Non-Profits, Competition, and Risk Segmentation in Consumer Lending Markets*

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Abstract

We study how competition between non- and for-profit lenders shapes the equilibrium distribution of credit risk across lending institutions. Using auto loan data, we document direct competition between credit unions and banks for a significant fraction of the market. However, a degree of market segmentation by borrower risk still exists: credit unions serve observably and unobservably lower-risk borrowers. Using exposure to bank mergers as quasi-exogenous variation in market structure, we provide evidence that price differences between credit unions and banks contribute to this segmentation, consistent with adverse selection on borrower risk. These results highlight potential unintended consequences of bank consolidation.

Keywords: non-profit competition, auto lending, credit unions

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1. Introduction

Non- and for-profit firms frequently interact in settings characterized by asymmetric information, including lending and healthcare markets. Because non-profits may place weight on the welfare of its members or the community, they may deviate from pure profit maximization. In these cases, adverse selection and profit-deviating incentives can jointly shape market outcomes. While previous work has separately examined the role of asymmetric information (Mahoney & Weyl, 2017; Crawford *et al.*, 2018; Yannelis & Zhang, 2023) and profit-deviating incentives (Lakdawalla & Philipson, 1998; Gaynor & Vogt, 2003; Shahidinejad, 2024) in various settings, our work instead analyzes their interaction, using the auto lending market as a laboratory.

In this paper, we characterize the competitive interactions between credit unions, which are non-profit cooperatives, and traditional banks. Credit unions differ from banks along a number of dimensions: they are member-owned, face different regulation, and are tax-exempt, non-profit institutions, which could lead them to deviate from pure profit maximization. If profit-deviating incentives are sufficiently strong, they could lead credit unions to offer advantageous loan prices. With adverse selection, this could lead safe (risky) borrowers to select into credit unions (banks), segmenting the market and increasing the credit risk faced by traditional banks. Given the debate about the degree to which credit unions deviate from pure profit maximization, we provide empirical evidence on the competitive interactions of credit unions and banks and their implications for the equilibrium composition of risk across these institutions.

Our first contribution is to document two stylized facts about the nature of competition between credit unions and banks in the auto loan market. Using the Equifax Analytic Dataset – a loan-level dataset derived from a 10% random, anonymous sample of US consumers tracked in Equifax's core consumer credit database – we document a combination of direct competition and segmentation by borrower risk. First, at a high level, credit unions and banks focus on relatively similar credit-risk segments in the auto loan market. In stark contrast to non-depository lenders, the relationship between market shares and credit scores is very similar for both lender types. Moreover, using consumer identifiers in our data, we show that approximately

40% of the time, credit union and bank borrowers switch to a different lender type for the next car loan. Second, differences in borrower composition and pricing show that credit unions charge lower interest rates than banks but that they also serve a lower-risk set of borrowers. Credit union borrowers have higher credit scores and lower default rates conditional on credit scores. Importantly, credit scores are observable at origination, while default is not.

In principle, these stylized facts are consistent with three potentially complementary forces playing a role. The first is "lender-driven" selection, where credit unions have private information on their borrowers and thereby select lower-risk borrowers (Petersen & Rajan, 1995; Hauswald & Marquez, 2006). The second is "borrower-driven" selection, where, due to adverse selection, lower prices at credit unions will induce borrowers to select into credit unions (Stiglitz & Weiss, 1981). The third is that, holding populations fixed, interest rates have a positive causal effect on default, arising from the higher repayment burden that comes with higher interest rates. To the extent that the membership model of credit unions binds in practice, we see scope for lender-driven selection. However, relative to other consumer credit markets, membership relationships have a lower impact on the auto loan market because car dealers intermediate the vast majority of loans (Grunewald *et al.*, 2023). Furthermore, among high credit score borrowers, where the scope for adverse selection is nearly eliminated, we observe credit unions offering lower prices – an observation that is particularly consistent with the idea of price-lead, borrower-driven selection.

While this descriptive evidence suggests the existence of both competition *and* segmentation along both observable and unobservable dimensions, it alone is not sufficient to conclude that variation in borrower risk across lender types is an equilibrium consequence of strategic interaction between credit unions and banks. Rather, it could be that geographies in which credit unions are present differ along unobservable dimensions from bank-dominant geographies.

Our second contribution, therefore, addresses this point by analyzing the strategic interaction directly. More specifically, we study variation in exposure to changes in bank concentration arising from large bank mergers. We combine the consumer credit data with dealer-based market definitions that capture the geographic scope of competition in auto lending and, in a difference-in-differences framework, compare markets based on the degree to which they were affected by bank mergers. We quantify the equilibrium responses to these mergers by lender type and document heterogeneity by the merger's expected change in market concentration.

In geographies experiencing large changes in concentration, bank mergers lead banks to raise interest rates, potentially reflecting an increase in market power. Relative to markets with low or no changes in concentration, we estimate an incremental effect of 8 basis points, on average. Credit unions, on the other hand, respond by *decreasing* their interest rates by a sizable magnitude of 16 basis points. The fact that credit unions respond suggests, by itself, that they do compete directly with banks. However, the lack of strategic complementarity in pricing indicates that changes in borrower composition could explain some of this effect and that adverse selection might lead to changes in risk composition. We test this explanation directly and find changes in default rates consistent with adverse selection (i.e., unexplained by adjustments in borrower or loan characteristics). Default rates rise at banks and fall at credit unions following mergers, driven by the response of near-prime borrowers, for whom problems of asymmetric information are likely to be more severe. We also conduct market-level regressions, which indicate that customers are switching from banks to credit unions, and that market size remains constant. We interpret this evidence as inconsistent with the explanation that higher interest rates are causally leading to higher default via higher repayment burden.

Together, these results suggest that high (low) interest rates draw in disproportionately high- (low-) risk borrowers, meaning mergers that increase concentration also increase the extent of risk segmentation across lender types. Furthermore, they suggest that credit union presence – and in particular their advantageous loan pricing – could lead to an unintended consequence of mergers. Large price differentials between banks and credit unions could exacerbate merger-induced risk segmentation, lowering the credit quality of borrowers served by banks. We formalize this intuition with a simple model that analyzes the interaction of profit-deviating incentives and adverse selection. Through the lens of the model, we show that the equilibrium response of credit unions to bank mergers can be explained by a change in risk composition driven by price changes (i.e., "borrower-driven" selection).

There is significant policy interest in understanding the nature of competition between credit unions and banks. Between 2014 and 2024, total loans outstanding at credit unions increased almost threefold from $653 billion to $1.63 trillion[1]. In 2021, President Biden signed an executive order, calling on the Department of Justice and bank regulators to update their banking merger guidelines.[2] One crucial piece of this process is determining whether to treat credit unions, fintech firms, and nonbanks in the same way as traditional banks. In a 2023 speech, Federal Reserve Governor Michelle Bowman stressed this point: "In our current system, many of the competitors and new entrants that we do have (nonbanks, fintech firms, credit unions) are systematically ignored. The baseline assumption in our current framework is that credit unions do not compete with banks, and yet, just last month we saw five announced acquisitions of community banks by credit unions."[3] While the agencies have begun to explicitly consider credit union presence in some cases, there does not appear to be a standard approach regarding their inclusion.[4]

The policy implications of our results are two-fold. First, the results suggest that relying upon bank-only deposit shares for prospective merger analysis could lead to misleading conclusions. Accounting for the role of credit unions is particularly relevant in consumer lending markets, where their presence is sizable and they compete directly with traditional banks. In addition to credit union presence, it is important to consider potential market segmentation effects of mergers, where increased pricing differentials between credit unions and banks could lead high-risk borrowers to disproportionately select into high-interest rate lenders. Second, these results have implications for the effects of credit union acquisitions of community banks, which

[1]See National Credit Union Administration Quarterly Data Summary Reports, available at https://ncua.gov/analysis/credit-union-corporate-call-report-data/quarterly-data-summary-reports.

[2]The White House. "FACT SHEET: Executive Order on Promoting Competition in the American Economy," available at https://www.presidency.ucsb.edu/documents/fact-sheet-executive-order-promoting-competition-the-american-economy.

[3]Board of Governors of the Federal Reserve System. "The Role of Research, Data, and Analysis in Banking Reforms ," available at https://www.federalreserve.gov/newsevents/speech/bowman20231004a.htm.

[4]For example, the FDIC highlighted the consideration of credit unions in rural markets in a 2024 policy statement. See Federal Deposit Insurance Corporation. "Final Statement of Policy on Bank Merger Transactions," available at https://www.fdic.gov/news/speeches/2024/final-statement-policy-bank-merger-transactions-1.

have been common in recent years. Our findings suggest that transfers of ownership from community banks to credit unions without existing local market presence might have the unintended effect of increasing market segmentation, depending on the size of pricing differentials between banks and credit unions. In the case of market overlap, we must also consider the potential for credit unions to exercise market power following the acquisition.

1.1. Related Literature

This paper relates to three main strands of literature. First, it contributes to the study of competition in selection markets. Both theoretical (Dell'Ariccia & Marquez, 2004; Hauswald & Marquez, 2003, 2006; Mahoney & Weyl, 2017) and empirical (Crawford *et al.*, 2018) work has studied the interaction of competition and asymmetric information in a variety of settings. Other papers focus on auto lending markets. Einav *et al.* (2012) analyze screening on contract characteristics in the subprime auto lending market. Yannelis & Zhang (2023) study the effect of competition on lenders' incentives to invest in fixed screening technology. Argyle *et al.* (2020) and Argyle *et al.* (2023) examine behavioral and search frictions in direct (non-intermediated) auto lending, while Grunewald *et al.* (2023) and Momeni (2024) analyze the role of dealer intermediation in the joint pricing of cars and loans. We contribute to the broader literature on competition in selection markets by highlighting the role of profit-deviating incentives in determining loan pricing and equilibrium risk composition across institutions. We also add, more specifically, to the auto lending literature by developing a novel procedure to define geographic markets when lending is intermediated by dealers.

Second, this paper contributes to the line of research on non-profits and cooperatives. Newhouse (1970) and Lakdawalla & Philipson (1998) incorporate the concept of altruism into firms' optimization problems, providing theoretical characterizations of non-profit incentives (or "profit-deviating preferences"). Other theoretical work presents alternative explanations for non-profit entities, for example, viewing such firms as cooperatives (Pauly & Redisch, 1973) or as a solution to market failures associated with noncontractible quality (Hansmann, 1980). Empirical work has documented the effect of such differences in incentives (Cororaton, 2019; van Rijn *et al.*, 2021; Shahidinejad, 2024) and studied competition between for- and non-profit entities or cooperatives in healthcare (Gaynor & Vogt, 2003; Hackmann, 2019), retail (Duarte *et al.*, 2025), and lending markets (Tokle & Tokle, 2000; Feinberg, 2001; Gissler *et al.*, 2020; Feinberg & Reynolds, 2025; Chen *et al.*, 2025). Our work extends this strand of literature by explicitly considering how asymmetric information shapes competition between banks and credit unions.

Finally, by leveraging variation induced by bank mergers, we contribute to a large literature on the effects of bank consolidation. Previous work has examined merger effects on deposit rates (Prager & Hannan, 1998; Focarelli & Panetta, 2003), loan rates and characteristics (Di Patti & Gobbi, 2007; Erel, 2011; Allen *et al.*, 2014; Liebersohn, 2024), and bank branching (Nguyen, 2019; Benson *et al.*, 2024). While not a merger retrospective, our work highlights one potential determinant of a bank merger's effects – namely, credit union presence and their impact on the distribution of borrower risk across lender types.

2. Institutional Background

Before detailing our data and empirical framework, it is first necessary to discuss a number of institutional details that are relevant for our analysis. We first highlight characteristics of credit unions – in regard to both organizational structure and regulation – that shape their competitive interactions with banks. We then discuss institutional details of auto lending to motivate the structure of our empirical analysis.

2.1. Credit Unions

Despite offering a similar product portfolio as traditional banks, credit unions are a distinct category of financial institution for a number of reasons. They are member-owned cooperatives, finance their operations using retained earnings rather than by issuing stock, are restricted to accepting individuals within their stated field of membership, and are tax-exempt, not-for-profit institutions (Shahidinejad, 2024). The final characteristic is particularly noteworthy in our setting and could contribute to differences in either lending costs or incentives to mark up above cost. Banking interest groups have argued that credit unions' tax-exempt status gives them an unfair competitive advantage, allowing them to offer advantageous rates.[5] Furthermore, as non-profits, credit unions may face "profit-deviating" incentives (Duarte *et al.*, 2025; Hackmann, 2019; Gaynor & Vogt, 2003; Lakdawalla & Philipson, 1998) even if there is no true cost advantage. Both of these sources could lead to heterogeneity in pricing patterns across credit unions and traditional banks.

Credit unions are also constrained in that they can only accept individuals within their stated field of membership, defined by either common bonds, like employment, or by geography. One might be concerned that these restrictions would inherently limit competition between credit unions and banks. However, the typical field of membership has expanded recently. Since 1997, when the Credit Union Membership Access Act was passed, over 1,000 credit unions have converted to community charters (van Rijn, 2024), which allow credit unions to define field of membership by geography. Subsequent relaxations of field of membership rules in 2010 (Gissler *et al.*, 2020) and 2017 (Chen *et al.*, 2025) gave credit unions further ability to expand their membership bases and compete with traditional banks.

2.2. Auto Lending

A second distinguishing feature of our paper is the focus on auto lending. Auto lending markets differ from other types of consumer lending markets along a few key dimensions. Most importantly, over 8 of 10 auto loans are "indirect," meaning they are intermediated by dealers (Grunewald *et al.*, 2023). Typically, once a consumer has agreed on a vehicle, its price, and wants to secure financing, they are referred to a financing agent at the dealership. That agent obtains rate quotes ("buy rates") from financial institutions – Grunewald *et al.* (2023) notes that dealers maintain active relationships with between 4 and 5 lenders – and presents the consumer with a single, final loan offer.[6] That offer typically includes a discretionary dealer markup. Dealers' significant involvement in auto lending motivates our market definition procedure, which we describe in detail in Section 3.

[5] See, for example, the American Bankers Association's discussion of "Credit Union Competition." Available at https://www.aba.com/advocacy/our-issues/credit-union-competition.

[6] Consumer Financial Protection Bureau. "What are the different ways to buy or finance a car or vehicle?" available at https://www.consumerfinance.gov/ask-cfpb/what-is-the-difference-between-dealer-arranged-and-bank-financing-en-759/.

Even though the dealer serves as an intermediary in this process, the lender typically holds the loan on its balance sheet. Previous estimates suggest that only approximately 15% of prime and 25% of subprime loans are securitized (Yannelis & Zhang, 2023; Klee & Shin, 2020), so the lenders bear the default and prepayment risk of auto loans. For prime borrowers, default rates on auto loans are low; the primary risk faced by lenders is that of prepayment. Near- and subprime borrowers default at higher rates, so lenders also face the risk of non-payment for these loans. For the majority of our subsequent analysis, we will focus attention on borrowers with Vantage 3.0 credit scores of at least 580, but we also provide results for prime and near-prime borrowers separately to account for differences in default rates across risk segments.

3. Data and Descriptive Analysis

3.1. Auto Loan Data

The main source of auto loan data for our analysis is Equifax's Analytic Dataset, a 10% random and anonymous sample of its core consumer credit database. The data includes all information reported to the credit bureau for each trade line, including credit cards, mortgages, and auto loans, between 2005 and 2025. We restrict to trade lines identified as auto loans with maturities of up to 7 years (84 months). This includes auto loans originated by banks, credit unions, and non-depository lenders (a combination of auto finance companies and captive lenders).

This dataset provides information on loan amounts, loan maturities, and payments over time. It also provides the lender type, including an indicator of whether the loan was originated by a credit union, and the geographic origin of the loan. While the dataset does not provide interest rates, we impute them using the initial loan amount, loan maturity, and monthly payment amount. Details are provided in Appendix A, where we also show that the imputed rates align closely – both in levels and in trends – with the "Finance Rate on Consumer Installment Loans at Commercial Banks" series released by the Federal Reserve Board. Note that these interest rates are the final rates paid by the consumer and are inclusive of any dealer markup. If dealers exhibit imperfect pass through, we expect our estimated estimated effects to be attenuated relative to the effects on buy rates. Furthermore, the final interest rates paid by consumers are of inherent interest from a borrower welfare perspective. In addition to loan characteristics, the dataset provides various borrower characteristics, like Vantage 3.0 credit score, a modeled measure of income –both of which we use as indicators of observable risk.

3.2. Descriptive Analysis

Before detailing our empirical approach, we present a number of descriptive analyses to characterize the structure of the auto lending market and associated borrower outcomes. This descriptive evidence serves two purposes. First, it documents that banks and credit unions participate in overlapping market segments, focusing on borrowers with credit scores above approximately 580, while non-depository lenders are more prevalent in the subprime segment. We also show that a substantial share of credit union and bank borrowers switch to a lender of the opposite type when originating a new loan. Together, these findings suggest a degree of substitutability between banks and credit unions. Second, the descriptive evidence shows that credit unions offer lower rates, given borrower observables, and that their borrowers are less risky on both observable and unobservable dimensions, suggesting a degree of risk segmentation still exists across lender types.

Figure 1 displays the market shares of each lender type by credit score groups.[7] Credit unions are displayed in red, banks in blue, and non-depository lenders – which includes auto finance companies and captive lenders – in yellow. The shaded, gray region denotes the total market size. Although bank market shares are larger, credit unions and banks originate auto loans to similar borrower credit score distributions. On the other hand, non-depository lenders hold a substantially larger market share at the bottom of the credit score distribution, even if the market is significantly smaller.

Although credit unions and banks focus on similar credit score segments, borrower characteristics not captured by the credit score could separate some of them into credit unions and others into banks. In an extreme case of such type of segmentation, credit union borrowers never borrow from a bank, and vice versa. Because our

[7]For a similar analysis of loan counts over time by lender type, see Appendix D, Figure 8 and Figure 9.

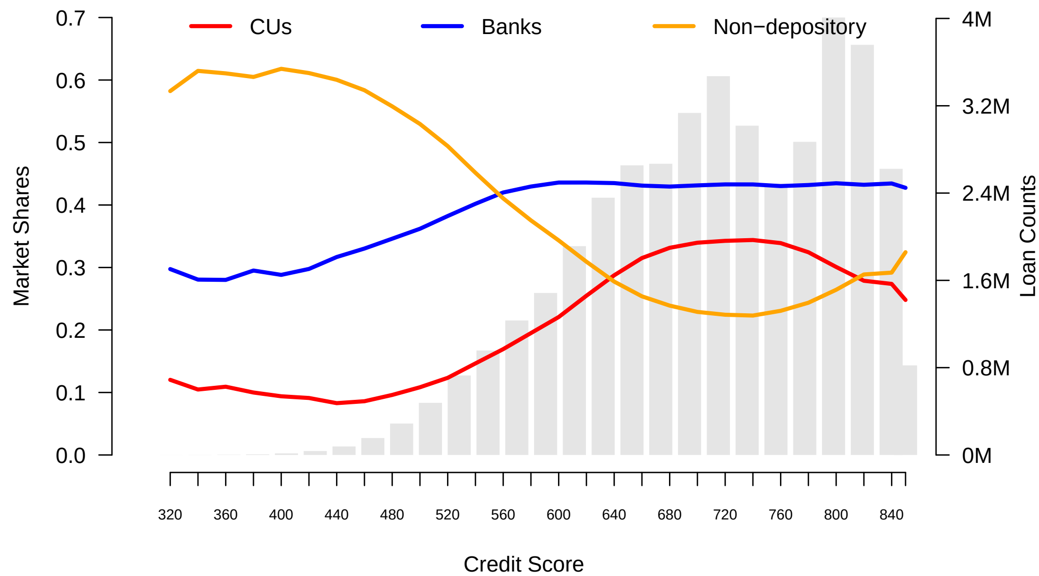


Figure 1: Market Shares by Lender Type and Borrower Credit Score. This figure displays market shares for each type of lender over the sample period (2005 - 2025) along the left vertical axis. Plotted against the right vertical axis, the grey bars show loan counts for all lenders.

dataset contains individual borrower identifiers, we can examine the plausibility of such a case by looking at borrower switching behavior among individuals who have taken out more than one loan during our sample period. For each of these borrowers, we sort the loans by origination date and calculate the probability of transitioning from one type of lender to another in subsequent loans. Figure 2 displays both the unconditional probabilities of borrowers transitioning from one lender type to another (Panel (a)) and the probabilities conditional on beginning at a borrower of a given type (Panel (b)). While borrowers frequently stay with the same lender type, 42.6%, 42.2% and 59.4% of new originations are associated with a change in lender type for credit unions, banks, and non-depository lenders, respectively. This suggests substantial churn between lenders and provides further support for competition between banks, credit unions, and non-depository lenders.

Despite the overlap among the higher-credit score borrower segments and the

Loan n		Loan n+1: CU	Loan n+1: Bank	Loan n+1: Non-depository
	CU	18.7%	9.0%	4.9%
	Bank	7.2%	24.5%	10.7%
	Non-depository	4.5%	10.4%	10.2%

(a) Unconditional Transition Probabilities

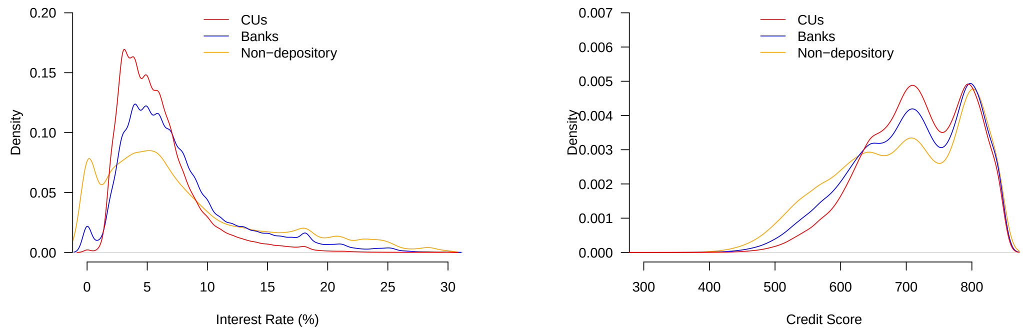
Loan n		Loan n+1: CU	Loan n+1: Bank	Loan n+1: Non-depository
	CU	57.4%	27.6%	15.0%
	Bank	17.0%	57.8%	25.2%
	Non-depository	17.9%	41.4%	40.6%

(b) Conditional Transition Probabilities

Figure 2: Transition Probabilities for Borrowers with Multiple Loans. Panel (a) displays the unconditional probability that a borrower transitions from one type of lender to another, while Panel (b) displays the probability of receiving a subsequent loan from a given lender type conditional on initially receiving one from each different type. We first restrict the sample to borrowers with more than one loan. Then, we sort by origination date and consider transition probabilities for each pair of loans adjacent in time.

extent of borrower transitions across lender types, credit unions and banks exhibit different pricing patterns. Figure 3a displays density plots of interest rates by lender type. In aggregate, for loans with a strictly positive interest rate, credit unions offer lower rates than banks. Banks do originate more zero-interest loans, although these loans comprise a small share of banks' auto lending portfolio. Relative to loans by non-depository lenders, the distributions of interest rates at banks and credit unions are similar. Non-depository lenders are much more likely to originate both zero-interest loans and loans with interest rates above 10%. This very likely reflects the fact that two different types of lenders are grouped together in our data: lenders specializing in high-risk auto loans and captive finance companies, which offer financing exclusively for their own-brand cars. This latter group likely treats the loan as a loss-leader meant to encourage the sale of their car. We take these price distributions as further evidence that captive lenders and lenders specializing in high-risk auto loans pursue different business models than banks and credit unions, which motivates our focus on analyzing the nature of competition between the two types of depository lenders.

While the differences in the interest rate distributions could be due to true differences in pricing rules across lenders, they may also reflect variation in borrower composition, both observable and unobservable to the lender at origination. Figure 3b shows that at least part of the difference in interest rates between credit unions



(a) Interest Rate Distribution

(b) Credit Score Distribution

Figure 3: Distributions of Interest Rates by Lender Type. This figure displays density plots of interest rates for each type of lender over the sample period (2005 - 2025). Interest rates are imputed using the procedure described in Appendix A. The distribution for credit unions is shown in red, the distribution for banks is shown in blue, and the distribution for non-depository lenders is shown in yellow.

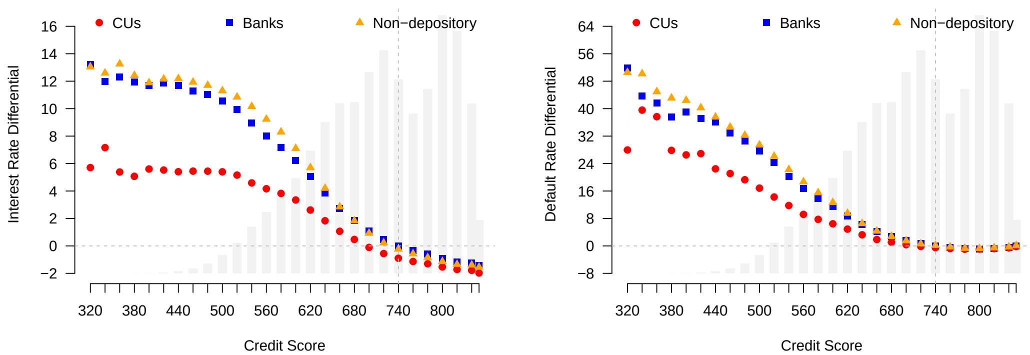
and banks can be explained by observable differences in borrower composition (Shahidinejad, 2024). Credit union borrowers have the highest credit scores, followed by banks, and then non-depository lenders. Although the distributions overlap more than they do not, we interpret Figure 3b as being suggestive of a degree of market segmentation on observable dimensions.

To isolate the pricing decisions across lender types conditional on a borrower's observable characteristics at loan origination, we regress interest rates on interactions of lender type with credit score categories, loan terms, loan sizes, and borrower income, controlling for whether there were joint holders of the debt. Specifically, we estimate:

$$InterestRate_l = \sum_{j \in \mathcal{J}} LenderType_l^j \times \left(\beta_s^j CreditScore_l + \beta_i^j Income_l + \beta_m^j Maturity_l + \beta_a^j Amount_l \right) + \epsilon_l \quad (1)$$

We then plot the coefficients of each set of interactions (e.g., β_s^j, β_i^j, etc.) to analyze differences in pricing patterns across lender types. Figure 4a displays the estimated interest rate differentials for credit unions in red, banks in blue, and non-depository lenders in yellow for each credit score group based on β_s^j. Credit unions offer lower rates across the entire credit score distribution. In Appendix D, Figure 10 shows that these differentials are particularly stark for lower credit score borrowers, small loans, and loans with long maturities, but they persist across loan and borrower characteristics.

In principle, such differences in interest rate conditional on observable characteristics may arise for various reasons. For example, they might reflect differences in service quality across lender types: borrowers may prefer the bundle of services offered by traditional banks and be willing to pay a premium. They may also reflect cost advantages of credit unions, stemming, for example, from tax advantages. They could also result from differences in credit union objectives (Lakdawalla & Philipson, 1998), whereby credit unions do not exercise their market power. Lastly, they could be due to private information that credit unions have access to and banks do not (Petersen & Rajan, 1995; Hauswald & Marquez, 2003).



(a) Interest Rates

(b) Default Probability

Figure 4: Interest Rate and Default Differentials by Lender Type. This figure displays the coefficients of a regression of interest rate on interactions of lender type with Vantage 3.0 credit score categories, loan terms, loan size categories, and borrower income categories. The coefficients for credit unions are shown in red, those for banks are shown in blue, while those for non-depository lenders are shown in yellow.

To better tease apart these potential explanations, we exploit the historical nature of our data, specifically the fact that we observe loan outcomes beyond origination and throughout the life of the loan. This allows us to explore whether there are systematic, but unobservable, characteristics that differ between lender types even after conditioning on the observable borrower characteristics. Using the same regression framework from Equation (1) to control for observable characteristics, we regress a negative loan outcome indicator on the same set of regressors. Our outcome variable is a binary indicator for whether the loan eventually experienced any negative outcome that is costly to the lender, ranging from short-term default to foreclosure and collections. For simplicity, we refer to any of these negative outcomes as default. Figure 4b shows the default rate differential across lender types and credit scores. At the top of the credit score distribution, there is no difference in default rates (although default is not common). However, for credit scores below 700 credit union loans are less likely to experience default.

We think these results suggest two generally plausible explanations or mechanisms, which are not mutually exclusive. The first is that credit unions have access to lower-risk borrowers and/or better information about them that allows them to better price their loans. The second is that because credit unions have nonprofit incentives, they charge lower markups, and this, in turn, will select for a set of lower-risk borrowers (Stiglitz & Weiss, 1981). The institutional features related to membership at credit unions (although lax) suggest there may be something to the first explanation. However, in the auto loan setting where dealers intermediate the majority of loans, we think this is less likely. When dealers intermediate loans, the lender and borrower often do not interact directly, which greatly limits the flow of private information. One aspect of these results that directly favors the second explanation based on nonprofit incentives and borrower self-selection is that credit union prices are lower even for the high credit score segments where there is no differential default probability. We consider this stronger evidence that there is some degree of market segmentation arising from borrowers self-selecting into lender types based on their unobservable characteristics.

Altogether, we think these descriptive results are strongly suggestive of two conclusions. First, credit unions and banks do compete directly with each other for large segments of auto loan borrowers. Second, in spite of the documented overlap, there is still some degree of risk segmentation based on both borrower observable and unobservable characteristics. Yet, because these results are purely descriptive, we cannot conclude that the observed differences between credit unions and banks are an equilibrium consequence of, for example, lenders' strategic pricing decisions. In the next section, we study quasi-exogenous variation in market structure to directly analyze the competitive interactions between these two categories of institutions. As we describe in Section 4, we rely on traditional bank mergers to provide the requisite variation.

4. Empirical Approach

To quantify the equilibrium response of traditional banks and credit unions to changes in market structures, we exploit geographic variation in exposure to large, traditional bank mergers. The mergers act to rotate the residual demand curve faced by the banks' competitors, allowing us to measure the equilibrium response of credit unions to this change in residual demand.

Between 2005 and 2022, banking markets experienced a large number of mergers, leading to the substantial geographic heterogeneity in exposure. Prior work relies on this variation to study, for example, the effect of mergers on bank branch closures (Benson *et al.*, 2024) or pricing in the mortgage market (Buchak & Jorring, 2024; Ratnadiwakara & Yerramilli, 2024). The validity of this approach in our setting requires that markets exposed to mergers not be selected on unobservables related to auto lending. Bank-wide strategies (Berger *et al.*, 1999) or non-profit maximizing managerial behavior (DeYoung *et al.*, 2009) are common drivers of these decisions, and the impetus of the mergers is therefore likely unrelated to trends in auto lending. The mergers then provide exogenous variation to study non-profit provision of credit and its impact on competitors and borrowers in the auto loan market.

For this analysis, we restrict attention to banks and credit unions. As discussed in Section 3, non-depository lenders likely have different business objectives; for example, captive lenders may treat auto loans as a loss-leader with the goal of providing incentives for car purchases. Moreover, the descriptive evidence suggests closer overlap between banks and credit unions throughout the credit score distribution and, in particular, for less risky borrowers. This finding motivates a second restriction: we focus attention on borrowers with credit scores above 580 (i.e., near-prime and prime borrowers). Even so, we explore extensions of our results in Appendix D, where we relax these restrictions.

Implementing our empirical approach requires us to first define markets that capture the geographic scope of competition in auto lending. Section 4.1 outlines our market definition procedure. We then identify a set of mergers that are (1) plausibly exogenous, and (2) allow us to identify a set of clean controls such that our estimated effects are not confounded by overlapping mergers. Section 4.2 provides detail on our final sample of mergers; it is important to note that our analysis sample does not include the universe of bank mergers, so we do not interpret our results as reflective of average merger effects. However, these restrictions provide credibly exogenous variation to study the competitive interaction of credit unions and banks, which is the question of interest in this paper. We conclude in Section 4.3 by detailing our main empirical specifications.

4.1. Geographic Market Definition

To define geographic markets for our empirical analysis, we leverage data on the locations of new and used car dealers. The YE Time Series, provided by the Business Dynamics Research Consortium, relies on information from DataAxle to assemble a comprehensive dataset of establishment locations and other establishment-level information. From this dataset, we obtain the latitude and longitude of relevant establishments. In particular, we restrict to businesses from NAICS codes 441110 (New Car Dealers) and 441120 (Used Car Dealers) that were operating as of 2022.

In the case of auto lending, determining the geographic scope of competition among lenders is challenging. As discussed, more than 80% of loans are intermediated by dealers (Grunewald *et al.*, 2023), meaning traditional geographic boundaries, such as counties, are unlikely to correctly capture the scope of competition. To overcome this challenge, we exploit the YE Time Series data on car dealer locations and develop a procedure to define geographic markets around clusters of dealerships. This procedure allows the geographic composition of dealerships – that frequently intermediate auto lending – to shape our market definitions.

We briefly summarize our market definition procedure here, but a full description can be found in Appendix C. The first step of the procedure involves identifying clusters of dealerships, capturing geographic areas to which people frequently travel to purchase vehicles. To do this, we rely on the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm, introduced by Ester *et al.* (1996). This algorithm partitions data – including spatial data – into clusters, relying on the idea that the density of points is higher within than outside of clusters. It does not require us to specify the number of clusters nor does it restrict the shape of the clusters, both attractive properties in our setting. Once we have dealership clusters, we map each Zip Code Tabulation Area (ZCTA) to the closest cluster, as measured centroid to centroid. Thus, our geographic markets are groups of ZCTAs, where each group corresponds to a given dealership cluster.

It is important to note that the clustering procedure requires us to specify two tuning parameters, described in more detail in Appendix C. For our baseline clusters and market definitions, we set these tuning parameters following the heuristics discussed by Ester *et al.* (1996). Figure 6 in Appendix C presents maps of the baseline clusters and market definitions. To examine the robustness of our results to the specification of these tuning parameters, we also define clusters and markets by using state-level minimum relevant market areas for auto dealerships, when available, to inform the tuning parameters.[8]

4.2. Identification of Mergers

To identify traditional bank mergers, we rely on the Summary of Deposits dataset provided by the Federal Deposit Insurance Corporation (FDIC) and the dataset of bank mergers from the National Information Center at the Federal Financial Institutions Examination Council (FFIEC). A detailed discussion of the method we use to identify mergers can be found in Appendix B. To summarize, we identify mergers that occur during the sample period of the auto loans data, involve commercial banks, and involve the transfer of at least 50 branches. Restricting attention to

[8]Minimum relevant market area regulations prevent multiple dealerships from opening within a specified geographic distance of one another. See Momeni (2024) for more details on relevant market areas for auto dealerships.

mergers that affect at least 50 branches helps to assuage the concern that mergers are chosen due to geographic market-specific trends in auto lending. As discussed above, banks' decisions to pursue large mergers are likely unrelated to such trends and, therefore, these mergers provide plausibly exogenous variation to study the competitive responses of other lenders in affected markets.

Given the large number of mergers that occur during our sample period, we must further restrict our set of at-issue mergers to ensure our estimated effects are not confounded by unrelated transactions occurring within the same analysis windows. We therefore focus attention on the set of mergers that (1) overlap in at least one geographic market, and (2) are not contaminated by contemporaneous mergers that would confound the estimated effects.[9] These restrictions reduce the number of mergers included in our analysis. Our final, baseline sample consists of 12 mergers, a full list of which can be found in Appendix B, Table 6.

	N	Mean	SD	25th Pct.	Median	75th Pct.
Year	12	2017.17	4.22	2016	2018	2019
Branches Acquired	12	181.17	188.95	70.50	106.00	172.00
Average HHI	12	210.15	88.86	159.20	194.49	267.66
Average DHHI	12	24.83	24.61	7.51	16.97	27.89
Max. HHI	12	2734.28	1877.30	1526.83	2011.52	3484.75
Max. DHHI	12	610.01	598.65	247.47	418.51	673.14

Table 1: Summary Statistics for Baseline Sample of Mergers. This table presents summary statistics for the baseline sample of 12 mergers. Statistics are computed across mergers. HHI is the post-merger HHI, calculated using bank deposit shares, and DHHI is the change in HHI. In both cases, these calculations assume shares of the merging parties do not change following the merger.

Table 1 presents summary statistics for these mergers. The mergers in our baseline sample tend to be large: the average number of branches acquired is approximately 181, while the 25th percentile is over 70. As discussed above, this is an attractive property for our empirical approach, as mergers of this size are likely to be driven by considerations unrelated to geographic market-specific trends in

[9] In our baseline specifications analyzing two-year windows around mergers, we define geographic markets as "contaminated" if another merger affected that market in the four years preceding or the two years following the merger at issue. Then, a merger is considered "contaminated" if all potential treatment or control markets are removed through this process.

auto lending. There is also substantial variation in market structures both across and within mergers. On average, post-merger HHI – calculated using bank-only deposit shares[10] – is 210, suggesting markets are generally unconcentrated. The naively-computed[11] change in HHI (DHHI) is only 24.8, although there is a long right tail with some mergers leading to larger changes in concentration. Despite the low post-merger HHI and DHHI, on average, there are geographic markets for which the mergers lead to substantial change in market structure. For example, 75 percent of mergers have at least one geographic market that experiences a change in HHI of over 247. As detailed later in the paper, our empirical approach will exploit this cross-geography variation in a merger's impact.

4.3. Regression Specifications

Our baseline strategy compares, in a difference-in-differences framework, post-merger changes in geographic markets that were exposed to bank mergers to those that were not. There are, however, two concerns with implementing this strategy. First, mergers are staggered across time and markets, which can bias the traditional two-way fixed effect estimator of treatment effects (Goodman-Bacon, 2021). Second, exposure to the merger is non-binary, as the magnitude of changes in market structure also matters. We therefore implement a stacked difference-in-differences design around a geographic market's exposure to a traditional bank merger. We define a market as treated if the merging lenders both had non-zero market share in the year preceding the acquisition. We restrict control markets to those that have a target-only or acquirer-only presence. This is motivated by the key idea of our research design: among markets affected by the merger, which market has overlap and which does not is quasi-random and this is unrelated to the decision to merge banks in the first place. Across treated and control markets, we require that they be "clean" in the sense that they either have never been treated by a different merger or have been treated more than two years in the past. Previous work (Cengiz *et al.*, 2019; Johnson

[10]We compute post-merger HHI and DHHI using local bank deposit shares, as this is consistent with the approach used by the Federal Reserve and DOJ to screen mergers (Benson *et al.*, 2024).

[11]Throughout the paper, post-merger HHI and DHHI are computed "naively." That is, we assume merging-party shares do not change in the post-merger period. This is the standard way HHI and DHHI are calculated in prospective merger analysis.

et al., 2023) has relied on similar designs (de Chaisemartin & D'Haultfoeuille, 2022) to circumvent the issues associated with staggered and non-binary treatment, and it is one approach discussed by Baker *et al.* (2022). This design requires us to stack merger-specific datasets, consisting of all treated and control units for each merger.

We begin by estimating loan-level regressions of the following form:

$$Y_{ijmtb} = \beta_1 Overlap_{mtb} + \beta_2 CU_j \times Overlap_{mtb} + \alpha_{jmb} + \gamma_{jtb} + \epsilon_{ijmtb}, \qquad (2)$$

where Y_{ijmtb} is the loan characteristic or outcome of interest for borrower i with loan from lender type j in geographic market m at event time t[12] as part of merger b. $Overlap_{mtb}$ is a post-merger indicator that both the target and the acquiror in merger b had strictly positive market shares in market m prior to the merger, and therefore isolates markets where and when two previously distinct banks are now one. α_{jmb} are lender type $\times$ market $\times$ merger fixed effects, and γ_{jtb} are lender type $\times$ time $\times$ merger fixed effects. For some specifications, we also include flexible controls for borrower and loan characteristics: loan amount, borrower income, credit score, and loan term.[13] Our coefficients of interest are β_1 and β_2, which quantify the weighted average merger effects for banks (β_1) and the incremental effect for credit unions (β_2). We cluster standard errors at the merger-market-lender type level.

Because the type-level effects recovered in Specification 2 mask heterogeneity across mergers and across geographies in their impact on market concentration, we estimate an additional specification that isolates markets in which a merger affects market concentration by a large amount. In particular, we categorize merger-market pairs by whether the naively-computed[14] change in the Herfindahl–Hirschman Index (DHHI) in the deposit market is greater than 100. We then estimate an adjusted

[12]We group time into six-month periods, relative to the merger event. In unreported specifications, we verify that results are robust to instead using quarters as our unit of time.

[13]Specifically, we include indicators for credit score bins of width 20. We specify loan amount bins of width 20,000 for amounts below 60,000, a bin from 60,000 – 100,000, a bin from 100,000–200,000, and a bin for amounts above 200,000. For borrower income, we define bins of 20,000 for incomes below 100,000, bins of 50,000 for incomes between 100,000 and 200,000, a bin from 200,000 – 300,000, and a bin for incomes above 300,000. We also include indicators for each loan term.

[14]To reiterate, by naively-computed, we mean that we calculate the change in HHI using only pre-merger shares and assuming that, after the merger, the merged entity holds a share equal to the sum of each merging entity's share.

version of Specification 2, which measures the effects on markets highly affected by the merger:

$$Y_{ijmtb} = \beta_1 HighDHHI_{mtb} + \beta_2 CU_j \times HighDHHI_{mtb} + \alpha_{jmb} + \gamma_{jtb} + \epsilon_{ijmtb}, \quad (3)$$

where $HighDHHI_{mtb}$ is a post-merger indicator of whether the naively-computed change in HHI in market m due to merger b is at least 100. A change in HHI of 100 is the threshold – for sufficiently concentrated markets – above which the 2023 Merger Guidelines trigger a rebuttable presumption that the merger is likely to lessen competition.[15] Mergers with sufficiently high DHHI are more likely to increase banks' ability to exercise market power and, consequently, alter the competitive response from credit unions.

Finally, to examine a number of market-level outcomes, we aggregate our stacked dataset to the market-pre/post-merger level and estimate analogues of Specifications 2 and 3. The goal of these specifications is to measure market-wide responses to the merger, and it is therefore useful to work at a higher level of aggregation. We also add non-depository lenders so that the results capture both substitution between banks and credit unions and also from outside options. In these specifications, we include market $\times$ merger and post $\times$ merger fixed effects and cluster standard errors at the merger-market level. All other regressors are defined as above.

5. Credit Union Competition, Pricing, and Borrower Composition

5.1. Loan-Level Effects of Traditional Bank Mergers

Table 2 displays the results of Specifications 2 and 3 in Panels A and B, respectively. These results first document the average effects of large, traditional bank mergers on loan and borrower characteristics at origination: interest rates, borrower credit score and income, and loan amounts and terms. We also examine the effects on

[15] While the threshold was higher under the 1995 Bank Merger Guidelines, the 2024 Banking Addendum issued by the Department of Justice clarified that the agency now relies upon the 2023 Merger Guidelines to assess bank mergers, as well. See "2024 Banking Addendum to 2023 Merger Guidelines," available at https://www.justice.gov/atr/media/1368576/dl.

loan outcomes post-origination: default and prepayment. Table 2 reports both baseline effects for banks as well as the incremental effects for credit unions. The identifying assumption of our stacked difference-in-differences design is that, absent the merger, markets in which the target and acquiring banks overlapped would have counterfactually followed the same trend as markets in which only of the two parties was present. While this assumption is untestable, an event-study version of Specification 3 in Appendix D, Figures 13 and 14 reveal that there are no statistically significant differences in trends in the pre-merger periods for treated and control markets. These plots provide supportive evidence that the treatment assignment is as good as random, and we can therefore interpret our findings as causal.

The CU $\times$ Overlap coefficient in Panel A of Table 2 shows that credit unions, on average, lower their interest rates by 10 basis points in total (13 basis points relative to banks) and select for borrowers with higher credit scores in response to the mergers in our sample. Except for a small increase in loan terms post-merger, the Overlap coefficient shows no statistically significant effect for banks. By themselves, these results may seem surprising, as credit unions appear to respond despite banks offering a similar set of loan characteristics following the mergers. However, these effects could mask heterogeneity across mergers; some mergers may be pro-competitive, while others are likely anti-competitive, and the average effect may not tell the full story.

We address the potential for heterogeneous merger effects in Table 2, Panel B, which presents results of Specification 3. This specification tests for effects in markets where the expected change in concentration (DHHI) of the merger was greater. The motivation for uncovering this type of potential heterogeneity is that, when changes in concentration are large, they likely lead to increases in banks' ability to exercise market power. Our results are consistent with this idea. The coefficient on High DHHI shows that in such markets, banks on average raise interest rates by 8 basis points. Adding the CU $\times$ High DHHI coefficient to the High DHHI coefficient shows that credit unions have a similar response as in all Overlap markets, albeit with a slightly larger magnitude.

Apart from the relatively sharper effects on interest rates, other results come into clearer focus when we restrict attention to High DHHI markets using Specification

3, which we consider the cornerstone of our paper's results. Following mergers, credit unions originate loans to a less risky set of borrowers than they did previously. This is true according to both the effect on credit scores (column 2) and default (columns 6 and 8). In contrast with credit unions, columns (6) and (8) show that the default of bank loans increases after mergers in High DHHI markets, although there is no detectable effect on credit scores. While lenders can observe credit scores before originating a loan, they cannot observe default. This has potentially important implications for the nature of selection at play, a point to which we turn in the next section. The coefficients on default and prepayment (columns 6-9) are similar whether we include controls or not. We interpret this as a confirmation that borrower controls do not capture all the relevant information about a borrower and that borrower-driven selection plays a role in responding to the mergers.

The total effect on credit unions' interest rates in high DHHI markets corresponds to a decline of 16 basis points, an estimate that is both economically and statistically significant. To place the magnitude of this finding in context, as of the first quarter of 2023, America's Credit Unions estimate the average gross spread (net income) for credit unions to be 301 (80) basis points (America's Credit Unions, 2024). The total decline of 16 basis points in high DHHI markets would lead to a 5.3% decline in gross spread or a 20.0% decline in net income, assuming all else is held equal. However, the lower interest rates could either be reflective of or lead to a safer composition of borrowers at credit unions. If this is the case, the 20.0% decline in net income would be an upper bound, as loss provisioning would adjust in response to the change in the borrower pool.

These results are consistent with banks exploiting their newly gained market power to increase the interest rates on their auto loans. Credit unions respond by decreasing interest rates, a finding which may seem counterintuitive from the perspective of competition among profit-maximizing firms. The two distinguishing features of our setting that help explain these results are that credit unions are not necessarily profit-maximizing and the auto loans market is a selection market. In particular, our results suggest borrower-driven selection ala Stiglitz & Weiss (1981) plays a role, where borrowers with residual private information about their risk sort in response to changes in prices. More concretely, when banks raise their interest

	Interest Rate	Credit Score	Loan Amount	Borrower Income	Loan Term	Default	Prepaid	Default	Prepaid
A: All Markets	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Overlap	0.03	0.20	0.17	0.01	0.31***	0.17	0.46	0.16	0.36
	(0.02)	(0.63)	(0.11)	(0.29)	(0.10)	(0.12)	(0.35)	(0.11)	(0.35)
CU x Overlap	-0.13**	2.56**	-0.13	0.23	-0.16	-0.31	-0.20	-0.24	-0.11
	(0.05)	(1.28)	(0.23)	(0.49)	(0.24)	(0.20)	(0.51)	(0.18)	(0.50)
R^2	0.48	0.04	0.09	0.06	0.07	0.01	0.05	0.04	0.07
B: High DHHI Only	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High DHHI	0.08**	-0.67	-0.03	-0.19	0.08	0.37**	0.31	0.34**	0.27
	(0.03)	(1.03)	(0.12)	(0.28)	(0.15)	(0.16)	(0.32)	(0.15)	(0.32)
CU x High DHHI	-0.24***	5.06***	0.02	0.38	0.10	-0.72**	-0.22	-0.59**	-0.20
	(0.06)	(1.60)	(0.25)	(0.50)	(0.29)	(0.29)	(0.65)	(0.26)	(0.63)
R^2	0.48	0.04	0.09	0.06	0.07	0.01	0.05	0.04	0.07
Borrower Controls	Yes	No	No	No	No	No	No	Yes	Yes
Observations	1,218,585	1,218,585	1,218,585	1,218,585	1,218,585	1,218,585	1,218,585	1,218,585	1,218,585
Dep. Var. Mean	5.6	730.77	24.75	56.35	65.78	2.53	88.42	2.53	88.42

Table 2: Merger Effects in Overlapping and High DHHI Markets. This table presents the results of Specification 2 in Panel A and Specification 3 in Panel B. Regressions are estimated using loans originated by banks and credit unions to borrowers with Vantage 3.0 credit scores above 580. All regressions include lender type × market × merger fixed effects as well as lender type × time × merger fixed effects. For more details, see Section 4.3. Standard errors, shown in parentheses, are clustered at the merger-market-lender type level.

rates, borrowers who privately know they are of unobservably low risk opt for lower interest credit unions, and consequently shift the composition of risk across lender types. While beneficial for credit union borrowers, this could exacerbate the risk faced by traditional banks.

5.2. Market-Level Effects of Traditional Bank Mergers

We run analogous market-level regressions to analyze the effect of these mergers on market size and market shares. To do so, we aggregate our loan-level data into market-level averages and get one observation for each combination of market, merger, and period (i.e., pre vs. post merger). We include market $\times$ merger and period $\times$ merger fixed effects, which are analogous to those in our loan-level regressions. Recall that we include non-depository lenders in these analyses, as we aim to document substitution between banks and credit unions and to/from other financing options.

Table 3 reports the results of these regressions. The first column shows that the mergers have no effect on the log of the total number of loans originated in the market, which we take as evidence that market size is not affected by the mergers. Columns 2-4 report the effect of the mergers on credit union, bank, and non-depository lender market shares (scaled by 100). The Overlap and High DHHI coefficients show that credit unions gain market share exclusively at the expense of bank market share, and that this effect is stronger in High DHHI markets. Altogether, these results reveal that the effects reported in Table 2 are driven by the intensive margin of substitution from banks to credit unions, and not from the extensive margins of non-depository borrowers or a net borrower entry or exit from the market. This evidence, as well as the direct response by credit unions to the merger, implies that the results cannot be explained exclusively by the mechanism of interest rates causally affecting default.

5.3. Heterogeneity by Credit Score

To provide further evidence of the role of adverse selection in these results, we examine the heterogeneity in merger effects by borrower credit score groups. The idea underlying this analysis is the following: if contract characteristics or lender behavior changes, they are likely to do so for borrowers across the distribution of

A: All Markets	log(N) (1)	CU (2)	Bank (3)	Non-Depository (4)
Overlap	-0.01	1.69**	-1.28**	-0.41
	(0.01)	(0.70)	(0.63)	(0.40)
R^2	>0.99	0.99	0.97	0.98
B: High DHHI Only	(1)	(2)	(3)	(4)
High DHHI	0.00	1.99***	-1.81**	-0.18
	(0.02)	(0.71)	(0.77)	(0.51)
R^2	>0.99	0.99	0.97	0.98
Observations	724	724	724	724
Dep. Var. Mean	4.58	21.77	38.04	40.19

Table 3: Market-Level Merger Effects in Overlapping and High DHHI Markets. This table reports market-level regressions analogous to Specification 2 in Panel A and Specification 3 in Panel B. Loan-level data are aggregated into market-level averages to obtain one observation for each combination of market, merger, and period (i.e., pre vs. post merger). Regressions are estimated using loans originated by banks, credit unions, and non-depository lenders to borrowers with Vantage 3.0 credit scores above 580. All regressions include market × merger and period × merger fixed effects. For more details, see Section 4.3. Standard errors, shown in parentheses, are clustered at the merger-market level.

A: Near-Prime	Interest Rate	Credit Score	Loan Amount	Borrower Income	Loan Term	Default	Prepaid	Default	Prepaid
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High DHHI	0.12***	-0.91	-0.21	-0.38	0.11	0.57**	0.37	0.50*	0.34
	(0.04)	(0.65)	(0.15)	(0.37)	(0.15)	(0.27)	(0.41)	(0.26)	(0.40)
CU x High DHHI	-0.27***	1.98**	0.09	0.52	0.11	-1.00**	0.31	-0.91*	0.29
	(0.08)	(0.98)	(0.30)	(0.49)	(0.35)	(0.50)	(0.74)	(0.47)	(0.71)
Observations	648,523	648,523	648,523	648,523	648,523	648,523	648,523	648,523	648,523
R^2	0.38	0.03	0.09	0.02	0.1	0.01	0.05	0.03	0.06
Dep. Var. Mean	6.92	674.24	23.55	42.23	67.01	4.36	89.08	4.36	89.08
B: Prime	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High DHHI	0.01	-0.59*	0.21	0.13	0.10	0.12	0.30	0.12	0.28
	(0.03)	(0.33)	(0.18)	(0.54)	(0.18)	(0.11)	(0.54)	(0.11)	(0.57)
CU x High DHHI	-0.24***	2.07***	-0.18	-0.79	0.20	-0.19	-0.59	-0.18	-0.65
	(0.06)	(0.79)	(0.31)	(0.74)	(0.31)	(0.13)	(0.94)	(0.13)	(0.95)
Observations	570,062	570,062	570,062	570,062	570,062	570,062	570,062	570,062	570,062
R^2	0.44	0.04	0.09	0.09	0.07	0	0.06	0.01	0.08
Dep. Var. Mean	4.09	795.09	26.11	72.4	64.39	0.46	87.67	0.46	87.67
Borrower Controls	Yes	No	No	No	No	No	No	Yes	Yes

Table 4: Merger Effects in Overlapping and High DHHI Markets. This table presents the results of Specification 3 separately for borrowers with credit scores of at least 740 on Panel A and near-prime borrowers with credit scores between 580 and 739 in Panel B. Regressions are estimated using loans originated by banks and credit unions. All regressions include lender type × market × merger fixed effects as well as lender type × time × merger fixed effects. For more details, see Section 4.3. Standard errors, shown in parentheses, are clustered at the merger-market-lender type level.

risk. For example, if lenders become more lax in their efforts to collect collateral, this change in policy is likely to apply regardless of borrower risk. On the other hand, if the adjustments to composition are driven by adverse selection, then the effects would be stronger for borrowers of higher credit risk, who likely face more severe problems of asymmetric information. In our sample, we find that the near-prime segment has greater scope for adverse selection than the prime segment: the default rate is 4.36% in near-prime, while it is only 0.46% in prime. Hence, we examine heterogeneity in merger effects across these two groups.

The results in Tables 4 and 5 are generally consistent with this idea. Table 4 displays the results of Specification 3 separately for prime borrowers with credit scores of at least 740 and near-prime borrowers with credit scores between 580 and 739. The complete set of merger effects identified in Table 2 is found in near-prime borrowers. Among prime borrowers, the results are directionally consistent, but in most cases weaker in magnitude and statistical significance. Two notable exceptions are interest rates and credit scores, where the merger effects for prime borrowers at credit unions are similar to those for near-prime, suggesting some scope institution-wide changes to policies.

The market-level regressions in near-prime and prime segments reported in Table 5 tell similar stories. There is significant substitution of near-prime borrowers from banks to credit unions following mergers. While the effects for prime borrowers are directionally the same, they are smaller in magnitude and statistically indistinguishable from zero. These results again provide support for interpreting the merger effects as reflective of borrower-driven selection. If the results were driven by other factors, such as changes in repayment burden, we would not expect to find such sizable shifts in borrower makeup across lender types following mergers.

5.4. Extensions and Robustness

In Appendix D, we report on several extensions and robustness checks to the main results we reported in Table 2, Panel B. Table 8 reports results for an extension where we include non-depository lenders in our sample. The regressions incorporate these lenders as a separate category and quantify their differential response to mergers. Consistent with the suggestive evidence in the descriptive analyses, we find no

A: Near-Prime	log(N) (1)	CU (2)	Bank (3)	Non-Depository (4)
High DHHI	0.00	2.18***	-1.98**	-0.20
	(0.02)	(0.83)	(0.77)	(0.62)
Observations	724	724	724	724
R^2	>0.99	0.98	0.97	0.98
Dep. Var. Mean	6.45	35.44	40.75	23.81

B: Prime	(1)	(2)	(3)	(4)
High DHHI	-0.01	1.38	-1.18	-0.20
	(0.03)	(0.95)	(1.15)	(0.82)
Observations	724	724	724	724
R^2	>0.99	0.98	0.95	0.95
Dep. Var. Mean	6.18	33.84	39.99	26.17

Table 5: Market-Level Merger Effects in Overlapping and High DHHI Markets. This table reports market-level regressions analogous to Specification 3 borrowers with credit scores of at least 740 on Panel A and near-prime borrowers with credit scores between 580 and 739 in Panel B. Loan-level data are aggregated into market-level averages to obtain one observation for each combination of market, merger, and period (i.e., pre vs. post merger). Regressions are estimated using loans originated by banks, credit unions, and non-depository lenders. All regressions include market × merger and period × merger fixed effects. For more details, see Section 4.3. Standard errors, shown in parentheses, are clustered at the merger-market level.

incremental response by or effect on non-depository lenders from the mergers. However, it is important to note these results are noisy, potentially driven by the fact that our dataset groups captive lenders with other lenders that focus on high credit-risk borrowers. These two sets of lenders likely have different incentives and would presumably react heterogeneously to changes in bank pricing.

Appendix D, Table 9 presents results of a robustness check, where we adjust the parameters of our market-definition procedure. We construct geographic markets by instead basing our tuning parameters for the DBSCAN algorithm on state-level relevant market areas. We find that our results are virtually unchanged.

Appendix D, Table 10 analyzes the response of subprime borrowers. Consistent with the market size and shares reported in the descriptive results, our sample size for this analysis is greatly reduced, which works against us detecting merger effects. The only detectable result is that prepayment of credit union loans decreases.

Appendix D, Table 11 reports an extension where we define the merger event windows to be one year long instead of two. This analysis acts both as an extension – where we examine the potential for dynamic merger effects – and a robustness check, as the shorter time window changes the composition of mergers by eliminating fewer markets considered "contaminated" by other mergers. The interest rate movements for both banks and credit unions maintain the same direction, but are attenuated relative to the two-year time window. There are no statistically significant effects on default. The interest rate event study Figure 13, Panel (a) suggests that the merger effects are perceived with some delay, stabilizing about one year after the merger. By restricting to a one-year window, we underestimate the incremental pricing effect and therefore also the incremental change in borrower composition.

With the exception of the subprime extension, these analyses consistently show that bank interest rates rise and credit union rates fall after a merger – this is our most consistent finding. Our results on borrower risk, however, are less consistent across our tests, in that we do not consistently find results with statistical significance. Importantly, we do not find any contradictory results within these analyses.

To summarize, in markets that experience large changes in concentration due to bank mergers, we find that banks serve borrowers with higher unobservable default risk at higher interest rates. Credit unions respond by lowering interest rates.

Across a number of specifications, we find that such a response leads to a safer set of borrowers and lower realized default rates at credit unions. This set of results suggests that credit union presence – and their subsequent pricing response – could cause compositional segmentation by borrower risk. In the next section, we develop a model of credit union and bank competition to better interpret these results and illustrate the role of profit-deviating incentives and borrower-driven selection.

6. Discussion and Policy Implications

6.1. Loan Pricing with Profit Deviation in a Selection Market

To better contextualize the empirical results, we develop a model of bank and credit union competition in auto lending. This model elucidates the role of profit deviation by credit unions and asymmetric information in contributing to the observed merger effects in Section 5. More specifically, we highlight how the model can explain the estimated merger effects through the lens of "borrower-driven" selection.

Suppose borrowers, indexed by i, are characterized by unobservable default risk, τ_i, with CDF F_τ and pdf f_τ. We assume this type maps to a probability of default, $d(\tau_i)$, where $d(\cdot)$ is strictly increasing. Note that we do not explicitly consider differences in observable default risk; however, we can think of this entire analysis as conditioning on a set of covariates observed by the lender. In other words, lenders compete separately for prime, near-prime, and sub-prime borrowers.

For simplicity, assume that each borrower i chooses between three options, loans offered by two lenders $j \in \{BANK, CU\}$, one bank and one credit union, as well as an outside option. This outside option captures car purchases without financing, as well as loans by non-depository lenders. We assume borrowers' interest-rate sensitivity is a function of their unobservable risk; namely, consistent with Einav *et al.* (2012), we assume the market is characterized by adverse selection and high-risk borrowers are *less* interest-rate sensitive than their lower-risk counterparts. This aspect of the model is what leads to "borrower-driven" selection.

This structure yields a lender's choice probability, conditional on the borrower's type, τ, as a function of the offered interest rate, r_j, and the competitor's interest rate, r_{-j}: $s_j \equiv s(r_j, r_{-j}, \tau)$.[16] Assume $s(\cdot)$ is decreasing in the lender's own price and increasing in its competitor's price. Note that we are agnostic about the microfoundation of this share function; this framework can capture, for example, a setting in which dealers solicit loan offers from a set of lenders, present a single offer to a borrower, and that borrower has the option to accept or take its outside option. This model also captures a setting in which borrowers directly shop for a lender.

We model lenders' objectives flexibly to allow for profit-deviating incentives. Lenders maximize a weighted sum of expected profit and borrower surplus for loans that are repaid, subject to making weakly positive expected profit. This payoff structure is consistent with the model of Duarte *et al.* (2025) who study consumer cooperatives in the Italian supermarket industry[17], albeit accounting for the role of selection on borrower risk. We assume lender j's payoff takes the following form:

$$\Pi_j = \alpha_j \pi_j(r_j, r_{-j}) + (1 - \alpha_j)\tilde{S}(r_j, r_{-j}) \text{ subject to } \pi_j(r_j, r_{-j}) \geq 0, \qquad (4)$$

where $\pi_j = \int [(1-d(\tau))r_j - c_j] s_j f_\tau(\tau)\, d\tau$ is lender j's expected profit of originating a loan with interest rate r_j if its competitor offers r_{-j} and its marginal cost of lending is c_j. $\tilde{S} = \int CS(r_j, r_{-j}, \tau)(1 - d(\tau)) f_\tau(\tau)\, d\tau$ is expected borrower surplus for loans that are repaid, where $CS(\cdot)$ is the expected maximum utility across all loan options, normalized by the marginal utility of income. α_j is the weight that a lender of type j places on profit relative to borrower surplus. We assume $\alpha_{BANK} = 1$ and consider the role of α_{CU}, which parameterizes the extent to which the credit union deviates from profit maximization.

To illustrate how profit-deviating incentives and selection affect the strategic interaction between credit unions and banks, it is useful to consider, like in Einav *et al.* (2012), the unconstrained marginal payoff of a credit union:

[16] We abstract away from dealer markups in this model. See Section 3 for further discussion of how dealer markups could affect our empirical results.

[17] Note that allowing consumer surplus to enter the payoff differs slightly from other papers studying non-profit competition (Lakdawalla & Philipson, 1998; Gaynor & Vogt, 2003; Hackmann, 2019), who model firms as maximizing a weighted average of profit and quantity. Given credit unions are cooperatives, we believe considering consumer surplus – rather than quantity itself – is a more natural objective.

$$\frac{\partial \Pi_j}{\partial r_j} = \alpha_j \Big[\int \Big[\underbrace{(1-d(\tau))s_j}_{\substack{\text{Gain in profit for} \\ \text{inframarginal borrowers}}} + \underbrace{[r_j(1-d(\tau))-c_j]\frac{\partial s_j}{\partial r_j}}_{\substack{\text{Forgone profit from} \\ \text{lost marginal borrowers}}} \Big] f_\tau(\tau)\, d\tau \Big] + (1-\alpha_j)\Big[\int \underbrace{\frac{\partial CS}{\partial r_j}(1-d(\tau))}_{\text{Loss in expected borrower surplus}} f_\tau(\tau)\, d\tau \Big]. \quad (5)$$

First, notice that this marginal payoff expression captures the standard interaction between market power and adverse selection, as described in Mahoney & Weyl (2017) and Crawford *et al.* (2018). For positive change in r_j, the first term captures the gain in profit for all *inframarginal* borrowers, while the second captures the same quantity for the *marginal* borrower. A for-profit lender's incentive to raise rates depends on the risk of the marginal borrower relative to the average borrower.

Where our model departs from this standard setting is in incorporating profit-deviating incentives for credit unions, captured by α_j. This incentive is captured in the third term of the marginal payoff expression, reflecting the loss in expected borrower surplus. The fact that raising the interest rate decreases expected borrower surplus for inframarginal borrowers disincentivizes a lender with $\alpha < 1$ from raising that rate and decreases the markup it would charge above its effective marginal cost of lending. This markup reduction is salient in the rate-setting expression that results from the credit union's optimization problem, assuming the zero expected profit constraint is not binding:

$$r_j = \underbrace{c_j \frac{\int \frac{\partial s_j}{\partial r_j} f_\tau(\tau)\, d\tau}{\int \frac{\partial s_j}{\partial r_j}(1-d(\tau)) f_\tau(\tau)\, d\tau}}_{\text{Effective Marginal Cost}} - \underbrace{\frac{\int (1-d(\tau))\big(s_j + \frac{1-\alpha_j}{\alpha_j}\frac{\partial CS}{\partial r_j}\big) f_\tau(\tau)\, d\tau}{\int \frac{\partial s_j}{\partial r_j}(1-d(\tau)) f_\tau(\tau)\, d\tau}}_{\text{Incentive-Adjusted Markup}}. \quad (6)$$

This rate-setting expression has two standard components: (1) an effective marginal cost that captures both the lender's cost of funds and the default risk of marginal borrowers, and (2) a markup term that in this case depends on the shape of demand and consumer surplus, and the extent to which the lender deviates from profit maximization. When profit deviation is greater (i.e., α_j is low), the lender weighs more heavily the impact of an interest-rate change on the consumer surplus of inframarginal borrowers, leading to a lower markup. At sufficiently low levels of α_j, the lender's participation constraint binds, and they set the loan's interest rate such that they earn zero expected profit.

6.2. Interpreting our Findings

Given the pricing incentives described above, what do our empirical findings suggest about credit unions' objectives and the role of borrower-driven selection in auto lending markets? One main finding in Section 5 is negative co-movement of interest rates; following mergers, banks raise rates, on average, while credit unions lower them in response. One explanation for this behavior is the following. A bank merger increases the merged entity's ability to exercise market power, and it finds it optimal to raise interest rates. Because low-risk borrowers are more interest-rate sensitive than high-risk borrowers (i.e., the "borrower-driven" selection condition discussed in Section 6.1), the borrowers that no longer want to borrow from the bank are of relatively low risk. As some of these borrowers migrate to credit unions, they decrease the risk of the credit unions' residual borrower pool.

Suppose that credit unions deviate sufficiently far from profit maximization that their zero expected profit constraint binds. In this case, they set interest rates such that they exactly break even in expectation. Because the merger-induced rise in interest rates at the bank leads credit unions to draw in a disproportionately safe set of borrowers, their default-adjusted costs of lending – and therefore the interest rates they charge – fall. In other words, because the credit unions face a lower probability of default, they can charge lower interest rates than they did previously and still earn zero profit in expectation.

It is important to note, however, one caveat to this discussion: negative co-movement in interest rates can also arise in a selection market even absent profit-deviating incentives. If the demand system and default function are such that an increase in a competitor's price *raises* the sensitivity of default (conditional on that lender being chosen) to the lender's own price, the lender may find it optimal to decrease its price, leading to strategic substitutability. Even so, the point remains that negative co-movement in prices leads to further segmentation by borrower risk in a market characterized by adverse selection. In other words, these results can be explained through the lens of "borrower-driven" selection. We next consider the implications of such borrower sorting for government policy.

6.3. Policy Implications

This evidence has implications for bank merger policy and the discussion surrounding the revision of the merger guidelines. In particular, it suggests that prospective bank merger analysis should consider a role for credit unions and that relying on bank-only deposit shares when evaluating mergers could be misleading. Credit unions do exhibit a response to bank mergers, and this response is an especially relevant consideration in geographies with large credit union shares and in consumer lending markets, where credit unions are traditionally active. However, it is also important for prospective merger analysis to account for potential unintended consequences of consolidation in selection markets. In markets with strong merger price effects, borrower risk becomes more segmented across lender types, exacerbating the credit risk faced by banks. Credit union presence can potentially magnify such selection effects due to their advantageous pricing strategies.

Furthermore, the results might also speak to the potential effects of credit union acquisitions of community banks. Since 2015, there has been substantial acquisition activity by credit unions. During this time period, 72 announced deals involved a credit union acquiring a bank, the vast majority of which have been community banks.[18] One potential unintended consequence of such acquisitions is an increase in market segmentation by borrower risk. If credit unions' profit-deviating incentives are sufficiently strong, replacing a community bank with a credit union – even in a market without pre-acquisition overlap – could have negative spillovers onto the credit risk of incumbent banks. Our results suggest some scope for this unintended consequence; while credit unions and banks compete directly for overlapping segments of borrowers, we do find evidence of borrower selection on unobservables. Obviously, in markets with pre-acquisition overlap, we must also account for any

[18] Seay, Lauren and Portes, Ronamil, "Credit unions launch bank buying spree with 5 deals in 1 week," S&P Global, available at https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/credit-unions-launch-bank-buying-spree-with-5-deals-in-1-week-77281711.

increases in credit unions' ability to exercise market power after the acquisition.

7. Conclusion

In this paper, we make two main contributions. First, we document two stylized facts that characterize the nature of competition between credit unions and banks in auto lending markets. The first stylized fact is that these two lender types compete directly for overlapping segments of borrowers. Banks and credit unions focus on near-prime and prime borrowers, while leaving the sub-prime segment to be served by non-depository lenders. We also document substantial switching between banks and credit unions, where nearly 40% of repeat borrowers originate a subsequent loan with a different lender type than their original loan. These findings highlight the extent of substitution between banks and credit unions. However, our second stylized fact suggests that there is still scope for market segmentation. Credit unions originate loans with lower interest rates than banks to a set of borrowers who are less risky on both observable and unobservable dimensions.

While the descriptive evidence is valuable in illustrating broad differences in pricing and borrower pools between banks and credit unions, our second contribution is to explain these differences as an equilibrium consequence of strategic pricing decisions and borrower-driven selection. To do so, we leverage variation in market structure caused by traditional bank mergers. We find that banks raise prices in markets that experience large changes in concentration due to mergers and they serve a set of borrowers with higher default risk, unexplained by standard borrower and loan characteristics. Credit unions respond to changes in bank behavior by lowering prices, conditional on loan and borrower characteristics. They also attract an unobservably safer set of borrowers, leading to greater market segmentation by credit risk. This result highlights two aspects of the competitive environment: (1) banks and credit unions compete for an overlapping set of borrowers, but (2) greater market power by banks could lead to larger pricing differentials between them and credit unions, magnifying risk segmentation across these institutions. Counterintuitively, even though they offer advantageous pricing, credit union presence could cause an unintended consequence of bank mergers for some borrower segments by magnifying credit risk differences in their pools of borrowers.

Our findings suggest potential routes for future work. Given the role of credit risk in shaping the competitive response to mergers, future work could explore whether the increasing prevalence of securitization by credit unions since 2023 (Martinez, 2024) could limit or amplify risk segmentation. On one hand, securitization could provide further incentive for credit unions to lower interest rates. Borrower-side selection could therefore magnify the extent of segmentation. On the other hand, securitization could lead to weaker screening incentives, which may offset some of effect of the borrower-side selection. While the relevant time period is outside the scope of our dataset, Regulation AB II data allow researchers to analyze patterns of securitization across lender types, which could help answer this question.

References

Allen, Jason, Clark, Robert, & Houde, Jean-François. 2014. The Effect of Mergers in Search Markets: Evidence from the Canadian Mortgage Industry. *American Economic Review*, **104**(10), 3365–96.

America's Credit Unions. 2024. *Monthly Credit Union Estimates*. Tech. rept.

Argyle, Bronson, Nadauld, Taylor, & Palmer, Christopher. 2020. Monthly Payment Targeting and the Demand for Maturity. *The Review of Financial Studies*, **33**, 5416–5462.

Argyle, Bronson, Nadauld, Taylor, & Palmer, Christopher. 2023. Real Effects of Search Frictions in Consumer Credit Markets. *The Review of Financial Studies*, **36**, 2685–2720.

Baker, Andrew C., Larcker, David F., & Wang, Charles C.Y. 2022. How Much Should We Trust Staggered Difference-in-Differences Estimates? *Journal of Financial Economics*, **144**(2), 370–395.

Benson, David, Blattner, Samuel, Grundl, Serafin, Kim, You Suk, & Onishi, Ken. 2024. Concentration and Geographic Proximity in Antitrust Policy: Evidence from Bank Mergers. *American Economic Journal: Microeconomics*, **16**(3), 107–133.

Berger, Allen N., Demsetz, Rebecca S., & Strahan, Philip E. 1999. The Consolidation of the Financial Services Industry: Causes, Consequences, and Implications for the Future. *Journal of Banking and Finance*, **23**, 135–194.

Buchak, Greg, & Jorring, Adam. 2024. Competition with Multi-Dimensional Pricing: Evidence from U.S. Mortgages. *Working Paper*.

Cengiz, Doruk, Dube, Arindrajit, Lindner, Attila, & Zipperer, Ben. 2019. The Effect of Minimum Wages on Low-Wage Jobs. *The Quarterly Journal of Economics*, **134**(3), 1405–1454.

Chen, Jiakai, Wang, Teng, & Zhang, Tim. 2025. Credit Union Expansion and the CU-Bank Bifurcation. *Working Paper*.

Cororaton, Anna. 2019. Banking on the Firm Objective. *Working Paper*.

Crawford, Gregory S., Pavanini, Nicola, & Schivardi, Fabiano. 2018. Asymmetric Information and Competition in Lending Markets. *American Economic Review*, **108**(7), 1659–1701.

de Chaisemartin, Clement, & D'Haultfoeuille, Xavier. 2022. Difference-in-Differences Estimators of Intertemporal Treatment Effects. *NBER Working Paper*.

Dell'Ariccia, Giovanni, & Marquez, Robert. 2004. Information and Bank Credit Allocation. *Journal of Financial Economics*, **72**(1), 185–214.

DeYoung, Robert, Evanoff, Douglas D., & Molyneux, Philip. 2009. Mergers and Acquisitions of Financial Institutions: A Review of the Post-2000 Literature. *Journal of Financial Services Research*, **36**, 87–110.

Di Patti, Emilia Bonaccorsi, & Gobbi, Giorgio. 2007. Winners or Losers? The Effects of Banking Consolidation on Corporate Borrowers. *The Journal of Finance*, **62**(2), 669–695.

Duarte, Marco, Magnolfi, Lorenzo, & Roncoroni, Camilla. 2025. The Competitive Conduct of Consumer Cooperatives. *The RAND Journal of Economics*, **56**(1), 106–125.

Einav, Liran, Jenkins, Mark, & Levin, Jonathan. 2012. Contract Pricing in Consumer Credit Markets. *Econometrica*, **80**(4), 1387–1432.

Erel, Isil. 2011. The Effect of Bank Mergers on Loan Prices: Evidence from the United States. *The Review of Financial Studies*, **24**(4), 1068–1101.

Ester, Martin, Kriegel, Hans-Peter, Sander, Jorg, & Xu, Xiaowei. 1996. A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise. *Pages 226–231 of:* Simoudis, Evangelos, Han, Jiawei, & Fayyad, Usama (eds), *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining*. AAAI press.

Feinberg, Robert M. 2001. The Competitive Role of Credit Unions in Small Local Financial Services Markets. *The Review of Economics and Statistics*, **83**(3), 560–563.

Feinberg, Robert M., & Reynolds, Kara M. 2025. The Impact of Credit Union Competition on Bank Loan Rates, 2010–2019. *Southern Economic Journal*, 1–11.

Focarelli, Dario, & Panetta, Fabio. 2003. Are Mergers Beneficial to Consumers? Evidence from the Market for Bank Deposits. *American Economic Review*, **93**(4), 1152–1172.

Garmaise, Mark J., & Moskowitz, Tobias J. 2006. Bank Mergers and Crime: The Real and Social Effects of Credit Market Competition. *The Journal of Finance*, **61**, 495–538.

Gaynor, Martin, & Vogt, William B. 2003. Competition among Hospitals. *The RAND Journal of Economics*, **34**(4), 764–785.

Gissler, Stefan, Ramcharan, Rodney, & Yu, Edison. 2020. The Effects of Competition in Consumer Credit Markets. *The Review of Financial Studies*, **33**, 5378–5415.

Goodman-Bacon, Andrew. 2021. Difference-in-Differences with Variation in Treatment Timing. *Journal of Econometrics*, **225**(2), 254–277.

Grunewald, Andreas, Lanning, Jonathan, Low, David, & Salz, Tobias. 2023. Auto Dealer Loan Intermediation: Consumer Behavior and Competitive Effects. *Working Paper*.

Hackmann, Martin. 2019. Incentivizing Better Quality of Care: The Role of Medicaid and Competition in the Nursing Home Industry. *American Economic Review*, **109**(5), 1684–1716.

Hansmann, Henry. 1980. The Role of Nonprofit Enterprise. *Yale Law Journal*, **89**(5), 835–901.

Hauswald, Robert, & Marquez, Robert. 2003. Information Technology and Financial Services Competition. *The Review of Financial Studies*, **16**(3), 921–948.

Hauswald, Robert, & Marquez, Robert. 2006. Competition and Strategic Information Acquisition in Credit Markets. *The Review of Financial Studies*, **19**(3), 967–1000.

Johnson, Matthew S., Lipsitz, Michael, & Pei, Alison. 2023. Innovation and the Enforceability of Noncompete Agreements. *NBER Working Paper*.

Klee, Elizabeth, & Shin, Chaehee. 2020. Post-Crisis Signals in Securitization: Evidence from Auto ABS. *Working Paper*.

Lakdawalla, Darius, & Philipson, Tomas. 1998. Nonprofit Production and Competition. *NBER Working Paper*.

Liebersohn, Jack. 2024. How Does Competition Affect Retail Banking? Quasi-experimental Evidence from Bank Mergers. *Journal of Financial Economics*, **154**.

Mahoney, Neale, & Weyl, E. Glen. 2017. Imperfect Competition in Selection Markets. *The Review of Economics and Statistics*, **99**(4), 637–651.

Martinez, Steve D. 2024. Credit Unions Make A Splash In 2023, Almost Tripling 2022's Auto Loan ABS Issuance. *S&P Global*.

Momeni, Morteza. 2024. Competition and Shrouded Attributes in Auto Loan Markets. *Working Paper*.

Newhouse, Joseph P. 1970. Toward a Theory of Nonprofit Institutions: An Economic Model of a Hospital. *The American Economic Review*, **60**(1), 64–74.

Nguyen, Hoai-Luu Q. 2019. Are Credit Markets Still Local? Evidence from Bank Branch Closings. *American Economic Journal: Applied Economics*, **11**(1), 1–32.

Pauly, Mark, & Redisch, Michael. 1973. The Not-For-Profit Hospital as a Physicians' Cooperative. *The American Economic Review*, **63**(1), 87–99.

Petersen, Mitchell A., & Rajan, Raghuram G. 1995. The Effect of Credit Market Competition on Lending Relationships. *Quarterly Journal of Economics*, **110**(2), 407–443.

Prager, Robin A, & Hannan, Timothy H. 1998. Do Substantial Horizontal Mergers Generate Significant Price Effects? Evidence from the Banking Industry. *Journal of Industrial Economics*, **46**(4), 433–452.

Ratnadiwakara, Dimuthu, & Yerramilli, Vijay. 2024. Effect of Bank Mergers on the Price and Availability of Mortgage Credit. *Working Paper*.

Shahidinejad, Andrés. 2024. Are (Nonprofit) Banks Special? The Economic Effects of Banking with Credit Unions. *Working Paper*.

Stiglitz, Joseph E., & Weiss, Andrew. 1981. Credit Rationing in Markets with Imperfect Information. *American Economic Review*, **71**(3), 393–410.

Tokle, Robert J., & Tokle, Joanne G. 2000. The Influence of Credit Union and Savings and Loan Competition on Bank Deposit Rates in Idaho and Montana. *Review of Industrial Organization*, **17**, 427–439.

van Rijn, Jordan. 2024. The Effects of Membership Expansion on Credit Union Risk and Returns. *International Review of Financial Analysis*, **93**, 103234.

van Rijn, Jordan, Zeng, Shuwei, & Hellman, Paul. 2021. Financial Institution Objectives and Auto Loan Pricing: Evidence from the Survey of Consumer Finances. *The Journal of Consumer Affairs*, **55**(3), 995–1039.

Yannelis, Constantine, & Zhang, Anthony Lee. 2023. Competition and Selection in Credit Markets. *Journal of Financial Economics*, **150**(2), 103710.

Appendices

A. Imputation of Interest Rates

Equifax's Analytic Dataset does not include information on loan interest rates. However, we observe original loan balance b, monthly payment m, and maturity t, which allows us to back out the implied interest rates, assuming a fixed rate and monthly payments. Applying the standard annuity formula,

$$b = \frac{m}{r}\left(1 - \frac{1}{(1+r)^t}\right),$$

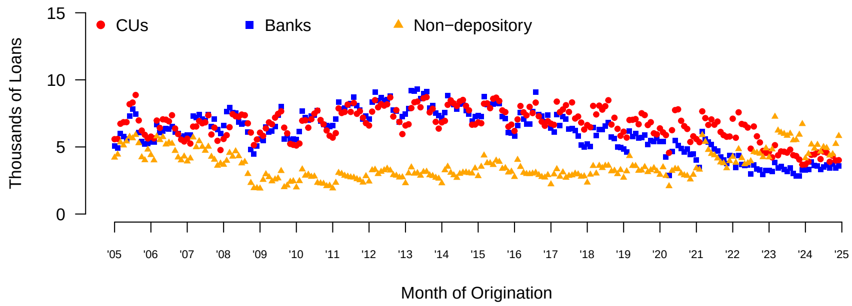
where r is the monthly interest rate. We then solve for r.

Figure 5 displays the average interest rates (APR) over time and across different loan terms for banks (blue), credit unions (red), and captives (yellow). We also overlay the "Finance Rate on Consumer Installment Loans at Commercial Banks" series for the corresponding loan maturity. These series are produced by the Federal Reserve Board and are available through FRED.[19]

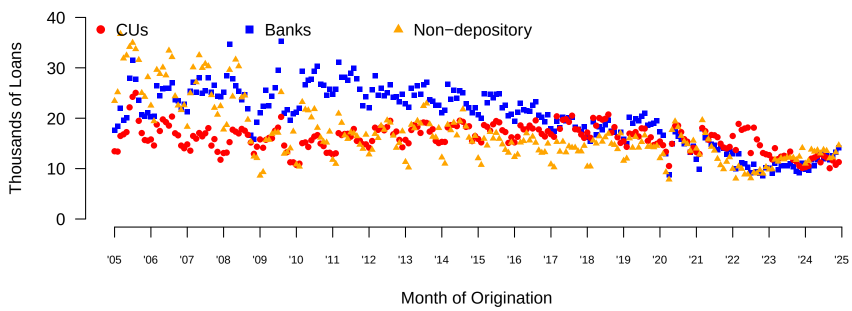
The first main takeaway of this figure relates to pricing differences across lender types. Except for small deviations in the beginning of the sample period, average interest rates at banks and credit unions are similar in magnitude and follow similar trends in the sample. Non-depository lenders tend to charge higher rates, on average, and exhibit different variation across time. It is important to note, however, that borrower risk composition also differs across these groups, and the differences in rates may – at least partially – be explained by that.

The second takeaway relates to the comparison with external data on auto loan rates. Given we impute our interest rates, it is important to validate our measures with such data. Using the auto loan series released by the Federal Reserve Board, we show that the levels and trends in our imputed interest rates closely mirror those in the external data, validating our imputation procedure.

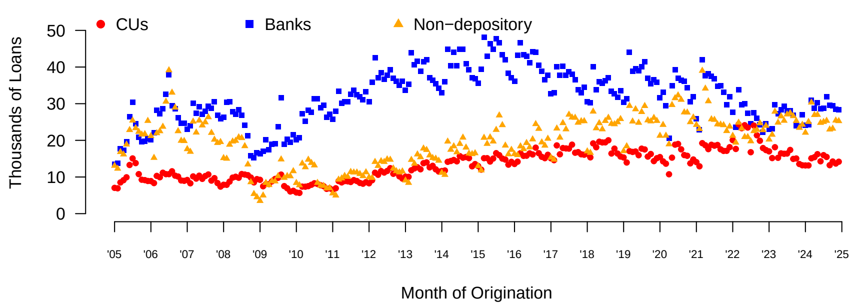
[19] See, e.g., "Finance Rate on Consumer Installment Loans at Commercial Banks, New Autos 60 Month Loan (RIFLPBCIANM60NM)", available at https://fred.stlouisfed.org/series/RIFLPBCIANM60NM.



(a) 48-Month Loans



(b) 60-Month Loans



(c) 72-Month Loans

Figure 5: Rates Over Time By Loan Term and Lender Type. This figure displays average interest rates (APR) for each type of lender over the sample period (2005 - 2025). The top panel displays rates for loans with 48-month terms, the middle panel for loans with 60-month terms, and the bottom panel for loans with 72-month terms.

B. Identification of Mergers

We identify traditional bank mergers using data on bank branch locations from the Summary of Deposits provided by Federal Deposit Insurance Corporation (FDIC) and bank merger data from the National Information Center at the Federal Financial Institutions Examination Council (FFIEC). The Summary of Deposits dataset provides branch-level data on deposits and therefore has information on branch ownership and location, including information on the bank holding company. The National Information Center dataset contains information on business transformations. We define bank mergers as transformations that (1) are classified as "Merger or Purchase & Assumption," and (2) for which the predecessor and successor RSSD ID (unique identifier for financial institutions used by the Federal Reserve) do not belong to the same bank holding company.[20] That is, we restrict to cases in which a bank is transferred from one holding company to another. We call these mergers.

For our main analysis sample, we first restrict attention to the 76 mergers that meet the criteria described in the main text: (1) the merger occurred between 2005 and 2023 to match with the time frame of the auto loans data, (2) the merger involved commercial banks and involved the transfer from one holding company to another, and (3) the merger affected at least 50 branches. We implement this final restriction to isolate market structure changes that are plausibly exogenous, as acquisitions of smaller numbers of branches are likely driven by geography-specific factors that might affect auto lending in these areas.

We then join the set of mergers to the SOD data on branch locations to identify the markets in which the target and acquirer overlapped and to determine which mergers must be dropped due to contamination. For our baseline specifications, we drop mergers for which either all treated geographies or all control geographies were exposed to another merger in the four years preceding or two years following the merger at issue. For robustness, we also examine a specification for which we consider a one-year window around each merger. In this case, we drop mergers for which either all treated or all control geographies were exposed to another merger

[20] This procedure is consistent with those used in Garmaise & Moskowitz (2006) and Ratnadiwakara & Yerramilli (2024).

in the two years preceding or one year following the merger at issue. The final two columns of Table 6 indicate which mergers are included in the baseline (2-year) specification and in the robustness (1-year) specification.

Year	Date	Avg. HHI	Avg. DHHI	Max. HHI	Max. DHHI	Branches Acquired	Target	Acquirer	2-Yr Sample	1-Yr Sample
2006	2006-11-04	287.4	65.6	7095.1	1409.7	699	AMSOUTH BANCORP.	REGIONS FIN. CORP.	Yes	Yes
2007	2007-09-22	363.1	2.5	8296.1	378.2	50	PLACER SIERRA BANCSHARES	WELLS FARGO & CO.	No	Yes
2011	2011-06-05	122.7	22.6	1649.6	186.0	168	WHITNEY HOLDING CORP.	HANCOCK HOLDING CO.	No	Yes
2011	2011-07-06	91.9	8.6	909.9	138.5	367	MARSHALL & ILSLEY CORP.	BANK OF MONTREAL	No	Yes
2013	2013-04-01	114.1	3.9	760.5	50.4	60	WEST COAST BANCORP	COLUMBIA BANKING SYSTEM, INC.	No	Yes
2014	2014-04-19	261.5	38.2	4261.9	2047.0	171	STERLING FIN. CORP.	UMPQUA HOLDINGS CORP.	Yes	Yes
2014	2014-05-10	274.2	41.1	2183.1	453.6	56	STELLARONE CORP.	UNION FIRST MKT. BANKSHARES CORP.	No	Yes
2015	2015-10-02	150.4	25.3	1582.5	552.2	96	SKBHC HOLDINGS LLC	BANNER CORP.	No	Yes
2016	2016-08-16	113.0	30.4	1031.8	484.1	370	FIRSTMERIT CORP.	HUNTINGTON BANCSHARES INC.	No	Yes
2016	2016-10-08	132.9	24.0	3225.7	546.2	407	FIRST NIAGARA FIN. GRP INC.	KEYCORP	Yes	Yes
2016	2016-11-11	387.9	24.4	1908.1	450.7	71	TALMER BANCORP INC.	CHEMICAL FIN. CORP.	Yes	Yes
2017	2017-12-01	90.3	16.8	890.3	442.5	152	CAPITAL BANK FIN. CORP.	FIRST HORIZON NATIONAL CORP.	Yes	Yes
2018	2018-04-01	286.1	78.7	3115.4	1053.9	101	MAINSOURCE FIN. GRP, INC.	FIRST FIN. BANCORP	Yes	Yes
2018	2018-06-25	86.4	15.9	807.6	159.6	63	BANK MUTUAL CORP.	ASSOCIATED BANC-CORP	Yes	Yes
2019	2019-07-01	197.9	4.7	4803.6	156.3	69	FIDELITY SOUTHERN CORP.	AMERIS BANCORP	Yes	Yes
2019	2019-09-01	168.0	0.3	1158.2	8.5	103	COOPERATIEVE RABOBANK UA	2011 TCRT	Yes	Yes
2019	2019-11-01	254.1	17.1	1780.9	374.7	54	UNITED FIN. BANCORP INC.	PEOPLE'S UNITED FIN., INC.	Yes	Yes
2019	2019-12-07	294.7	61.6	4251.7	814.5	1243	SUNTRUST BANKS INC.	BB&T CORP.	No	Yes
2022	2022-01-04	112.5	0.1	2100.1	2.5	84	CIT GRP INC.	FIRST CITIZENS BANCSHARES INC.	No	Yes
2022	2022-02-01	191.1	3.8	2114.9	276.8	175	GREAT WESTERN BANCORP INC.	FIRST INTERSTATE BANCSYSTEM, INC.	Yes	Yes
2022	2022-02-16	178.2	8.4	1649.7	394.6	109	FIRST MIDWEST BANCORP INC.	OLD NATIONAL BANCORP	Yes	Yes

Table 6: Transactions in Sample. This table lists the mergers that satisfy the screening criteria: the mergers occurred after 2004, involved the transfer from one holding company to another, affected at least 50 branches, and yields both treated and untreated geographic markets. HHI and DHHI are computed using deposit shares. We then take the average or maximum across geographic markets, as defined in Section 3. The final two columns denote whether the merger makes it into our analysis sample when using 2-year and 1-year windows, respectively, around the merger completion dates.

C. Geographic Market Definitions

Defining geographic markets for auto lending is complicated by the fact that much of this lending is intermediated by dealers. To overcome this challenge, we leverage data on the location of auto dealerships, defining markets around dealership clusters.

C.1. Identifying Dealership Clusters

We begin with a panel dataset – the YE Time Series – containing all U.S. establishments operating as of 2016 with an NAICS code of 441110 ("New Car Dealers") or 441120 ("Used Car Dealers"). These data are provided by the Business Dynamics Research Consortium: a project of the University of Wisconsin, Institute for Business and Entrepreneurship.

To identify clusters of dealerships, we rely on the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm presented in Ester *et al.* (1996), which has previously been used by policymakers to identify industrial clusters in the UK.[21] This algorithm exploits the fact that, within clusters, the density of points is typically much higher than that outside of clusters; in other words, it relies on a "density-based notion of clusters."

This algorithm has a number of advantages in our context. First, it does not require us to specify the number of clusters – this number is an outcome of the procedure. Second, the algorithm does not impose any restrictions of the shape of the clusters, which is valuable for spatial data. Finally, the algorithm can be used with any distance function: we compute the haversine distance between points.

The algorithm requires us to set two tuning parameters – ϵ and $MinPoints$ – which define the algorithm's measure of density. For every point a in a cluster, there must be a point b in that cluster so that a is within an ϵ-neighborhood of b, and the ϵ-neighborhood of b contains at least $MinPoints$. The algorithm then searches for the largest set of points that satisfy this property and are "density-connected" (See Ester *et al.* (1996) for a formal definition of density-connectedness). Ester *et al.*

[21] For more information, see "Density-Based Spatial Clustering: Identifying industrial clusters in the UK." November 2017. Department for Business, Energy & Industrial Strategy. Available at https://assets.publishing.service.gov.uk/media/5a81e201e5274a2e8ab5655c/identifying-industrial-clusters-in-UK-methodology-report.pdf.

(1996) provide a heuristic to set ϵ and $MinPoints$, and we rely on this heuristic to form our baseline clusters.[22] Because dealer density differs substantially across geographies, we allow ϵ to vary by state, setting ϵ state-by-state using the heuristic.

As a robustness check, we also set ϵ equal to the minimum relevant market area, where available.[23] Momeni (2024) discusses relevant market areas for auto dealerships in detail.

C.2. Defining Markets using Dealership Clusters

Identifying dealership clusters is a necessary input to our procedure to define geographic markets, and we define these markets around each of the dealership clusters. In the end, the geographic markets we define are contiguous, non-overlapping, and span the United States.

We begin with Zip Code Tabulation Areas (ZCTAs), which are maintained by the United State Census Bureau. We obtain the centroids of each ZCTA from a dataset provided by the National Bureau of Economic Research. We then compute the distance from the centroid of a given ZCTA to the centroids of each cluster of dealerships. We assign the ZCTA to the nearest cluster.

C.3. Geographic Markets

C.3.1. Baseline

As discussed above, because dealership density varies substantially across states, it is natural to allow the values of the tuning parameters to vary by state. In this second procedure, we manually inspect the plots of the sorted distances to the 4th-nearest neighbor ("4-dist") for each set to set the values of ϵ. Baseline values of ϵ for each state are displayed in Table 7.

Figure 6 displays the dealership clusters and associated geographic markets for the baseline specification in which the tuning parameters of the DBSCAN algorithm

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[22]The paper suggests setting $MinPoints$ equal to four and visually inspecting the plot of sorted distances to the 4th-nearest neighbor. It advocates setting ϵ equal to the distance to the 4th-nearest neighbor of the first "valley" in this plot.

[23]See https://www.dealernews.com/DN-Academy/Management/post/franchise-law-roundup-relevant-market-area-rma/2016-12-19 for a list of relevant market areas by state.

State	ϵ (km)	State	ϵ (km)
Alabama	20	Montana	18
Alaska	20	Nebraska	30
Arizona	8	Nevada	10
Arkansas	20	New Hampshire	12
California	8	New Jersey	6
Colorado	10	New Mexico	10
Connecticut	7	New York	15
Delaware	5	North Carolina	15
District of Columbia	5	North Dakota	50
Florida	10	Ohio	20
Georgia	10	Oklahoma	20
Hawaii	8	Oregon	20
Idaho	25	Pennsylvania	12
Illinois	20	Rhode Island	6
Indiana	15	South Carolina	20
Iowa	22	South Dakota	20
Kansas	25	Tennessee	15
Kentucky	20	Texas	15
Louisiana	30	Utah	10
Maine	20	Vermont	15
Maryland	10	Virginia	15
Massachusetts	8	Washington	15
Michigan	20	West Virginia	15
Minnesota	30	Wisconsin	20
Mississippi	20	Wyoming	40
Missouri	25		

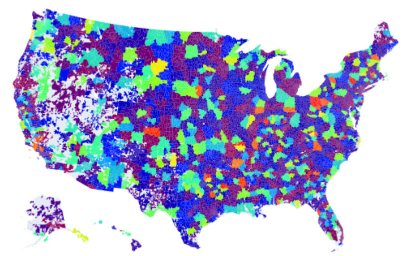
Table 7: Values of ϵ by State. This table displays the tuning parameter, ϵ, for each state. We choose each of these tuning parameters using the heuristic described by Ester *et al.* (1996).

are set state-by-state.

C.3.2. Using Relevant Market Areas

Figure 7 displays the dealership clusters and associated geographic markets for the specification in which the tuning parameters of the DBSCAN algorithm are set at the state level, but ϵ is equal to the minimum relevant market area (RMA) for that state if available.

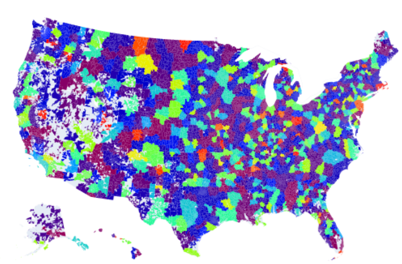
(a) Clusters



(b) Geographic Markets

Figure 6: Clusters and Geographic Markets for Baseline Specifications. The left-hand panel displays the clusters identified using the DBSCAN algorithm where ϵ is set at the state level. The right-hand panel displays the corresponding markets, where each ZCTA is mapped to the nearest dealership cluster.

(a) Clusters



(b) Geographic Markets

Figure 7: Clusters and Geographic Markets using Tuning Parameters Defined by RMAs. The left-hand panel displays the clusters identified using the DBSCAN algorithm where ϵ is set at the state level, using the minimum relevant market area (RMA) for that state if available. The right-hand panel displays the corresponding markets, where each ZCTA is mapped to the nearest dealership cluster.

D. Additional Tables and Figures

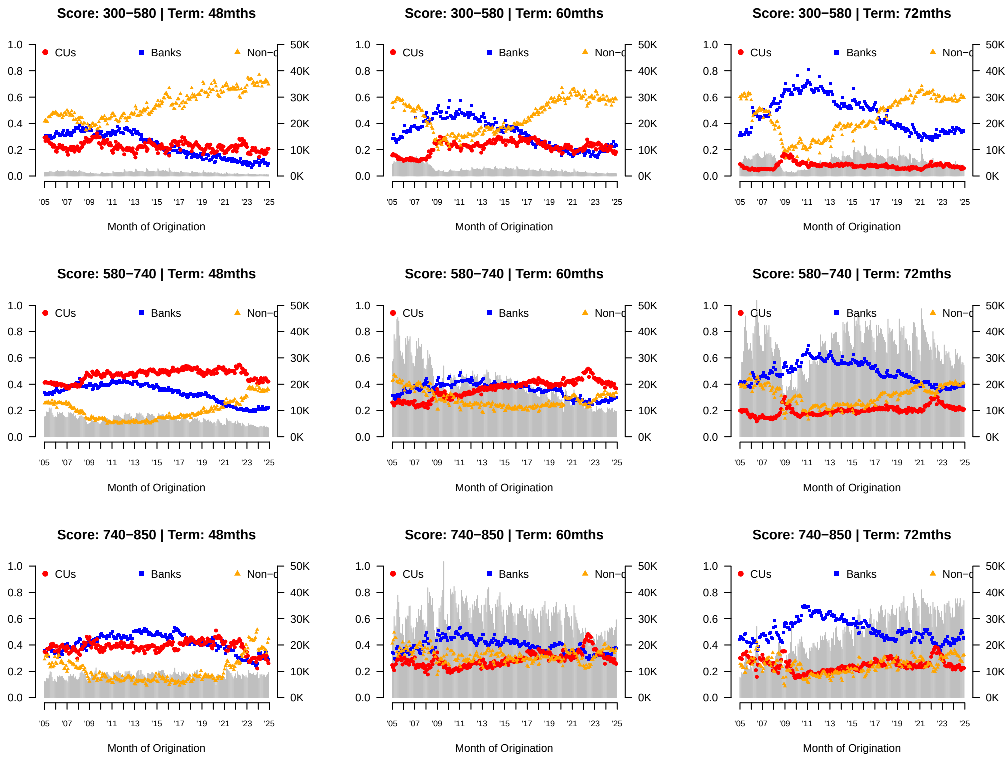
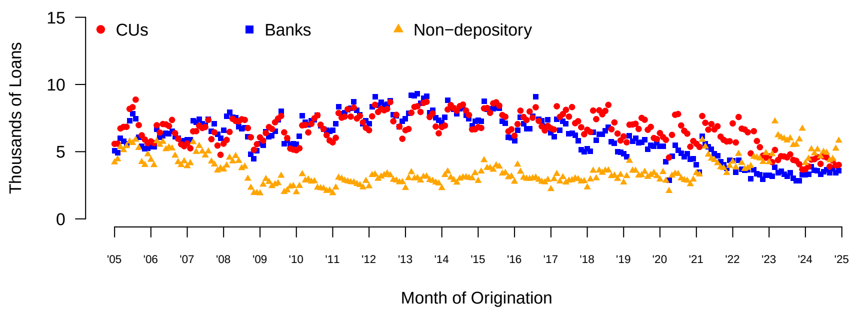
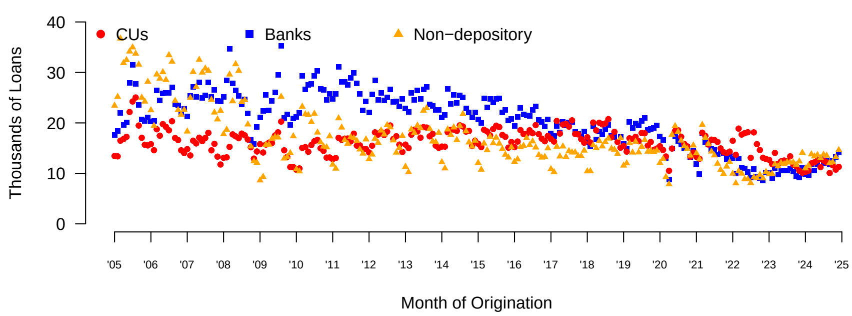


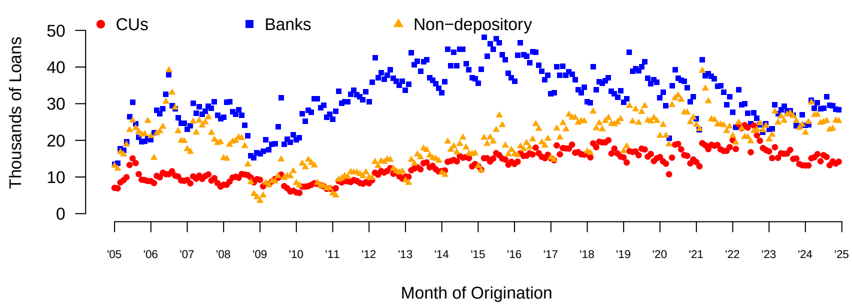
Figure 8: Market Shares Over Time By Loan Term, Lender Type, and Borrower Credit Score. This figure displays market shares for each type of lender over the sample period (2005 - 2025). The left-hand column displays shares for loans with 48-month terms, the middle column for loans with 60-month terms, and the right-hand column for loans with 72-month terms. The top row displays shares restricting to borrowers with Vantage 3.0 credit scores between 300 and 580, the middle row restricts to borrowers with scores between 580 and 740, and the bottom row restricts to borrowers with scores between 740 and 850.



(a) 48-Month Loans

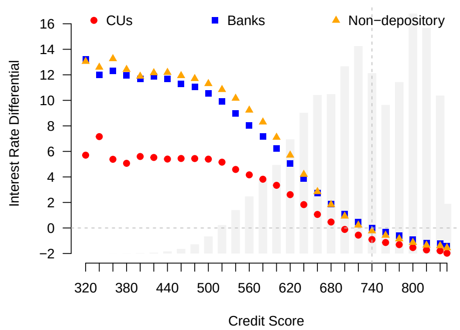


(b) 60-Month Loans

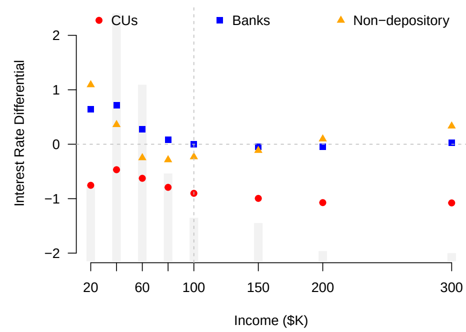


(c) 72-Month Loans

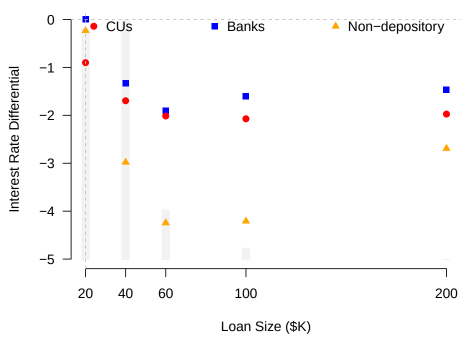
Figure 9: Loan Counts by Lender Type and Term over Time. This figure displays the number of loans (in thousands) for each type of lender and loan term over the sample period (2005 - 2025). The top panel displays rates for loans with 48-month terms, the middle panel for loans with 60-month terms, and the bottom panel for loans with 72-month terms.



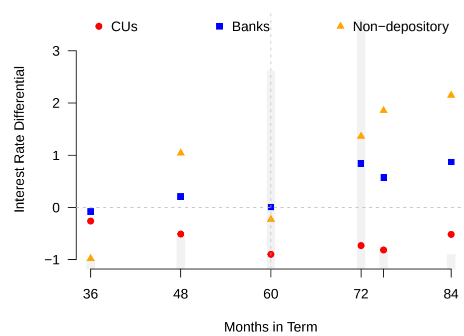
(a) Credit Score



(b) Borrower Income

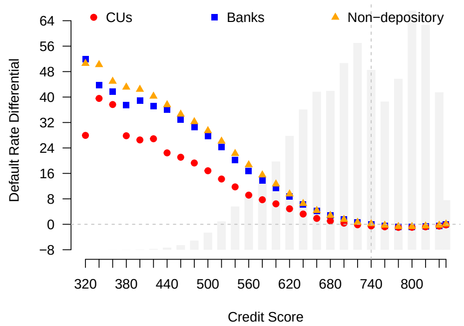


(c) Loan Amount

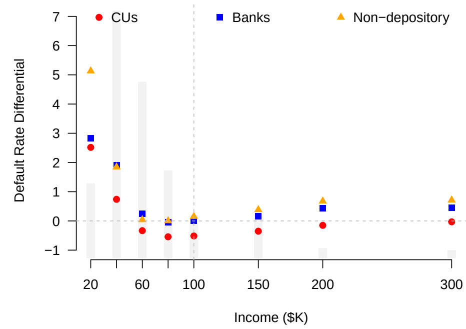


(d) Loan Terms

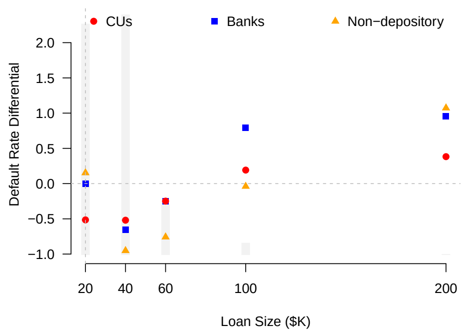
Figure 10: Interest Rates by Lender Type. This figure displays the coefficients of a regression of interest rate on saturated interactions of lender type with Vantage 3.0 credit score categories, loan terms, loan size categories, and borrower income categories. The coefficients for credit unions are shown in red, those for banks are shown in blue, while those for non-depository lenders are shown in yellow.



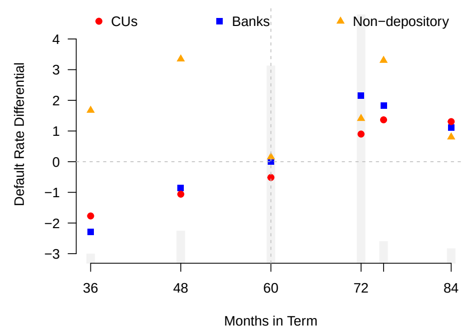
(a) Credit Score



(b) Borrower Income

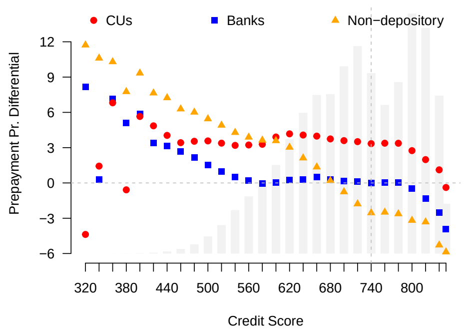


(c) Loan Amount

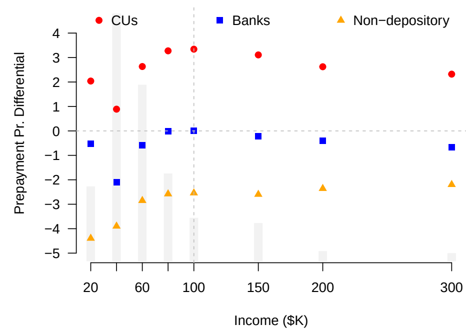


(d) Loan Terms

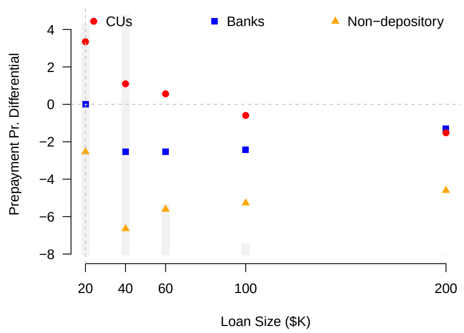
Figure 11: Default Rates by Lender Type. This figure displays the coefficients of a regression of a default indicator variable on saturated interactions of lender type with Vantage 3.0 credit score categories, loan terms, loan size categories, and borrower income categories. The coefficients for credit unions are shown in red, those for banks are shown in blue, while those for non-depository lenders are shown in yellow.



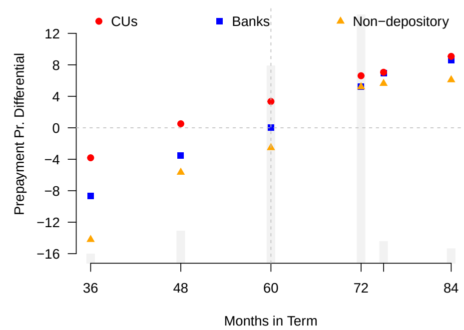
(a) Credit Score



(b) Borrower Income

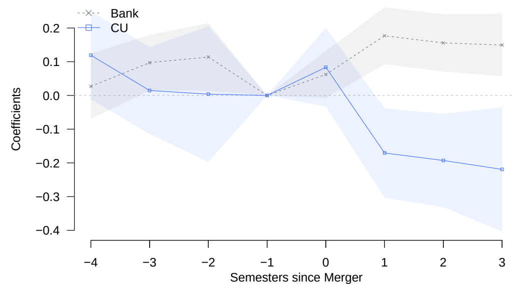


(c) Loan Amount

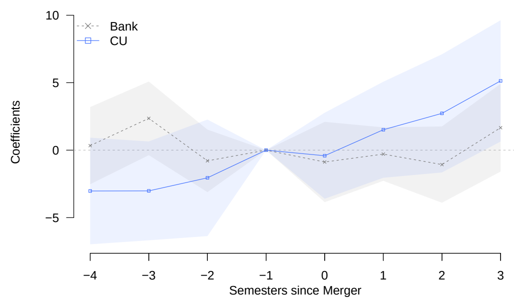


(d) Loan Terms

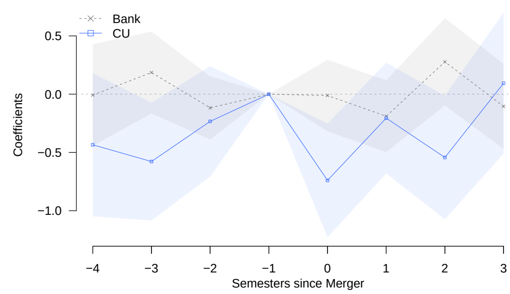
Figure 12: Prepayment Rates by Lender Type. This figure displays the coefficients of a regression of a prepayment indicator variable on saturated interactions of lender type with Vantage 3.0 credit score categories, loan terms, loan size categories, and borrower income categories. The coefficients for credit unions are shown in red, those for banks are shown in blue, while those for non-depository lenders are shown in yellow.



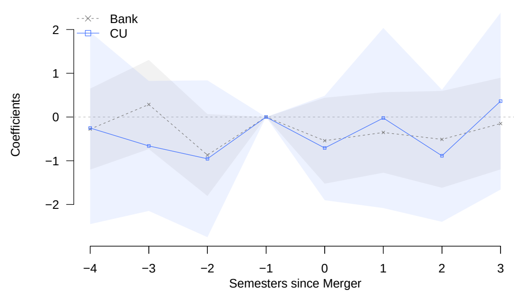
(a) Interest Rate (with Controls)



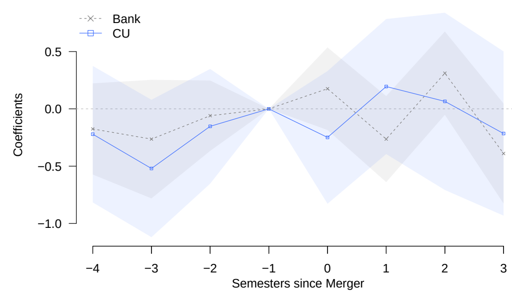
(b) Credit Score



(c) Loan Balance

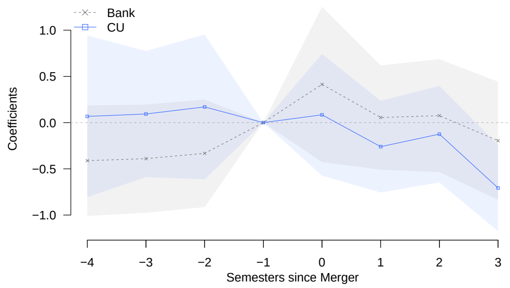


(d) Borrower Income

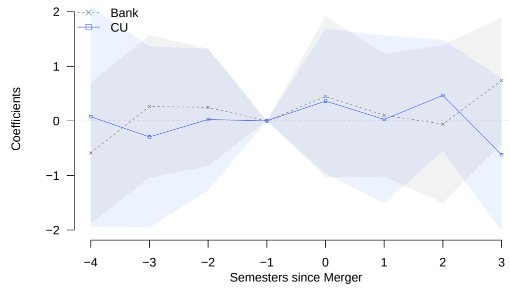


(e) Loan Term

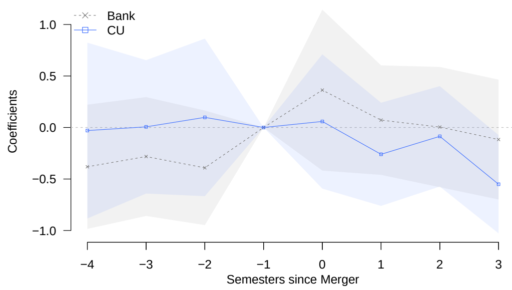
Figure 13: Event Study Plots for Loan and Borrower Characteristics, High DHHI Markets. This figure presents event study results for an adjusted version of Specification 2. For four semesters preceding and following a merger, we plot the coefficient and 95% confidence interval of regressions of the relevant characteristic on interactions of time fixed effects, treatment indicators, indicators of lender type, and indicators of high DHHI markets. We plot the coefficients for banks in black and the total coefficients for credit unions (bank coefficient + credit union incremental effect) in blue.



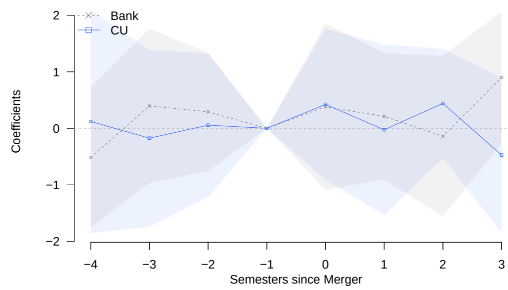
(a) Default



(b) Prepaid



(c) Default (with Controls)



(d) Prepaid (with Controls)

Figure 14: Event Study Plots for Loan Outcomes, High DHHI Markets. This figure presents event study results for an adjusted version of Specification 2. For four semesters preceding and following a merger, we plot the coefficient and 95% confidence interval of regressions of the relevant characteristic on interactions of time fixed effects, treatment indicators, indicators of lender type, and indicators of high DHHI markets. We plot the coefficients for banks in black and the total coefficients for credit unions (bank coefficient + credit union incremental effect) in blue.

	Interest Rate (1)	Credit Score (2)	Loan Amount (3)	Borrower Income (4)	Loan Term (5)	Default (6)	Prepaid (7)	Default (8)	Prepaid (9)
High DHHI	0.07**	-0.67	-0.03	-0.19	0.08	0.37**	0.31	0.34**	0.27
	(0.03)	(1.03)	(0.12)	(0.28)	(0.15)	(0.16)	(0.32)	(0.15)	(0.33)
ND x High DHHI	0.04	0.10	-0.18	-0.57	-0.21	-0.36	0.53	-0.38	0.59
	(0.07)	(1.60)	(0.23)	(0.47)	(0.23)	(0.28)	(0.56)	(0.27)	(0.57)
CU x High DHHI	-0.23***	5.06***	0.02	0.38	0.10	-0.72**	-0.22	-0.57**	-0.20
	(0.06)	(1.60)	(0.25)	(0.50)	(0.29)	(0.29)	(0.65)	(0.26)	(0.63)
Controls	Yes	No	No	No	No	No	No	Yes	Yes
Observations	1,598,213	1,598,213	1,598,213	1,598,213	1,598,213	1,598,213	1,598,213	1,598,213	1,598,213
R^2	0.46	0.05	0.09	0.05	0.07	0.01	0.06	0.05	0.08
Within R^2	0.38	0	0	0	0	0	0	0.04	0.02
Dep. Var. Mean	5.63	730.82	25.28	56.36	65.49	2.76	87.68	2.76	87.68

Table 8: Merger Effects in High DHHI Markets, Including Non-Depository Lenders. This table presents the results of Specification 3. Regressions are estimated using loans originated by banks, credit unions, and non-depository lenders to borrowers with Vantage 3.0 credit scores above 580. All regressions include lender type $\times$ market $\times$ merger fixed effects as well as lender type $\times$ time $\times$ merger fixed effects. For more details, see Section 4.3. Standard errors, shown in parentheses, are clustered at the merger-market-lender type level.

	Interest Rate	Credit Score	Loan Amount	Borrower Income	Loan Term	Default	Prepaid	Default	Prepaid
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High DHHI	0.08**	-1.00	-0.05	-0.37	0.22	0.51***	0.69**	0.48***	0.59**
	(0.03)	(0.87)	(0.11)	(0.33)	(0.15)	(0.16)	(0.29)	(0.15)	(0.30)
CU x High DHHI	-0.27***	5.20***	0.14	0.26	0.15	-0.85***	-0.69	-0.73***	-0.65
	(0.07)	(1.74)	(0.22)	(0.57)	(0.31)	(0.26)	(0.63)	(0.23)	(0.59)
Controls	Yes	No	No	No	No	No	No	Yes	Yes
Observations	1,185,377	1,185,377	1,185,377	1,185,377	1,185,377	1,185,377	1,185,377	1,185,377	1,185,377
R^2	0.49	0.04	0.09	0.05	0.08	0.01	0.06	0.04	0.07
Within R^2	0.37	0	0	0	0	0	0	0.03	0.02
Dep. Var. Mean	5.7	729.52	24.42	54.87	65.72	2.55	88.46	2.55	88.46

Table 9: Merger Effects in High DHHI Markets, with State-Based RMAs. This table presents the results of Specification 3. Regressions are estimated using loans originated by banks and credit unions to borrowers with Vantage 3.0 credit scores above 580. All regressions include lender type $\times$ market $\times$ merger fixed effects as well as lender type $\times$ time $\times$ merger fixed effects. For more details, see Section 4.3. Standard errors, shown in parentheses, are clustered at the merger-market-lender type level.

	Interest Rate (1)	Credit Score (2)	Loan Amount (3)	Borrower Income (4)	Loan Term (5)	Default (6)	Prepaid (7)	Default (8)	Prepaid (9)
High DHHI	0.31	-1.09	0.10	0.15	-0.14	-0.50	0.59	-0.47	0.64
	(0.19)	(0.94)	(0.19)	(0.25)	(0.24)	(0.91)	(1.10)	(0.90)	(1.11)
CU x High DHHI	-0.29	1.94	0.07	-0.22	0.72	0.19	-5.30**	0.02	-5.52***
	(0.32)	(2.08)	(0.47)	(0.38)	(0.72)	(1.54)	(2.10)	(1.55)	(2.10)
Controls	Yes	No	No	No	No	No	No	Yes	Yes
Observations	82,787	82,787	82,787	82,787	82,787	82,787	82,787	82,787	82,787
R^2	0.25	0.03	0.11	0.03	0.19	0.04	0.05	0.06	0.06
Within R^2	0.1	0	0	0	0	0	0	0.02	0.01
Dep. Var. Mean	12.87	541.28	18.01	26.51	65.04	17.32	87.43	17.32	87.43

Table 10: Merger Effects in High DHHI Markets, Restricted to Sub-Prime Borrowers. This table presents the results of Specification 3. Regressions are estimated using loans originated by banks and credit unions to borrowers with Vantage 3.0 credit scores below 580. All regressions include lender type × market × merger fixed effects as well as lender type × time × merger fixed effects. For more details, see Section 4.3. Standard errors, shown in parentheses, are clustered at the merger-market-lender type level.

	Interest Rate (1)	Credit Score (2)	Loan Amount (3)	Borrower Income (4)	Loan Term (5)	Default (6)	Prepaid (7)	Default (8)	Prepaid (9)
High DHHI	0.04^{*}	-0.41	0.07	-0.05	-0.01	-0.08	0.23	-0.08	0.23
	(0.02)	(0.62)	(0.09)	(0.23)	(0.10)	(0.19)	(0.38)	(0.17)	(0.36)
CU x High DHHI	-0.11^{**}	0.83	0.03	0.18	0.12	-0.06	-0.40	-0.07	-0.42
	(0.04)	(1.01)	(0.14)	(0.37)	(0.16)	(0.22)	(0.51)	(0.21)	(0.50)
Controls	Yes	No	No	No	No	No	No	Yes	Yes
Observations	2,361,126	2,361,126	2,361,126	2,361,126	2,361,126	2,361,126	2,361,126	2,361,126	2,361,126
R^2	0.5	0.05	0.11	0.06	0.08	0.02	0.05	0.06	0.06
Within R^2	0.36	0	0	0	0	0	0	0.04	0.02
Dep. Var. Mean	6.33	723.76	23.34	54.77	64.95	3.44	86.33	3.44	86.33

Table 11: Merger Effects in High DHHI Markets, with One-Year Event Windows. This table presents the results of Specification 3, but restricts the event window to be one year before and after the merger, instead of two years before and after – as in the standard specifications. Regressions are estimated using loans originated by banks and credit unions to borrowers with Vantage 3.0 credit scores above 580. All regressions include lender type $\times$ market $\times$ merger fixed effects as well as lender type $\times$ time $\times$ merger fixed effects. For more details, see Section 4.3. Standard errors, shown in parentheses, are clustered at the merger-market-lender type level.