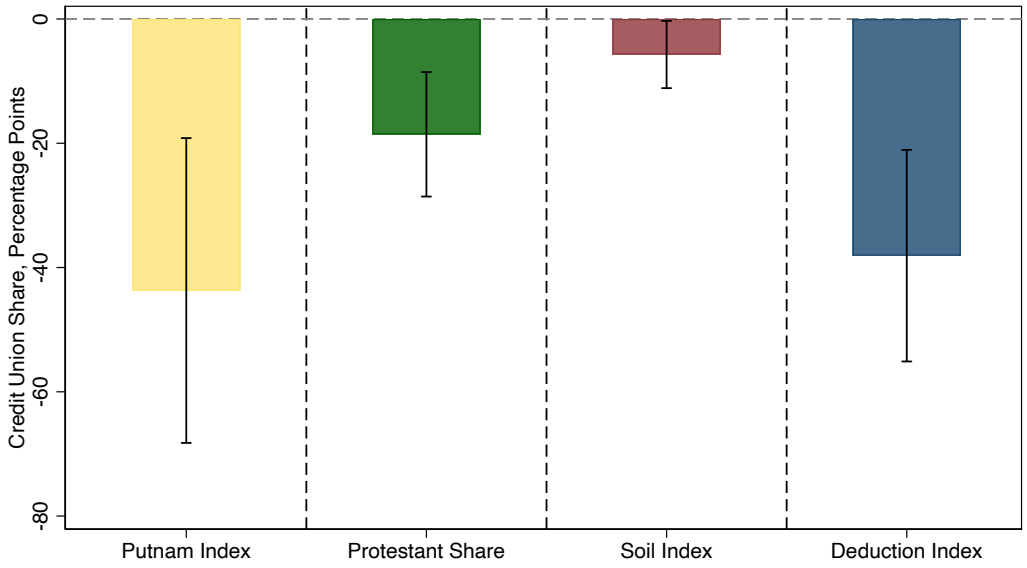

Figure IV: **Relationship between Social Capital and Local Credit Union Presence** This figure presents the coefficients of the coefficient on the social capital proxies in equation (3), with 95% confidence intervals. In all regressions, standard errors are clustered at the state level.

Table I: **Summary Statistics**

This table reports summary statistics at the institution-product-quarter level for all depository institutions (Panel A), for credit unions (Panel B), and for banks (Panel C). Appendix Section A.1 provides details on data construction.

	Mean	P10	P50	P90	Observations
Panel A. All Depository Institutions					
Outcome Variables					
Default Rate - Mortgages (%)	2.02	0.00	0.74	5.24	1,204,340
Default Rate - Vehicle Loans (%)	1.39	0.00	0.25	3.73	663,189
Default Rate - Credit Cards (%)	1.75	0.00	0.81	4.40	328,598
Explanatory Variables					
Credit Union Dummy	0.48				1,237,351
Low Num. Branches Dummy	0.56				1,237,351
Medium Num. Branches Dummy	0.37				1,237,351
High Num. Branches Dummy	0.06				1,237,351
Control Variables					
Num. Employees	172.24	1.00	21.00	153.00	1,203,887
Asset Size (Millions)	1,270.27	3.96	78.49	716.50	1,205,458
Num. Branches	8.01	1.00	2.00	10.00	1,231,724
Panel B. Credit Unions					
Outcome Variables					
Default Rate - Mortgages (%)	1.43	0.00	0.00	3.79	598,878
Default Rate - Vehicle Loans (%)	1.10	0.00	0.04	3.08	362,209
Default Rate - Credit Cards (%)	1.74	0.00	0.91	4.42	263,285
Explanatory Variables					
Credit Union Dummy	1.00				598,878
Low Num. Branches Dummy	0.72				598,878
Medium Num. Branches Dummy	0.25				598,878
High Num. Branches Dummy	0.03				598,878
Professional Common Bond Dummy	0.70				598,878
Geographic Common Bond Dummy	0.25				598,878
Religious Common Bond Dummy	0.05				598,878
Control Variables					
Number Employees	37.54	0.00	6.00	82.00	598,878
Asset Size (Millions)	184.43	1.48	20.85	312.95	598,878
Number Branches	2.98	1.00	1.00	6.00	598,878

Table I: **Summary Statistics (Cont.)**

This table reports summary statistics at the institution-product-quarter level for all depository institutions (Panel A), for credit unions (Panel B), and for banks (Panel C). Appendix Section A.1 provides details on data construction.

	Mean	P10	P50	P90	Observations
Panel C. Banks					
Outcome Variables					
Default Rate - Mortgages (%)	2.61	0.00	1.47	6.24	605,462
Default Rate - Vehicle Loans (%)	1.75	0.00	0.40	4.62	300,980
Default Rate - Credit Cards (%)	1.80	0.00	0.30	4.30	65,313
Explanatory Variables					
Low Num. Branches Dummy	0.42				638,473
Medium Num. Branches Dummy	0.49				638,473
High Num. Branches Dummy	0.09				638,473
Control Variables					
Num. Employees	305.57	10.00	40.00	218.00	605,009
Asset Size (Millions)	2,342.33	38.13	166.27	1,111.11	606,580
Num. Branches	12.77	1.00	3.00	14.00	632,846

Table II: **Altruism vs. Social Pressure: Default Rates by Collateral Types**
This table reports results at the bank-quarter level for regressing 30-day default rates on mortgages (Panel A), vehicle loans (Panel B), and credit card debt (Panel C) on an indicator capturing credit unions and the set of controls and fixed effects indicated at the bottom of the table. Standard errors are clustered at the state level: *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
		Panel A: Mortgages		
Credit Union	-1.04***	-1.02***	-1.02***	-1.01***
	(0.11)	(0.10)	(0.09)	(0.08)
Constant	2.29***	2.25***	1.92***	1.79***
	(0.13)	(0.07)	(0.14)	(0.20)
Observations	1,203,887	1,203,767	1,203,767	1,202,984
		Panel B: Vehicle Loans		
Credit Union	-0.23**	-0.17*	-0.13	-0.14
	(0.09)	(0.10)	(0.08)	(0.08)
Constant	1.46***	1.39***	0.81***	0.74***
	(0.11)	(0.08)	(0.20)	(0.23)
Observations	571,858	571,802	571,802	571,181
		Panel C: Credit Cards		
Credit Union	0.84***	1.07***	0.72***	0.70***
	(0.19)	(0.17)	(0.10)	(0.09)
Constant	0.29	-0.10	0.75***	1.11***
	(0.22)	(0.24)	(0.28)	(0.25)
Observations	609,427	609,408	609,408	608,615
Control: Log(Employees)	Yes	Yes	Yes	Yes
State-by-YearQuarter FE	No	Yes	Yes	Yes
Asset Size Pct FE	No	No	Yes	Yes
Num. Branches FE	No	No	No	Yes

Table III: **Altruism vs. Social Pressure: Heterogeneity by Tightness of Social Groups**
This table reports results at the bank-quarter level for regressing 30-day default rates on mortgages (column (1)), vehicle loans (column (2)), and credit card debt (column (3)) on an indicator capturing credit unions, interactions of the indicator with dummy variables capturing groups of banks by their number of branches, and the set of controls and fixed effects indicated at the bottom of the table. Standard errors are clustered at the state level: *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1) Mortgages	(2) Vehicle Loans	(3) Credit Cards
Credit Union	-1.16***	-0.47***	0.79*
	(0.11)	(0.12)	(0.40)
Credit Union×	0.25**	0.54***	-0.07
Medium Num. Branches (3-15)	(0.10)	(0.10)	(0.58)
Credit Union×	0.33***	0.68***	-0.87*
High Num. Branches (>15)	(0.10)	(0.13)	(0.45)
Medium Num. Branches (3-15)	-0.14*	-0.19***	0.74**
	(0.08)	(0.07)	(0.30)
High Num. Branches (>15)	-0.36**	-0.33**	1.32***
	(0.16)	(0.13)	(0.38)
Log(Employees)	0.22***	0.26***	0.22**
	(0.05)	(0.07)	(0.09)
Constant	1.97***	1.04***	0.73**
	(0.15)	(0.20)	(0.35)
State-by-YearQuarter FE	Yes	Yes	Yes
Asset Size Pct FE	Yes	Yes	Yes
Num. Branches FE	Yes	Yes	Yes
Observations	1,202,984	571,802	609,408

Table IV: **Altruism vs. Social Pressure: Heterogeneity by Strength of Common Bond**
This table reports results at the bank-quarter level for regressing 30-day default rates on mortgages (column (1)), vehicle loans (column (2)), and credit card debt (column (3)) on an indicator capturing credit unions, interactions of the indicator with dummy variables capturing groups of credit unions by their common bond type, and the set of controls and fixed effects indicated at the bottom of the table. Standard errors are clustered at the state level: *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
	Mortgages	Vehicle Loans	Credit Cards
Credit Union	-1.06***	-0.14	0.71***
	(0.09)	(0.09)	(0.10)
Credit Union×	0.15**	0.00	-0.02
Geographic Common Bond	(0.07)	(0.06)	(0.20)
Credit Union×	0.57***	0.25*	-0.25
Religious/Fraternal Common Bond	(0.18)	(0.14)	(0.25)
Log(Employees)	0.24***	0.30***	0.21**
	(0.06)	(0.07)	(0.08)
Constant	1.77***	0.73***	1.12***
	(0.19)	(0.23)	(0.24)
State-by-YearQuarter FE	Yes	Yes	Yes
Asset Size Pct FE	Yes	Yes	Yes
Num. Branches FE	Yes	Yes	Yes
Observations	1,202,984	571,181	608,615

Table V: **Credit Union Loan Characteristics**

This table reports the regression results for equation 2 for the various HDMA-available proxies of demand-side and supply-side alternative explanations. *High DTI* (Column (1)) is a dummy variable equal to one if the borrower's debt-to-income ratio is above 50%, and 0 otherwise. *LTV* (Column (2)) is the loan-to-value ratio of the mortgage. *Intro. Rate* (Column (3)) is a dummy variable equal to 1 if the mortgage features an introductory rate and 0 otherwise. *Int. Payment* is a dummy variable equal to 1 if the mortgage offers an interest-only feature and 0 otherwise. Standard errors are clustered at the lender and state level: *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1) High DTI	(2) LTV	(3) Intro. Rate	(4) Int. Payment
Credit Union	0.50	-13.24	-4.08**	3.45**
	(0.36)	(26.13)	(2.00)	(1.45)
Observations	30,521,920	31,439,167	34,065,454	34,065,454
R-squared	0.06	0.00	0.19	0.20
Control: Log(Employees)	Y	Y	Y	Y
State-by-YearQuarter FE	Y	Y	Y	Y
Asset Size Pct FE	Y	Y	Y	Y
Num. Branches FE	Y	Y	Y	Y

Table VI: **Credit Union Loan Characteristics by Number of Branches**

This table reports the regression results for equation 2 for the various HDMA-available proxies of demand-side and supply-side alternative explanations, with credit unions split by branch sizes. *High DTI* (Column (1)) is a dummy variable equal to one if the borrower's debt-to-income ratio is above 50%, and 0 otherwise. *LTV* (Column (2)) is the loan-to-value ratio of the mortgage. *Intro. Rate* (Column (3)) is a dummy variable equal to 1 if the mortgage features an introductory rate and 0 otherwise. *Int. Payment* is a dummy variable equal to 1 if the mortgage offers an interest-only feature and 0 otherwise. The omitted category are 1 to 2 branch credit unions. Standard errors are clustered at the lender and state level: *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1) High DTI	(2) LTV	(3) Intro. Rate	(4) Int. Payment
Credit Union	-2.81	2.53	12.35	17.12*
	(2.16)	(31.53)	(11.86)	(9.68)
Credit Union ×	0.91	-76.98	-25.44**	-13.23
Medium Num. Branches (3–15)	(2.07)	(92.42)	(11.26)	(9.44)
Credit Union ×	5.49**	6.40	-11.29	-20.36**
High Num. Branches (15+)	(2.20)	(27.75)	(11.66)	(9.50)
Medium Num. Branches (3–15)	0.72	83.09	18.68***	4.85
	(1.95)	(100.36)	(5.59)	(3.12)
High Num. Branches (15+)	-1.43	-35.59*	22.31***	17.01***
	(2.18)	(20.38)	(6.48)	(4.05)
Observations	30,521,921	31,439,167	34,065,454	34,065,454
R-squared	0.04	0.00	0.15	0.13
Control: Log(Employees)	Y	Y	Y	Y
State-by-YearQuarter FE	Y	Y	Y	Y
Asset Size Pct FE	Y	Y	Y	Y

Table VII: **Credit Union Loan Characteristics by Common Bond**

This table reports the regression results for equation 2 for the various HDMA-available proxies of demand-side and supply-side alternative explanations, with credit unions split by branch sizes. *High DTI* (Column (1)) is a dummy variable equal to one if the borrower's debt-to-income ratio is above 50%, and 0 otherwise. *LTV* (Column (2)) is the loan-to-value ratio of the mortgage. *Intro. Rate* (Column (3)) is a dummy variable equal to 1 if the mortgage features an introductory rate and 0 otherwise. *Int. Payment* is a dummy variable equal to 1 if the mortgage offers an interest-only feature and 0 otherwise. The omitted category are professional common bond credit unions. Standard errors are clustered at the lender and state level: *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1) High DTI	(2) LTV	(3) Intro. Rate	(4) Int. Payment
Credit Union	0.47	-17.60	-3.89*	3.49**
	(0.43)	(27.06)	(2.12)	(1.46)
Credit Union ×	0.21	29.69	-0.77	-0.06
Geographic Common Bond	(1.04)	(43.73)	(3.24)	(3.15)
Credit Union ×	-1.04	-130.75	-25.46***	-11.51**
Religious Common Bond	(1.10)	(157.67)	(9.08)	(5.11)
Observations	30,521,920	31,439,167	34,065,454	34,065,454
R-squared	0.06	0.00	0.19	0.20
Control: Log(Employees)	Y	Y	Y	Y
State-by-YearQuarter FE	Y	Y	Y	Y
Asset Size Pct FE	Y	Y	Y	Y
Num. Branches FE	Y	Y	Y	Y

Online Appendix to
BANKING SOCIALLY[*]

Francesco D'Acunto[†] Quentin Dupont[‡] Agustin Hurtado[§]

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[†]Georgetown University.

[‡]Georgetown University.

[§]University of Maryland.

A.1. Data Sources and Construction

This section provides additional details on the construction of the data used in the paper. Our analysis combines quarterly regulatory filings for commercial banks and credit unions, newly collected information on credit unions' common bonds, institution and branch characteristics, public Home Mortgage Disclosure Act data, and county-level measures of social capital. We first construct the relevant measures within each original data source and then harmonize them across institution types and over time.

A.1.1. Call Report Data and Default Measures

Our primary data on lending and repayment come from the FFIEC 031/041 Call Reports for commercial banks and the NCUA 5300 Call Reports for credit unions. The unit of observation in the resulting repayment panel is an institution-product-quarter. Both reporting systems provide quarterly information on outstanding loan balances and delinquent balances, including information disaggregated by major consumer credit products. They also contain institution characteristics used throughout the analysis.

The two reporting systems differ in their product definitions and delinquency classifications, and these classifications change over time. We therefore construct the bank and credit union panels separately before harmonizing them. For each institution type and product, we identify the regulatory fields measuring outstanding balances and the corresponding fields measuring delinquent balances. We require the delinquent balance used in the numerator of the default rate to correspond to the same underlying loan category as the outstanding balance used in the denominator.

A.1.1.1. Delinquency Reporting

Our primary repayment outcome is the 30+ day default rate. Throughout the paper, we use "default" as shorthand for delinquency of at least 30 days. For each institution, product, and quarter, we construct the default rate as the dollar amount of loans at least 30 days delinquent divided by the corresponding dollar amount of loans outstanding, expressed in percentage points.

The 30-day threshold is determined by the reporting structure of the underlying regulatory data. Credit unions report delinquent balances using relatively fine days-past-due categories, but these categories change in 2022. Prior to 2022, NCUA filings report balances that are 30–59, 60–179, 180–359, and at least 360 days past due. Beginning in 2022, the categories are 30–59, 60–89, 90–179, 180–359, and at least 360 days past due.

Bank Call Reports also distinguish delinquency by days past due, including balances that are 30–89 days past due, balances that are 90 or more days past due, and nonaccrual balances for the relevant products. The availability of the underlying product-level series varies over time, as reported in Appendix Table A.3.1.

These reporting conventions imply that a separate 90+ day delinquency measure cannot be constructed for credit unions before 2022. In contrast, we can aggregate the underlying categories

to construct a 30+ day delinquency measure for both institution types over the harmonized sample period for each product. We therefore use 30+ day delinquency throughout the paper. This choice maintains a common economic definition of default across banks and credit unions and preserves that definition through the change in NCUA reporting in 2022.

Appendix Table A.3.1 reports the availability of outstanding balances, 30+ day delinquent balances, and 90+ day delinquent balances for each institution type and product, together with the resulting harmonized sample periods.

A.1.1.2. Mortgages

For commercial banks, mortgage lending includes revolving, open-end loans secured by one-to-four-family residential properties and extended under lines of credit, together with closed-end loans secured by first liens on one-to-four-family residential properties. For credit unions, the corresponding categories consist of loans and lines of credit secured by a first lien on a one-to-four-family residential property.

We map credit union loans to the corresponding closed-end mortgage category in the bank data and credit union lines of credit to the corresponding revolving, open-end category in the bank data. We apply the same product mapping separately to outstanding and delinquent balances, which ensures that the numerator and denominator of the default rate refer to the same underlying mortgage products.

Credit union mortgage balances are available beginning in 1994q2, while the corresponding 30+ day delinquency series is also available beginning in 1994q2. Bank mortgage balances are available beginning in 1990q1, while the bank 30+ day delinquency series is available beginning in 2003q1. The resulting harmonized mortgage sample therefore covers 2003q1 through 2024q4.

A.1.1.3. Vehicle Loans

Commercial banks report vehicle lending as automobile loans. Credit unions report new and used vehicle loans separately. We sum new and used vehicle loans for credit unions and match this combined category to automobile loans for commercial banks. We use the same mapping for outstanding balances and delinquent balances.

Credit union vehicle loan balances are available beginning in 1994q1, but the corresponding 30+ day delinquency series is available beginning in 2013q2. For banks, both outstanding automobile loan balances and 30+ day delinquent balances are available beginning in 2011q1. The common vehicle loan sample therefore begins in 2013q2 and extends through 2024q4.

A.1.1.4. Credit Cards

For credit cards, no product mapping is necessary because both banks and credit unions report credit card loans as a distinct category. We can therefore directly match outstanding credit card balances to the corresponding delinquent balances within each reporting system.

Credit union credit card balances are available beginning in 1994q1 and the corresponding 30+ day delinquency series is available beginning in 2003q1. Bank credit card balances are available beginning in 1990q1 and the corresponding 30+ day delinquency series is available beginning in 2001q1. The harmonized credit card sample therefore covers 2003q1 through 2024q4.

A.1.2. Credit Union Common Bond Data

A distinctive feature of our data is that we observe the type of common bond linking credit union members. We obtained *Type of Membership* (TOM) codes and their official descriptions from the National Credit Union Administration through a Freedom of Information Act request covering 2003 through 2024.

We combine these newly collected descriptions with TOM codes reported in the quarterly NCUA 5300 filings. From the NCUA filings, we construct a panel containing each credit union's charter number, institution name, reporting quarter, and TOM code. The underlying TOM codes in the regulatory filings are available from 1994q4 through 2024q4. Linking the official TOM descriptions to this panel allows us to classify credit unions according to the nature of their common bond.

We classify TOM codes into three mutually exclusive groups.

Religious or associational common bonds. We classify TOM codes 01, 02, and 03 as religious or associational:

- TOM 01: Associational religious, other than those designated low income.
- TOM 02: Associational fraternal, other than those designated low income.
- TOM 03: Associational other than religious or fraternal, or low-income associational institutions.

Geographic or community common bonds. We classify TOM codes 00, 06, 36, 66, and 77 as geographic or community:

- TOM 00: Community credit unions, urban or rural, other than those designated low income.
- TOM 06: Federal, state, and local government.
- TOM 36: Multiple group, primarily federal, state, and local government.
- TOM 66: Community Rural District.
- TOM 77: Community CBSA(+) Adjacent.

We classify TOM codes 06 and 36 as geographic rather than professional because these institutions primarily organize membership around a public-sector employer associated with a common locality, such as a state, county, city, or district, while potentially encompassing

heterogeneous occupations. Treating these institutions as professional would pool individuals from economically distinct occupations and weaken the interpretation of professional bonds as capturing occupational cohesion. Grouping them with geographic common bonds instead preserves the common geographic component of the field of membership.[1]

Professional or occupational common bonds. We classify all remaining TOM codes as professional or occupational. These codes capture employer-, trade-, industry-, and profession-based fields of membership, including educational institutions, health care workers, manufacturing workers, transportation workers, military personnel, and employees of individual firms or related groups. Appendix Table A.3.2 reports the complete set of TOM codes and their official descriptions.

We link the resulting common bond classifications to the credit union panel using NCUA charter numbers. Appendix Figure A.2.1 reports the evolution of both the number and share of credit unions in each common bond category over time.

A.1.3. Institution Characteristics and Branch Data

We use four institution-level characteristics in the main repayment analysis: total assets, number of employees, headquarters location, and number of branches. For both commercial banks and credit unions, these measures come from the corresponding call reports.

Total assets capture balance sheet size and financial capacity, while employment provides a complementary measure of organizational scale and labor intensity. Headquarters location allows us to compare institutions exposed to the same state-level economic conditions. Institution-level branch counts measure each institution's physical footprint and provide the variation used in our analysis of the tightness of the communities served by the lender.

In the heterogeneity analysis, we classify institutions into three groups according to the number of branches: institutions with one or two branches, institutions with 3–15 branches, and institutions with more than 15 branches. The first group forms the set of institutions for which the potential borrower community is most geographically concentrated.

For analyses requiring the geographic location of individual branches rather than simply the institution-level branch count, we use separate branch-level sources. Credit union branch locations come from the NCUA Credit Union Branch Information files, which are available beginning in 2013. Commercial bank branch locations come from the FDIC Summary of Deposits. We use these branch-level sources for the county-level social capital analysis described below.

A.1.4. Social Capital Data

For the analysis in Section V, we use four measures of social capital at the county level. The measures capture different aspects of local social connectedness and are constructed from

[1]The NCUA definitions pool federal, state, and local government memberships within TOM codes 06 and 36. We therefore cannot consistently separate federal-only memberships from state and local government memberships. We apply the same classification throughout the sample.

independent sources.

Social Capital Index. Our first measure is the 2014 Putnam Index, based on Rupasingha et al. (2006). The index is constructed as the first principal component of county-level measures of per capita sociocultural associations and nonprofit organizations, together with measures of participation in the Census and federal elections. These inputs capture dimensions of civic participation and associational activity emphasized by Putnam (2000).[2]

Protestant share. Our second measure is motivated by Putnam (1993), who emphasizes the role of religious organizations and shared values in the formation of social capital. We use the share of Protestants in each U.S. county from the Association of Religious Data Archives' 2010 Religious Membership and Congregations Survey (ARDA, 2010).

Soil heterogeneity. Our third measure follows Raz (2025), who studies the relationship between soil heterogeneity, social learning, and the formation of close-knit communities. Greater soil heterogeneity makes agricultural knowledge less transferable across individuals and is associated with weaker community formation. We therefore use the negative of Raz's county-level soil heterogeneity index, *SHI25*, so that larger values correspond to greater social capital. We use the 1940 value because it is the most recent period available in the source data.

Itemized deductions. Our fourth measure uses the IRS Statistics of Income data for 2013, 2014, and 2015. These data report income tax information at the ZIP code level. Motivated by Putnam (2000)'s emphasis on philanthropy as an expression of social capital, we begin with the share of tax filings reporting itemized deductions.

Because the propensity to itemize is strongly related to income, we regress the share of filings with itemized deductions on average logged adjusted gross income in the county and use the residual as our measure of social capital. The underlying IRS data are reported by ZIP code, so we aggregate them to counties using the HUD–USPS ZIP Code Crosswalk.

Itemized deductions are not exclusively charitable contributions. We therefore interpret this variable as a proxy rather than a direct measure of charitable giving.[3]

County-level credit union presence. For the social capital analysis, we use branch-location data from 2013 through 2015. We aggregate bank and credit union branches to the county-year level and count the number of branches of each institution type in each county. For county c and year t, we define the credit union share as

[2]Some organizations included in the underlying associational measures could potentially include credit unions. This possibility is unlikely to account for our results because the index combines a substantially broader set of civic and associational measures and because our results are qualitatively similar using the three alternative measures described below, which do not mechanically incorporate credit union presence.

[3]The original data construction is motivated in part by evidence from the Urban Institute and Brookings Institution Tax Policy Center that charitable deductions account for a large component of itemized deductions. See https://taxpolicycenter.org/briefing-book/how-large-are-individual-income-tax-incentives-charitable-giving.

$$Credit\,Union\,Share_{c,t} = 100 \times \frac{Number\ of\ Credit\ Union\ Branches_{c,t}}{Number\ of\ Credit\ Union\ Branches_{c,t} + Number\ of\ Bank\ Branches_{c,t}}$$

We merge these county-year observations to the Social Capital Index, Protestant share, and soil heterogeneity data using county identifiers. We first use the HUD–USPS crosswalk to aggregate the IRS Statistics of Income variables to counties and then merge the resulting measures to the county-year branch panel.

A.1.5. Public HMDA Data

For the analysis in Section IV, we complement the institution-level regulatory data with public Home Mortgage Disclosure Act data covering 2018 through 2025. HMDA provide information at the mortgage application level, including lender identity, application outcomes, loan and property characteristics, property location, applicant income, race and Hispanicity, and information about coapplicants.

HMDA play a different role from the Call Reports in our analysis. The Call Reports provide the repayment outcomes used in our main tests but contain comparatively little information about individual borrowers. HMDA provide substantially richer borrower-level information but do not contain subsequent delinquency outcomes. We therefore use HMDA to characterize the observable mortgage borrower pools served by credit unions and commercial banks and to assess their comparability, rather than to construct default rates.

We identify HMDA reporters as credit unions or commercial banks by linking HMDA lender identifiers to the corresponding regulatory institutions. Specifically, we use the HMDA Lender File (also known as the Avery File) to link HMDA reporters to NCUA charter identifiers and bank RSSD identifiers.

A.1.6. Merges, Sample Screens, and Final Analysis Samples

Credit unions. We begin with the product-level outstanding and delinquent balances constructed from the NCUA 5300 filings. We merge these observations to the common bond panel using NCUA charter numbers and then add the institution characteristics required for the corresponding empirical specification.

This procedure yields matches for 99.9% of credit unions in the initial sample. We drop credit unions without valid identifiers across the required datasets, observations with missing information needed to construct the relevant loan or default measure, and institutions that report zero total lending throughout their observed history.

Commercial banks. For commercial banks, we begin with the product-level outstanding and delinquent balances constructed from the FFIEC 031/041 Call Reports. We merge institution characteristics using Research, Statistics, Supervision, and Regulation (RSSD) identifiers.

This procedure yields matches for 99.8% of banks in the initial sample. We drop observations with missing information needed to construct the relevant loan or default measure and institutions that report zero lending activity throughout their observed history.

Because the unmatched share is economically small for both institution types, the main text summarizes these procedures as retaining approximately 99.9% of the institutions in the underlying samples.

Final repayment samples. The final sample period differs across products because the underlying regulatory series become jointly available at different dates. The harmonized mortgage and credit card samples cover 2003q1 through 2024q4. The harmonized vehicle loan sample covers 2013q2 through 2024q4.

Appendix Table A.3.1 provides the availability of the underlying loan and delinquency measures that determine these sample periods.

A.2. Figures

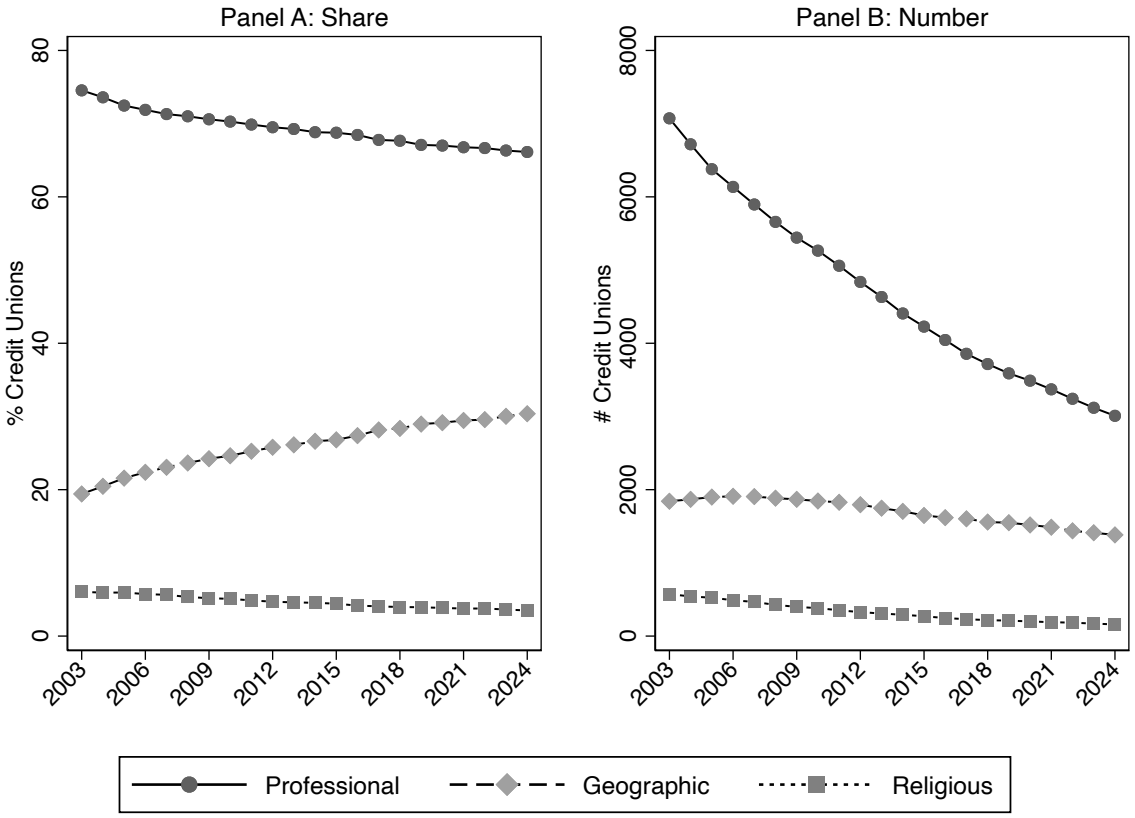

Figure A.2.1: **Credit Union Share and Number by Common Bond Type.** This figure reports the share (Panel A) and number (Panel B) of credit unions across different common bond types. Professional bonds encompass employees of the same firm or related entities, as well as "trade, industry, or profession" bonds that group individuals by sector or occupation, such as health care workers or teachers. Geographic common bonds are defined by residence, schooling, employment, or worship within a specific geographic area. Religious bonds extend membership through affiliation with a church, fraternal organization, or labor union. Vertical axes show the share of credit unions (Panel A) and the number of credit unions (Panel B) for each common bond type. Both panels are based on call report and common bond data obtained through a FOIA request covering the period 2003-2024.

A.3. Tables

Table A.3.1: **Data Availability and Harmonized Default Samples**

This table reports the availability of the underlying regulatory series used to construct product-level default measures for commercial banks and credit unions. Loan Amount refers to outstanding loan balances. The 30+ and 90+ Default Amount columns report the availability of balances at least 30 and 90 days delinquent, respectively. Our main outcome is the 30+ default rate, defined as balances at least 30 days delinquent divided by the corresponding outstanding loan balance. We use the 30+ threshold because it is the only delinquency measure that can be constructed consistently across banks and credit unions and over time, including the change in NCUA delinquency reporting in 2022. The final column reports the harmonized sample period used in the paper. Section II.B and the Online Appendix provide details on the reporting conventions, delinquency buckets, and product mappings.

Institution	**Product**	**Loan Amount**	**30+ Default Amount**	**90+ Default Amount**	**Harmonized 30+ Sample**
Credit Union	Mortgages	1994q2–2024q4	1994q2–2024q4	2022q1–2024q4	2003q1–2024q4
Bank	Mortgages	1990q1–2024q4	2003q1–2024q4	1990q1–2024q4	2003q1–2024q4
Credit Union	Vehicle Loans	1994q1–2024q4	2013q2–2024q4	2022q1–2024q4	2013q2–2024q4
Bank	Vehicle Loans	2011q1–2024q4	2011q1–2024q4	2011q1–2024q4	2013q2–2024q4
Credit Union	Credit Cards	1994q1–2024q4	2003q1–2024q4	2022q1–2024q4	2003q1–2024q4
Bank	Credit Cards	1990q1–2024q4	2001q1–2024q4	1990q1–2024q4	2003q1–2024q4

Code	Description
04	Educational
05	Military
10	Manufacturing - chemicals
11	Manufacturing - petroleum refining
12	Manufacturing - primary and fabricated metals
13	Manufacturing - machinery
14	Manufacturing - transportation equipment
15	Manufacturing - all other
20	Service - finance, insurance, real estate, trade
21	Service - health care
22	Service - transportation
23	Service - communications and utilities
24	Single common bond - other
34	Multiple group - primarily educational
35	Multiple group - primarily military
40	Multiple group - primarily chemical
41	Multiple group - primarily petroleum refining
42	Multiple group - primarily primary and fabricated metals
43	Multiple group - primarily machinery
44	Multiple group - primarily transportation equipment
49	Multiple group - primarily other manufacturing
50	Multiple group - primarily finance, insurance, real estate, trade
51	Multiple group - primarily health care
52	Multiple group - primarily transportation
53	Multiple group - primarily communications and utilities
54	Multiple common bond - other
98	Multiple group - other
99	Non-Federal Credit Union

Table A.3.2: **TOM Codes and Descriptions for Professional Common Bonds.** This table lists Type of Membership (TOM) codes and descriptions used to classify professional common bond credit unions. The data are obtained from NCUA common bond classifications through a FOIA request covering 2003-2024.

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