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Essays on Policy Issues in the Financial Services Industry

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ABSTRACT

In the first chapter, I estimate structural equilibrium models that identify the degree of overlap in products and services, and hence competition, between community banks and large credit unions in 1,771 local US financial services markets. Large credit unions offer some of the products and services as community banks, leading many to question if federal tax exemptions are needed to facilitate the provision of such goods. My results suggest that large credit unions do not displace community banks, suggesting that they primarily serve different customer bases with different types of products. Counterfactual simulations suggest that the overlap in product and services between community banks and large credit unions reduces the number of community banks by only 2.5 percent. In addition, the results indicate that the presence of large credit unions lead to 13.5 percent more institutions, suggesting that they facilitate variety in products and services.

In the second chapter, I investigate if non-binding fee caps can be used as focal points by payday lenders to facilitate tacit collusion in 1,978 local markets in the United States. The results show that, after controlling for local demand and cost characteristics, sufficiently high fee caps can increase payday lender entry and profitability relative to lenders in markets without fee caps. The evidence suggests that the use of non-binding fee caps can be an effective tool for tacit collusion.

In the third chapter, I investigate the relationship between interest rate swaps and growth in mortgage lending by US credit unions from 2011 to 2017. I exploit a rule change by the National Credit Union Association in 2014, which allowed certain credit unions access to financial derivatives, to identify this effect using a difference-in-differences approach. I find that credit unions using interest rate swaps experience greater growth in mortgage lending, where growth in fixed-rate mortgage lending is most significant, than credit unions that do not use these financial instruments.

DEDICATION

To perseverance.

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CHAPTER 1

CAN COMMUNITY BANKS AND CREDIT UNIONS COEXIST? EVIDENCE FROM LOCAL FINANCIAL SERVICES MARKETS

1.1 Introduction

Credit unions' common bond structure and tax exemption status allow them to offer loans and deposits at appealing rates to retail-oriented customers. Over the last two decades, the average credit union has evolved from offering only automobile loans and depository services to also supplying loans more in line with banks such as real estate and commercial loans. Coupled with credit unions' growth in size and tax exemption status, community banks — banks with less than $1 billion of assets who also rely on retail-oriented business — argue that the current competitive playing field in the market is unfair.[1] The ability of credit unions to use their tax exempt status to undercut banks on rates and use their size as an advantage against traditional financial services firms is leading many to consider if they have a significant impact on the financial services market.

The growing similarities between credit unions and community banks has led to policy discussion surrounding the merits of the federal tax exemption. After the passing of the Tax Cuts and Job Act of 2017, policymakers discussed remov-

[1] "Consolidation within the credit union industry has created credit unions far larger than many of the community banks they compete against, thus providing credit unions a double advantagethey are much bigger than many of their taxpaying competitors, yet pay no federal income taxes." American Bankers Association (2013)

ing the credit union tax exemption in order to offset the costs of the bill. The tax exempt status of credit unions is a significant cost to the US treasury, as it was estimated to have cost $2.9 billion in terms of lost income for the fiscal year 2016 (Joint Committee on Taxation, 2017). Policymakers' main justification for this proposal was the growing similarities in products and services between credit unions and banks.[2] As stated by the Federal Credit Union Act of 1934, the mission of credit unions in the United States is to facilitate the provision of credit to consumers outside the traditional banking industry. Critics contend that credit unions have abandoned this mission and now operate as tax-exempt banks, thus deserving the same policy treatment as traditional financial services firms.[3] However, credit unions assert that, while their asset size has grown, their traditional focus on consumer loans and member accounts still remains.[4] As the tax exemption is a significant cost to the treasury and a sensitive issue for community bankers, it is likely that policymakers will revisit the issue in the future.

The assertion that the federal tax exemption gives unfair cost advantages to credit unions is dependent on the premise that their products and services are substitutes to those offered by community banks, leading to credit unions displacing community banks in markets. Although studies in the literature find that banks and credit unions compete on deposits and automobile loans (e.g., Feinberg (2001) and

[2]"Many of the larger credit unions operate in the same manner as banks. These activities include purchasing previously for-profit banks and buying the naming rights to sports stadiums." U.S. Senator Orrin Hatch (2018)

[3]"Many credit unions are now indistinguishable from banks, yet they still pay no federal income taxes. The credit unions tax exemption gives them a distinct advantage when they compete directly with banks, especially smaller banks." American Bankers Association (2016)

[4]See https://www.pscu.org/membership/credit-union-difference/ (Accessed April 13th, 2018)

Hannan (2002)), the literature lacks empirical evidence that credit unions significantly impact the entry, and thus profitability, of community banks. In this study, I estimate discrete models of entry and product choice to address this relationship. Since product-specific data are unavailable for many of the services offered by credit unions and banks, models that use the presence of a firm to encapsulate the total competitive effect provide a more useful and practical approach. These models capture the intrinsic endogeneity in the ordered entry decisions of the firms. As a result, I can predict in counterfactual analyses how market structure would change if the competitive pressure of credit unions was eliminated.

My study relates to previous work in the literature in three ways. First, it contributes to the understanding of how credit unions interact and compete with other financial services firms. Since market-level data on interest rates and profits are difficult to obtain in the financial services industry, few studies on the competitive relationship between banks and credit unions exist. Feinberg (2001) finds a negative relationship between credit union market share and new vehicle and unsecured loan rates. Hannan (2002) finds a positive relationship between credit union market presence and money market, checking, and certificate of deposit rates. Tokle and Tokle (2000) find that higher competition from credit unions increases banks deposit interest rates. Emmons and Schmid (2000) find that households respond to bank concentration by shifting accounts to credit unions. While these studies provide partial evidence of competition for particular financial products, my endogenous entry model allows me to more comprehensively measure how the profitability and viability of different types of institutions are impacted by the presence of competition. Differences between own and other type competitive effects allows for me to determine if large credit unions and community banks offer products and service that are strong or weak substitutes. Hence, my contribution focuses on the overall competitive impact of credit unions on community banks.

Second, my study contributes to the literature on competition and product differentiation between non-profit or not for profit firms in the context of entry. Harrison and Seim (2017) investigate the crowd-out effect of different tax treatment of non-profit gyms on for-profit entry. They find that non-profit and for-profit gyms serve different consumer groups. Ballou (2008) determines that asymmetric competitive effects between ownership types such that the absence of a nonprofit nursing home increases the for-profits entry probability, but not the other way around. Cohen et al. (2013) produce evidence that crowd-out effects between government substance abuse clinics and for-profit and nonprofit clinics are more significant than between the for-profit and the nonprofit. My study compliments the findings of these studies by providing additional evidence that tax-exempt not-for-profits and for-profits can coexist in markets.

Last, my study follows other applications of entry models to the financial service industry. Cetorelli (2002) uses an endogenous entry model similar to that of Bresnahan and Reiss (1991) to analyze the competitive conduct of conventional banks in the financial services markets. He finds that conventional banks may behave competitively after the third entrant. Using an endogenous entry model with product differentiation, Cohen and Mazzeo (2007) find that multi-market, savings and loans, and single-market banks are not perfect strategic substitutes for one another. Their results imply that banking markets can exist with multiple types of firms. Coelho et al. (2013) model the entry decision of private banks with the presence of public banks in the Brazilian banking market. They find that public banks have an economically insignificant impact on the competitive conduct of private banks. Feinberg (2008) uses an entry model similar to Bresnahan and Reiss (1991) to determine the competitive effect of entry in credit union markets. My study extends these results by including credit unions in the endogenous entry model of traditional financial services firms. My results indicate that differentiation may allow for credit union and traditional financial services firms to operate in the same geographies.

Although my study lacks market-level data on variable profits, prices, and costs, the competitive presence of credit unions on bank entry can be identified using techniques from the industrial organization literature. The empirical analysis focuses on the entry decisions of community banks and large credit unions as theory suggests they have similar production technologies and descriptive statistics show they may overlap in certain product and services. A structural model of endogenous entry, which allows for firms of different types and is robust to equilibrium assumptions (Cleeren and Verboven, 2010), estimates the parameters of firms' objective functions for a cross-section of 1,771 local financial services markets in 2010 and 2015. This approach allows for the identification of the impact of a firm of a given type, and thus the aggregate effect of all their products and services, on each type of firm's entry decision. Competitive parameters in the model allow me to assess the degree to which the two compete and the likelihood that community banks and large credit unions can coexist. Locations of banks and credit unions come from the FDIC Summary of Deposits and the NCUA Credit Union Branch Information Report. Maximum likelihood estimation produces estimates of parameters that identify the effect of demand and competitive characteristics on entry.

Basic entry models do not accommodate for the event when either firm would prefer to enter if the other one did not (e.g., Schaumans and Verboven (2008) and Gayle and Luo (2015)). I follow Cleeren and Verboven (2010) by including an order of entry assumption that chooses community banks entry when equilibria where either could enter are produced. Additionally, I obtain estimates from a cross-section from a different period to ensure the robustness of the results to the dynamic assumptions of the model. Finally, counterfactuals are used to determine the extent to which competition from large credit unions impact the entry of community banks.

The results of my study suggest that it would take eight to ten large credit unions to have the same impact as a rival community bank on community bank entry. These competitive effects reveal that the products and services of community banks and large credit unions do not overlap in markets that are important to the profitability of community banks. Moreover, entry decisions appear to by driven by different factors. Credit union entry responds primarily to population, while community bank entry is driven by the demand for housing and the number of businesses and farms. Current institutional features such as regulation and market strategy may limit large credit unions from competing more directly with community banks. Coupled with these results, large credit unions' cost advantage may not substantially affect community bank profitability.

My results are robust to assumptions of the order of entry, market dynamics, and market definitions. Since competition between community banks and large credit unions is not substantial, estimates of the competitive effects from models that accommodate for the multiplicity problem are not significantly different from the basic entry model. In addition, insignificant differences in estimated competitive effects for markets in the years 2010 and 2015 suggest that institutional changes in the market have not affected community banks ability to differentiate their services from those offered by large credit unions. Last, the results are robust to the assumption of market definition, as estimates from selected rural markets are similar to the those produced from the total sample.

Counterfactual analysis supports the claim that large credit unions have a economically negligible impact on the profitability of community banks. Using estimates from the entry model for markets in 2015, I simulate a scenario where community banks and large credit unions do not compete. Under this condition, the total number of community banks rises by only 2.2 percent, suggesting that competition from large credit unions does not have an substantial impact on community bank entry. In addition, the simulation implies that the presence of large credit unions leads to 13.5 percent more financial institutions in the sample markets, implying that large credit unions' focus on retail-oriented business and their existence may lead to a greater variety in products and services in the market.

My study proceeds as follows. Section 2 presents relevant background information about the local financial services industry and the role of community banks and large credit unions in the sector. I then present in Section 3 an empirical equilibrium model of entry by ownership type. Section 4 outlines the data that I use to estimate the parameters of the model. I then turn to the results of my estimation in Section 5. I conclude in Section 6 with a discussion of my results and the potential policy implications.

1.2 Industry background

According to the US Treasury, a credit union is differentiated from other financial services firms through five characteristics (U.S. Treasury, 1997). First, credit unions are member-owned, member-directed depository institutions. Credit unions do not issue capital stock. Rather, they derive their net worth from their accumulated retained earnings. Second, credit unions rely on unpaid, volunteer boards of directors elected by, and drawn from, each credit unions membership. Third, credit unions do not operate for profit. Fourth, credit unions have a public purpose. Last, credit unions have certain limitations on their membership, limitations generally based on a common bond among members.

In 1998, the US Congress passed the Credit Union Membership Access Act, allowing for credit unions to have multiple common bonds with their customers. Following the successful passing of this act, the asset size of credit unions grew larger, as the total assets in the credit union industry swelled from $294 billion in 1998 to 1.25 trillion in 2017, despite the number of credit unions falling from 12,201 to 5,689.[5] At the same time, the financial portfolio of credit unions changed dramatically, as the total amount of real estate loans expanded from roughly $50 to $500 billion, outpacing the growth in automobile loans, which grew from roughly $75 to $350 billion. As the scale of production size of credit union grows, they are likely to continue to diversify their portfolio, as Goddard et al. (2008) find evidence that, concerning portfolio diversification, the positive direct exposure effect outweighs the adverse indirect exposure effect only for credit unions of the most substantial size.

During roughly the same period, the community banking industry experienced a dramatic change. From 1990 to 2016, the number of community banks declined from 11,858 to 4,507 (Federal Reserve Bank of St.Louis, 2016). Of the community banks operating in 1984, 25 percent exited through merger, while 59 percent consolidated and 8 percent failed by 2011 (FDIC, 2011). Moreover, total assets held by community banks remained stagnant, about $2 trillion, while large banks saw their total assets rise from $2 to $12 trillion (FDIC, 2011). Recently, the issues faced by community banks has featured prominently in policy discussion.[6]

The growth in size and changes in products and services of credit unions may have greater implications for community banks than for other traditional financial services firms. Similarities in production technology may lead credit unions to offer products traditionally provided by community banks. In particu-

[5] Unless specified otherwise, loan statistics are derived from the NCUA and FDIC call report database.

[6] E.g., the 2016 Council of Economics Advisers Issue Brief "The performance of community banking over time".

lar, both firms may find themselves competing in markets where local knowledge is important. Anecdotal evidence suggests that community banks benefit from "relationship lending". Close relationships with customers may give community banks a greater ability to gauge the creditworthiness of local borrowers than financial services firms with larger production scale, which is particularly relevant to issuing commercial loans (e.g., Berger and Udell (1995)). Community banks often rely on this advantage in competing with larger banks, as Marsh and Sengupta (2017) find that community banks respond to large bank entry by obtaining more assets into markets where relationship lending is essential. Indeed, the composition of community bank assets reflects the importance of local loans as real estate and commercial loans represented roughly 20 and 18 percent of total loans in 2014.

Similarly, credit unions may benefit from "relationship lending". Consumers must be members before a financial transaction can occur at a credit union. By interacting with members frequently, credit unions may be able to gauge potential borrowers in a similar manner to community banks. In addition, credit unions and community banks may provide a relatively similar customer service experience. Of small businesses sampled in 2016, 78 percent reported satisfaction with credit union services, compared to 80 percent of small banks and 61 percent with large banks (New York Federal Reserve Bank, 2016).

However, limitations in technology of smaller credit unions, regulation, and organization strategy of credit unions may lead to them offering different products and services than community banks. Smaller credit unions often rely on volunteer workers to manage deposits and issue loans. These volunteers may not have the expertise to offer anything other than consumer loans (Goddard et al., 2008). Indeed, in 2014, new and used automobile loans constituted roughly half of the total loans of credit unions with assets less than $100 million. Current regulation limits the extent of products credit unions can provide. For example, regulations currently exist that limit credit unions to placing 12.5 percent of total assets to business loans. In 2014, approximately 1000 credit unions were near or close to this cap (NCUA, 2014). Although real estate loans constituted roughly half of total loans of credit unions with assets greater than $100 million in 2014, they still had a substantial presence in new and used automobile loans. Of these credit unions at the, new and used automobile loans represented roughly 30 percent of total loans. In comparison, automobile loans accounted for only 4.9 percent of total bank loans in 2010 (FDIC, 2010). Although credit unions are getting larger, it appears they have not abandoned their traditional role as providers of automobile loans.

1.3 A model of endogenous entry with product differentiation

In the spirit of Cleeren and Verboven (2010), to examine the competitive effect of large credit unions in local financial services markets I employ a three-stage model of oligopoly market entry under product differentiation in the context of the local financial services market. In this setting, discrete choices (e.g., enter or dont enter a given market) are arrived at by calculating the profitability of the potential alternatives. In this case, entry occurs until the characteristics of a market's demand and cost characteristics lead to no profitable, or positive value producing, entry by a firms of each type, producing a equilibrium market configuration.

1.3.1 Structure of objective functions

Assume a market m with a total of N potential participants, divided into N_{CB} community banks and N_{LCU} large credit unions. Participants play a three period game, where the first period firms are endowed with a type, the second period firms sequentially choose to enter or not to enter, and the third period firms compete. Entry decision by firms of type τ are predicated on maximizing the objective function Π_τ, which is influenced by the nature of demand and competitive characteristics in a market. While I assume the community bank's objective is to maximize profits, following the non-profit entry literature (e.g., Harrison and Seim (2017), Rennhoff and Owens (2012), and Gayle et al. (2012) I assume that large credit union's objective is to maximize welfare of the community. To avoid confusion, I use value to describe the output of the objective function for the maximization problem. I specify the reduced form objective function of a firm of type τ in market m as

$$\Pi_{\tau,m} = \pi_{\tau,m}(\boldsymbol{X_m}, N_{CB,m}, N_{LCU,m}) + \varepsilon_{\tau,m} = \boldsymbol{X_m}\beta_\tau + g(\boldsymbol{\theta_\tau}; N_{CB,m}, N_{LCU,m}) + \varepsilon_{\tau,m}. \tag{1.1}$$

Market specific shifters are contained in $\boldsymbol{X_m}$ and β_τ represents the effect of market shifters on firm τ's value. The $g(\boldsymbol{\theta_\tau}; N_{CB,m}, N_{LCU,m})$ portion of the objective function represents the effect of competitors on value. Parameters in $g(\boldsymbol{\theta_\tau}; N_{CB,m}, N_{LCU,m})$

can differentiate between the impacts on value of same-type firms and the competitive effects of firms of the different type. I specify the set of parameters to capture the incremental effects of additional firms of each type. Observe that the parameter vector differs across types. This specification potentially permits the competitive effects to differ by type. I allow the competitive effects of the same type of firm to impact value non-linearly and the competitive effects of the different type to affect value linearly. This specification results in

$$g(\boldsymbol{\theta_{CB}}; N_{CB,m}, N_{LCU,m}) = \theta_{CB,LCU} N_{LCU,m} + \sum_{i=1}^{4} \theta_{CBi} \mathbf{1}(N_{CB,m} \geq i) \quad (1.2)$$

for community banks and

$$g(\boldsymbol{\theta_{LCU}}; N_{CB,m}, N_{LCU,m}) = \theta_{LCU,CB} N_{CB,m} + \sum_{i=1}^{1} \theta_{LCUi} \mathbf{1}(N_{LCU,m} \geq i) \quad (1.3)$$

for large credit unions. Note that the effects of same type competitors on value for community banks and large credit unions are truncated at four and one, respectively. This truncation is due to the restrictions on the maximum number of community banks and large credit unions to five and two respectively in order to facilitate estimation. I tried estimating the model with up to six community banks and three large credit unions and found that I did not have enough useful observations to identify the estimates. In addition, following previous studies of endogenous entry (e.g., Mazzeo (2002), Schaumans and Verboven (2008)and Cohen and Mazzeo (2007)) I assume that the unobserved portion of value $\varepsilon_{\tau,m}$ is drawn from an independent standard bivariate normal distribution.[7]

1.3.2 Equilibrium concepts

The unobserved part of value relates to the observed number of firms by a set of equilibrium assumptions. Omitting the market subscript, a firm of type τ chooses to enter if it earns non-negative value $\Pi_\tau(\boldsymbol{X}, N_{CB}, N_{LCU})$ in a given market, given the local characteristics of demand and competition from incumbents. Alternatively, if a firm receives negative value upon entry, it chooses to stay out of the market and earns zero value. In equilibrium, firms enter a market until the next entrant earns negative value, given the market's demand and competitive characteristics. Omitting the market subscript, the equilibrium conditions describing an optimal firm-configuration of community banks and large credit unions (N^*_{CB}, N^*_{LCU}) are

$$\pi_{CB}(\boldsymbol{X}, N^*_{CB}, N^*_{LCU}) + \varepsilon_{CB} \geq 0 > \pi_{CB}(\boldsymbol{X}, N^*_{CB} + 1, N^*_{LCU}) + \varepsilon_{CB}, \quad (1.4a)$$

$$\pi_{LCU}(\boldsymbol{X}, N^*_{CB}, N^*_{LCU}) + \varepsilon_{LCU} \geq 0 > \pi_{LCU}(\boldsymbol{X}, N^*_{CB}, N^*_{LCU} + 1) + \varepsilon_{LCU}. \quad (1.4b)$$

Moreover, I assume that firms of a type are substitutes for the other type and are better substitutes for firms of the same type than firms of a different type. For an equilibrium market configuration (N^*_{CB}, N^*_{LCU}) these assumptions result

[7] Although it is possible to allow for correlated unobserved values in the derivation of the likelihood, I determined that the correlation can not be empirically identified given the variation in my data and restrict it to zero for all models.

in

$$\pi_{CB}(\boldsymbol{X}, N_{CB}^*, N_{LCU}^*) + \varepsilon_{CB} \geq \pi_{CB}(\boldsymbol{X}, N_{CB}^*, N_{LCU}^* + 1) + \varepsilon_{CB}, \tag{1.5a}$$

$$\pi_{CB}(\boldsymbol{X}, N_{CB}^*, N_{LCU}^*) + \varepsilon_{CB} > \pi_{CB}(\boldsymbol{X}, N_{CB}^* + 1, N_{LCU}^* - 1) + \varepsilon_{CB} \tag{1.5b}$$

and

$$\pi_{LCU}(\boldsymbol{X}, N_{CB}^*, N_{LCU}^*) + \varepsilon_{LCU} \geq \pi_{LCU}(\boldsymbol{X}, N_{CB}^* + 1, N_{LCU}^*) + \varepsilon_{LCU}, \tag{1.6a}$$

$$\pi_{LCU}(\boldsymbol{X}, N_{CB}^*, N_{LCU}^*) + \varepsilon_{LCU} > \pi_{LCU}(\boldsymbol{X}, N_{CB}^* - 1, N_{LCU}^* + 1) + \varepsilon_{LCU}. \tag{1.6b}$$

Since the observed market configuration is the equilibrium product of repeated interaction between firms, it is consistent with a long run equilibrium. This assumes that my observations resemble a long-run equilibrium across my cross-section of markets. To test the model's sensitivity to this assumption, I compare parameter estimates derived from observations in two distinct periods.

1.3.3 Multiplicity problem

In an ideal setting, the entry model would predict a unique equilibrium market configuration given the characteristics of the market. For sufficiently large or small realizations of the unobserved portion of value ε_{CB} and ε_{LCU}, the model could predict a unique market configuration in equilibrium.[8] However, if firms entry decisions are endogenous to entry decisions of firms of a different type, the conditions above will not produce a unique equilibrium (Berry, 1992). In particular, insufficiently large or small realizations of the unobserved portions of value ε_{CB} and ε_{LCU} can lead to the model predicting multiple equilibrium.

Figure 1 displays the problem in a straightforward game with one potential entrant for each type. The vertical lines indicate when the community bank can earn non-negative value upon entry, given that the large credit union also enters, (1,1), or given that the large credit union does not enter, (1,0). The horizontal lines are similar value lines for the large credit union, given the community banks entry decision. For low realizations draws of ε_{CB} and ε_{LCU}, the unique Nash equilibrium is (1,1), both firms enter. Alternatively, for large realizations draws of ε_{CB} and ε_{LCU} the unique Nash equilibrium is (0,0). Market configurations (1,0) or (0,1) may also be obtained as unique Nash equilibria for a range of draws of ε_{CB} and ε_{LCU} (the upper left and bottom right areas). However, for medial draws of ε_{CB} and ε_{LCU} the market configurations (1,0) or (0,1) are both Nash equilibria, the middle square. In other words, for these draws there is a coordination problem, and either the community bank or large credit union enters the market. If the multiplicity problem is present in the market, portions of the likelihood function that represents market configurations with multiple equilibria will not be defined.[9]

[8]See Cleeren and Verboven (2010) for proof.
[9]See Collard-Wexler (2007)

Cleeren and Verboveen (2010) show that, for the general case, the area of multiplicity for a Nash Equilibrium (N^*_{CB}, N^*_{LCU}) is the area that overlaps with the Nash equilibria $(N^*_{CB}+1, N^*_{LCU}-1)$ and $(N^*_{CB}-1, N^*_{LCU}+1)$. The area of multiplicity for $(N^*_{CB}+1, N^*_{LCU}-1)$ is

$$\pi_{CB}(\boldsymbol{X}, N^*_{CB}+1, N^*_{LCU}-1) \geq \varepsilon_{CB} > \pi_{CB}(\boldsymbol{X}, N^*_{CB}+1, N^*_{LCU}), \tag{1.7a}$$

$$\pi_{LCU}(\boldsymbol{X}, N^*_{CB}, N^*_{LCU}) \geq \varepsilon_{LCU} > \pi_{LCU}(\boldsymbol{X}, N^*_{CB}+1, N^*_{LCU}). \tag{1.7b}$$

To address the potential outcome of multiple equilibria, I put additional structure on the entry game by assuming that firms enter sequentially. Mazzeo (2002) controls for the multiplicity problem by assuming the most profitable firm enters over the other firm. However, if in reality, entry is not sequential, the most profitable firm may not enter over the less profitable firm. Since entry of community banks predate entry of large credit unions, this approach may not be suitable for the financial service industry.[10] Following Cleeren and Verboven (2010), I assume that community banks enter the market first, meaning that in cases of multiplicity, community banks enter over large credit unions.[11] While I could use an equilibrium selection rule similar to Berry (1992) and Jia (2008), the results in the next section show that estimated parameters are stable under different equilibrium assumptions.

[10] For a history of community banks in the US see Kahn et al. (2003).

[11] In Section 5, I examine the sensitivity of the results to this assumption.

Assuming that community banks enter first, (N^*_{CB}, N^*_{LCU}) is the unique sub-game perfect equilibrium if the unobserved portions of value ε_{CB} and ε_{LCU} satisfy the equilibrium conditions defined in equations 4a-6b. However, the position of ε_{CB} and ε_{LCU} violate the previous conditions if they overlap with the equilibrium that results in more community banks, as defined by the area of multiplicity with $(N^*_{CB} + 1, N^*_{LCU} - 1)$ specified in equations 7a-b. Hence, the probability of observing a market configuration (N^*_{CB}, N^*_{LCU}) as the unique sub-game perfect equilibrium outcome is

$$\begin{aligned}\text{Prob}(N_{CB}, N_{LCU}) = &\int_{\pi_{CB}(\boldsymbol{X},N_{CB}+1,N_{LCU})}^{\pi_{CB}(\boldsymbol{X},N_{CB},N_{LCU})} \int_{\pi_{LCU}(\boldsymbol{X},N_{CB},N_{LCU}+1)}^{\pi_{LCU}(\boldsymbol{X},N_{CB},N_{LCU})} \phi(u_{CB}, u_{LCU}) du_{CB} du_{LCU} \\ &- \int_{\pi_{CB}(\boldsymbol{X},N_{CB}+1,N_{LCU})}^{\pi_{CB}(\boldsymbol{X},N_{CB}+1,N_{LCU}-1)} \int_{\pi_{LCU}(\boldsymbol{X},N_{CB}+1,N_{LCU})}^{\pi_{LCU}(\boldsymbol{X},N_{CB},N_{LCU})} \phi(u_{CB}, u_{LCU}) du_{CB} du_{LCU},\end{aligned} \tag{1.8}$$

where ϕ is the standardized bivariate normal density function with correlation parameter equal to zero. Note that the first and second terms in Equation 8 relate to the equilibrium condition described in Equations 4a-b and Equations 7a-b. Also observe that the second term in Equation 8 is equal to zero if community banks and large credit unions have no direct effect on each others objective functions. In this setting, only the first term exists, and the model reduces to a bivariate ordered probit model. I use maximum likelihood to estimate the parameters of the objective function parameters that maximize the probability of the observed market configurations across the sample.

1.4 Data

The following sub-sections document the data sources, characteristics of banks and credit unions, and description and definition of financial services markets. I follow Cohen and Mazzeo (2007) in constructing the market definition and including demand characteristics which shift the demand for financial services market. I deviate from Cohen and Mazzeo (2007) in that I define the institutions in the sample markets as community banks, large banks, and large and small credit unions rather than single-market, multi-market, and thrift banks.

1.4.1 Data sources

The data are based on a cross-section for 2010 and 2015 and are from several sources. Federally insured bank and credit union locations are derived from the Federal Deposit Insurance Corporation (FDIC) summary of deposits and the National Credit Union Association (NCUA) branch locations data, respectively. Bank and credit union asset characteristics come from the FDIC and the NCUA balance sheet and income statement information (call report) for the fourth quarter of 2010 and 2015. Demographic variables are from the U.S. Census Bureau, the Bureau of Economic Analysis, and the U.S. Department of Agriculture.

Given the format of the data, there are many potential units of aggregation. Although the literature generally defines a banking market by Metropolitan Statistical Area (MSA) (e.g., Dick (2007)), political boundaries of a MSA may not reflect economic characteristics. Following Cohen and Mazzeo (2007) I define a banking market as a Labor Market Area (LMA). The U.S. Bureau of Labor Statistics defines a LMA as an economically integrated geographic region within which individuals can reside and find employment within a reasonable distance or can readily change employment without changing their residence.

To identify the parameters of the model, units of observations must include distinct markets. I eliminate urban and large rural markets from the sample markets (markets with population sizes less than or equal to 100,000 inhabitants) which are likely to have more than one distinct markets. As a result, the sample is composed of 1,771 small, rural markets. Table 1 displays descriptive statistics for profit shifters in these markets.

1.4.2 Definitions of banks and credit unions

I define the unit of entrant as the presence of a uniquely owned bank or credit union. Banks or credit unions with two or more branches are treated similarly to those with one branch. Since participants are unlikely to add additional branches that diminish their profitability in a market, including the count of branches would likely underestimate the competitive effects of entry.

Following the U.S. Office of the Comptroller of the Currency, I define a community banks as a bank with less than $1 billion 2015 USD (United States Dollars) in assets.[12] Also, I define large banks as banks with assets greater than or equal to $1 billion 2015 USD in assets. Following the NCUA, I define large

[12] The Federal Reserve Board and Government Accountability Office defines community banks as banks with less than $10 billion in assets.

credit unions as credit unions with assets greater than or equal to $100 million 2015 USD. Moreover, I define small credit unions as credit unions with asset less than $100 million 2015 USD. During the period in the sample, no credit unions or banks changed classifications. Table 1 shows that from 2010 to 2015, community bank, large credit union, and small credit union entry grew modestly while large bank entry declined. When I truncate the number of community banks and large credit unions at five and two, respectively, the average market in the sample has roughly 2.78 community banks and 0.46 large credit unions.

1.4.3 Financial and physical characteristics of banks and credit unions in the sample

The resulting 2010 sample markets contain 5,265 community bank and 708 large credit union branches. In the analyses, I treat branches of the same type as homogeneous competitors — I do not differentiate between single and multi-outlet branches in the same market — thereby focusing on the count of branches in the market. Moreover, I consider the community banks and large credit unions in the sample to be representative of all of those that operate in the United States. The FDIC and NCUA data contain balance sheet information that permits me to determine the soundness of these assumptions. Branches in the sample typically operate few outlets; 80 percent of large credit unions and community bank branches in the sample operate two or fewer outlets. While the large credit union branches in the sample are in line in terms of balance sheet information with the representative of branches at the national level, the community bank branches in the sample are significantly smaller than their national average. For large credit unions, the average total assets and deposit held by the parent entities of branches in the sample are 6 percent greater ($2.1 billion vs. $2.0 billion) and 10 percent less ($1.7 billion vs. $1.8 billion) than their national average. For community banks, the average total assets and deposit held by the parent entities of branches in the sample are 41 percent ($251 million vs. $355 million) and 29 percent ($207 million vs. $293 million) less than their national average. Hence, the results are likely to capture the competitive effects of the average large credit union in the United States on the entry decision of smaller community banks in the United States.

Tables 2 and 3 contain counts of market configuration of large credit unions and community banks in 2010 and 2015, respectively. At least one community banks is in nearly 1,500 markets in the sample. I observe roughly 500 markets with community banks and large credit unions. Hence, the presence of community banks is heavily represented in the sample. Note that the count of community banks is declining with the count of large credit unions. The likelihood of community bank entry increases in the count of community bank competitors: Markets with four or fewer community banks are less likely on average to have a large credit union present, with approximately 34 percent of these markets having a large credit union. Alternatively, markets with seven or more community banks have a large credit union entry rate of roughly 51 percent.

The distribution of community bank counts has a long right tale; roughly 87 percent of the sample has at most five community banks and the maximum number of observed community banks in the sample is eighteen. In addition, the number of markets with more than two credit unions composes 2.3 percent. As discussed in the previous section, the number of community banks and large credit unions in a market are truncated at five and two due to not enough. Convergence problems arise in the estimation procedure when including six or more community banks and three or more large credit unions.

1.4.4 Characteristics of local banking markets

The succeeding variables are included as exogenous market covariates that may affect the profitability of community banks and large credit unions across the markets in the sample: the number of farms, the number of non-farm establishments, population, per capita income, the housing unit occupancy rate, the number of large banks, and the number of small credit unions. Table 1 presents summary statistics for these unscaled co-variates for 2010 and 2015. These variables are intended to capture the demand for financial services products (e.g., loans and deposits) and competitive effects of institutions outside the scope of this study. If the number of potential membership groups (e.g., teachers) rises with population, the number of credit unions may be more significant in markets with larger population size. The magnitude of farms and business establishments are likely correlated with the demand for commercial loans. Moreover, the degree of occupancy rate is likely correlated with the demand for mortgage loans. Each non-competitive covariate was re-scaled by dividing each observation by the mean of that variable. These transformed variables all have a mean of one, which facilitates estimation.

1.5 Results

The subsequent sub-sections present the results of the empirical analyses. The first sub-section reports estimates from the baseline model that assumes that community bank and large credit union entry are independent. Second, results from the sequential equilibrium model are reported to examine the stability of the estimates under different assumptions. Next, I estimate the sequential equilibrium model using data from 2015 to test the long run equilibrium properties of the model. Last, I report counterfactual estimates that demonstrate the competitive effects of large credit unions on the entry of community banks and the market structure of financial services firms.

1.5.1 Estimates from single-equation ordered probit models

Table 4 presents maximum likelihood estimates for ordered probit models of the number of community banks competitors and large credit union competitors using a cross-section of markets from 2010. These specifications control for the entry decision of the other type, assuming their decision as exogenous and not imposing the equilibrium conditions in Equation 8. Hence, the models do not ensure a unique equilibrium market configuration. Table 5 presents the average simulated effect of a one percent change in the covariates on the total number of community banks and large credit unions.

The first panel provides estimates taking large credit union entry as exogenous and concentrating on community bank entry. As expected, the estimates of the characteristics that relate to the demand for financial products and services are positive and statistically significant. These results suggest that per capita income is an important driver for community bank and large credit union entry. A one percent increase in per capita income results in a 0.35 and 0.44 percent increase in community banks and large credit unions, respectively. Large credit unions and community banks may be more likely to overlap in markets with more high income individuals, potentially due to the positive relationship between per capita income and demand for deposits (e.g. Dick, 2008).

In addition, markets with more significant business activity and home-ownership increases the value of community banks; a one percent increase in business establishments and occupancy rate increases the number of community banks by 1.02 and 0.19 percent, respectively. On the other hand, the number of farms, establishments, and occupancy rate has an economically insignificant effect on large credit union entry, all effects are close to zero. These results suggest that community banks and large credit unions may not have significant overlap on commercial and mortgage loans.

Last, population is a major driver for large credit union entry, while being an economically insignificant motivator of community bank entry. A one percent increase in population results in a 0.13 and 1.06 percent increase in community banks and large credit unions, respectively. Population may be correlated with the number of potential consumer loan customers, resulting in more large credit unions in markets with greater populations. On the other hand, larger markets may be disadvantageous for community banks, as "relationship lending" may become more difficult or less useful in larger markets.

The effects of own type entry on community bank entry are negative, with value declining most strongly in moving from a monopoly to a duopoly market, and narrowing as more community banks enter. The decreasing relationship between the number of community banks and their competitive effects suggests that the competitive impact of the first community bank is greater than the following entrants. These effects are consistent with a standard Cournot model of competition, as the additional competitive impact of entry declines as the number of firms rise. The presence of large credit unions has a statistically significant impact on community bank entry. However, the effect is small in comparison to the effect of a rival community bank on community bank entry, as it would take 8 to 10 large credit unions to arrive at the same impact. This result suggests that differences and products and services between the two diminishes the competitive effect of large credit unions on community bank entry, Although the negative sign and statistical significance of the coefficient imply the multiplicity problem may bias the estimate. Additional modeling techniques are required in order to ensure robustness of the results.

In addition, the effect of the presence of community banks on large credit union entry is small and statistically insignificant. However, as there are very few observations where large credit unions are active and community banks are not, this effect may not be identified.

Note that the effect of the presence of large banks on community bank entry is negative, statistically significant, and nearly double the impact of large credit unions. This is expected, as Cohen and Mazzeo (2008) found evidence that multi-market and single-market banks compete to a degree. Although this variable is likely to have similar multiplicity problems with community banks as large credit union, the inclusion of the large bank co-variate does not significantly affect the estimate of the parameter for the effect of large credit union entry on community bank value. This result suggests that potential bias in the large credit union competitive effect on community bank entry arising from the correlation of large credit union and large bank entry is negligible.

Similar to large banks and community banks, the presence of small credit unions has a negative and statistically significant impact on large credit union entry. This results is in line with expectations, since small and large credit unions offer similar products, automobile loans. However, the multiplicity problem may bias the estimate.

1.5.2 Estimates from endogenous entry model

Table 6 reports estimates of competitive effects on community bank and large credit union entry decisions from the endogenous entry model. Since the estimates of the effects of the demand characteristics do not change significantly in these models, I omit them from the table. The first column displays estimates from the model that assumes that community banks enter first when values of unobserved portions of profit produce multiple equilibria, while the second column shows estimates from the model that assumes that large credit unions enter first. The results of these models show little discernible difference between the basic model and the one that corrects for the multiplicity problem. This finding suggests that community bank and large credit union are independent of one another.

The most notable difference from Table 5 is the cross-competitive effects; the competitive effects of large credit union entry are generally statistically insignificant after including the equilibrium assumptions. This result suggests that large credit unions and community banks serve separate markets, once market characteristics are controlled for. Assuming the robustness of the long run equilibrium properties of the model, these results imply that large credit union do not crowd out community banks.

1.5.3 Boundaries of local markets and the endogenous entry model

An important assumption of the model is that markets do not overlap with other markets. If the markets in the sample are not sufficiently isolated, the estimates of the effect of competition on profits for each type will be biased downwards, since institutions in nearby geographies could have already created a competitive environment. In order to ensure that the estimates are not biased by these effects, similar to Cohen and Mazzeo (2007) I estimate the parameters of the profit functions using rural markets that are at least ten miles away from a Metropolitan Statistical Area. Table 7 reports the estimates of the parameters in the endogenous entry model for community bank and large credit unions using 565 rural markets.

The results of the estimation procedure demonstrate that the results are robust to the assumption of market isolation. The effect of large credit union entrants on community bank entry in rural markets are similar to those shown in the baseline endogenous entry model. Moreover, the competitive effects of credit unions on community bank entry in rural markets are smaller than the baseline estimates, suggesting that potential market overlap does not bias the baseline estimates downward.

1.5.4 Long run properties of the endogenous entry model

To test the dynamic properties of the endogenous entry model described in the previous subsection, I estimate the model using a cross section of data from 2015. From 2010 to 2015, banking markets experienced regulatory and demand changes. Most notably, the Dodd-Frank Wall Street Reform and Protection Act—regulation that increased federal compliance—was implemented and executed in the early 2010's. At the same time, many large banks closed branches in rural markets.[13]

Table 8 reports parameter estimates of the endogenous entry model for 2015. Competitive parameter estimates using 2015 data are similar to the parameter estimates previously described; which demonstrates that the results are robust to the dynamic assumptions of the model. Although the estimate of large credit unions effect on community banks is slightly larger in magnitude, the results suggest that large credit unions serve different markets. Furthermore, these results imply that the long-term viability of markets with both large credit unions and community banks.

[13] See Nguyen (2014).

1.5.5 Counterfactuals

To understand the extent that the presence of large credit unions have on the entry of community banks, I run a series of exercises that examine counterfactual markets under a scenario of perfect differentiation between their products and services. Doing this will allow for clarity in how competition from large credit unions affects the viability of community bank entry and if large credit unions represent more variety in products and services for consumers. To better capture recent institutional realities of the market, the counterfactuals use parameter inputs from 2015 displayed in Table 9.

First, I calculate the expected number of community banks and large credit unions as

$$E(N_{CB}) = \sum_{i=1}^{5} \sum_{j=0}^{2} i \cdot \text{Prob}(N_{CB} = i, N_{LCU} = j) \tag{1.9}$$

and

$$E(N_{LCU}) = \sum_{i=0}^{5} \sum_{j=1}^{2} j \cdot \text{Prob}(N_{CB} = i, N_{LCU} = j) \tag{1.10}$$

where $\text{Prob}(N_{CB} = i, N_{LCU} = j)$ is the probability of observing a market configuration (i, j) as defined in equation 8. Second, I calculate the expected number of community banks and large credit unions in the "base" case with the actual demand and market configuration characteristics. The simulation predicts 2.78 community banks and 0.46 large credit unions, roughly equal to the observed average number of community banks and large credit unions. This confirms that the model with the estimated parameter fits the data reasonably well.

Next, I measure how the competitive impact of large credit unions affects the entry of community banks. I accomplish this by comparing the actual market structure from the sample with a scenario where community banks and large credit unions do not compete, and thus offer completely separate products and services. This is done by setting the competitive effect of large credit unions on community bank entry to zero and vice versa. After eliminating competition between the two, the number of community banks grows by 2.2 percent and the number of large credit unions grows by 4.5 percent. This is not an economically significant change. To put it into context, the increase in community banks is only 14.7 percent of the large credit unions in the sample. These results provide further evidence of the existence of economically significant differentiation between community banks and large credit unions.

Alternatively one can interpret the results of the counterfactual to how large credit unions affect the total number of institutions in the market. If large credit unions were removed from the market, the removal of their competitive pressure would result in fewer community banks replacements than large credit union removals. Without large credit unions, the total number of institutions would decline from 5,722 to 5,040 or by 13.5 percent. Since large credit unions have significantly more assets than community banks, this result likely understates the effect the impact they have on financial services availability.

1.5.6 Discussion

The findings of the empirical analysis reveal that although there is overlap between community banks and large credit unions product and services, it is not large enough to significantly impact the entry of community banks. Counterfactual exercises reveal that competition from large credit unions reduces the number of community banks by only 2.5 percent or by 124 locations. This suggests that enough differences in their products and services allows for community banks to operate profitably in markets with large credit unions.

The findings of the counterfactural suggest that the presence of large credit unions provides more financial options for consumers. The counterfactual exercise reveals that large credit unions may increase product and service variety for consumers, as the total number of institutions is 13.5 percent greater due to their presence. As large credit unions are significantly greater in asset size than community banks, this one-to-one replacement line of reasoning likely understates their impact on the market.

The results of my study support the notion that large credit unions provide services and products to unique consumer groups. Credit unions' focus on retail-oriented products and services may allow for community banks to operate profitably by focusing on commercial loans. Policies that encourage large credit union entry, such as the federal corporate income tax exemption, may lead to more products and services for consumers. However, these results hold only at the current regulatory regime. If large credit unions are granted greater access to commercial loan markets or allowed to expand their membership pools to more consumers, the competitive effect may increase. The results of this study should be reevaluated in the event that policy changes take place.

1.6 Conclusion

This study sought to determine the extent to which large credit unions compete with community banks in 1,771 local financial services markets. Recent policy evaluation of the necessity for credit union tax exemption brings the need for analysis on the effect of credit unions on community bank entry. In order to identify this effect, I estimated a structural model of entry that allowed me to capture the causal relationship of competition on market structure, while also addressing the multiplicity problem.

Estimated competitive parameters derived from a model of endogenous entry suggest that while large credit unions have a statistically significant negative effect on the entry of community banks, they are disproportionately small compared to the effect of other community bank competitors, suggesting that economically significant differentiation between products and services exist between the two. Moreover, my results are robust to order of entry, dynamics, and market boundary assumptions. Competitive pressure from large credit unions only result in 2.5 percent fewer community banks. On the other hand, large credit unions provide 13.5 percent more locations, suggesting that large credit unions serve different markets than community banks.

There exist many potential interpretations of these results. One is that the goals of large credit unions to offer consumers loans, such as automobile loans, steers them away from markets important to community banks. Automobile loans are still a significant portion of large credit union loans and they do not appear to be moving away from this service. The other is that regulation on member business loans prevent large credit unions from competing with community banks on commercial loans. Last, consumers may simply prefer credit unions for some loans, such as vehicle loans, while community banks for others, such as business and mortgage loans.

The results of my study suggest that further expansion of credit unions into local markets may provide unique services to consumers. Any policies that discourage the entry of credit unions, such as lifting tax exemption status, may lead to a decrease in financial services firms in local financial services markets. As a result, policymakers should be aware that enacting policies under the guise of leveling the competitive field may hurt consumers. In addition, the notion that products and services of large credit unions should be constrained to encourage community bank entry is a fruitless one. Enough separation of products and services currently allows for a mixture of community banks and large credit unions in markets.

As credit unions continue to expand in asset size and product services, competition may become more intense, and the role of credit unions in anti-trust calculations may require updates. Policymakers should continue to evaluate the competitive impact of credit unions on large banks and community banks in future policy discussions.

Table 1.1: Descriptive statistics, profit shifters

	2010			
Variable	Mean	Std. Dev	Min	Max
Population (000s)	23.46	20.18	0.30	99.64
Per capita income (000s)	32.27	7.03	14.36	105.40
# of farms (00s)	5.50	4.92	0.00	55.91
# of establishments (00s)	5.40	5.25	0.00	62.65
Occupancy rate	0.80	0.10	0.17	0.95
# of LBs	2.47	1.73	0.00	5.00
Pres of SCU	0.37	0.48	0.00	1.00
Community banks	2.67	1.59	0.00	5.00
Large credit unions	0.40	0.64	0.00	2.00
	2015			
Variable	Mean	Std. Dev	Min	Max
Population (000s)	23.38	20.29	0.30	98.88
Per capita income (000s)	38.97	10.42	16.00	143.47
# of farms (00s)	6.27	4.59	0.00	55.91
# of establishments (00s)	5.30	5.15	0.00	6.22
Occupancy rate	0.79	0.11	0.16	0.95
# of LBs	2.18	1.73	0.00	5.00
Pres of SCU	0.41	0.49	0.00	1.00
Community banks	2.78	1.60	0.00	5.00
Large credit unions	0.46	0.64	0.00	2.00
Number of Markets = 1,771				

Note: Numbers of large banks and community banks are truncated at five
and numbers of large credit unions and small credit unions are truncated at 1 and 2.

Table 1.2: Market configurations for 2010

		Large Credit Unions						
		0	1	2	3	4	5	Total
Community banks	0	103	31	6	2	0	0	142
	1	256	72	17	5	1	0	351
	2	267	75	19	3	3	0	367
	3	250	68	23	4	0	1	346
	4	155	44	15	5	2	0	221
	5	84	42	12	4	0	0	142
	6	51	23	7	2	0	0	83
	7	22	12	4	2	1	0	41
	8	14	6	6	0	1	1	28
	9	11	4	2	2	0	0	19
	10	2	6	1	1	0	0	10
	11	5	2	2	1	0	0	10
	12	5	2	0	0	0	0	7
	13	0	2	1	0	0	0	3
	17	1	0	0	0	0	0	1
	18	1	0	0	0	0	0	1
	Total	1,227	389	115	31	8	2	1,771

Table 1.3: Market configurations for 2015

		Large Credit Unions						
		0	1	2	3	4	5	Total
Community banks	0	87	45	8	2	0	0	142
	1	194	81	27	4	1	0	307
	2	251	74	24	5	3	1	358
	3	243	75	20	7	2	0	347
	4	150	57	21	2	2	0	232
	5	97	42	12	4	1	0	156
	6	60	26	7	2	0	0	95
	7	22	14	4	1	2	0	43
	8	17	9	4	1	0	0	31
	9	8	8	4	3	1	1	25
	10	8	6	2	0	0	0	16
	11	4	2	1	2	0	0	9
	12	5	3	1	0	0	0	9
	13	0	0	0	1	0	0	1
	17	1	0	0	0	0	0	1
	18	1	0	0	0	0	0	1
	Total	1,148	442	135	34	12	2	1,771

Table 1.4: Single-equation ordered probit models of the numbers of community banks and large credit unions

	Number of Community Banks		Number of Large Credit Unions	
	(1)	(2)	(3)	(4)
Population	0.23***	0.26***	0.84***	0.79***
	(0.07)	(0.07)	(0.06)	(0.09)
Per capita income	0.68***	0.69***	0.31*	0.33*
	(0.13)	(0.13)	(0.18)	(0.18)
# of farms	0.41***	0.41***	−0.04	−0.03
	(0.03)	(0.03)	(0.04)	(0.04)
# of establishments	0.38***	0.37***	−0.10	−0.09
	(0.06)	(0.06)	(0.08)	(0.06)
Occupancy rate	2.01***	2.01***	−0.08	−0.04
	(0.18)	(0.18)	(0.28)	(0.28)
# of LCUs		−0.08***		
		(0.01)		
# of CBs				−0.02
				(0.02)
Pres of SCUs	0.12	0.11	−0.28***	−0.28***
	(0.06)	(0.06)	(0.07)	(0.07)
# of LBs	−0.23***	−0.22***	0.14***	0.13***
	(0.02)	(0.02)	(0.02)	(0.03)
# of CBs = 2	−0.97***	−0.97***		
	(0.05)	(0.05)		
# of CBs = 3	−0.68***	−0.68***		
	(0.05)	(0.03)		
# of CBs = 4	−0.63***	−0.63***		
	(0.03)	(0.03)		
# of CBs = 5	−0.50***	−0.50***		
	(0.03)	(0.03)		
# of LCUs = 2			−1.13***	−1.13***
			(0.05)	(0.05)
Log Likelihood	−2,759.04	−2,761.89	−1,176.28	−1,146.09

Number of Markets = 1,771

Note: *,**, and *** represent p-value $\leq$ 10%, 5%, and 1%, respectively.

Table 1.5: Average simulated effect of of change in the covariates on the total number of community banks and large credit unions

	Community Banks	Large Credit Unions
Population	0.13%	1.06%
Income per capita	0.35%	0.44%
# of farms	0.21%	−0.04%
# of establishments	0.19%	−0.12%
Occupancy rate	1.02%	−0.06%
# of LBs	−2.86%	4.52%
Pres of SCUs	0.20%	−1.37%

Note: Reported estimates represent percent changes in entrants after a one percent increase in the control variable.

Table 1.6: Comparison of endogenous entry model estimates under alternative assumptions of order of entry

	Community Banks Move First	Large Credit Unions Move First
	(1)	(2)
Select Community Bank Value Shifters		
# of LCUs	-0.09	-0.12^{*}
	(0.06)	(0.07)
Pres of SCUs	0.11^{*}	0.10^{*}
	(0.06)	(0.06)
# of LBs	-0.22^{***}	-0.22^{***}
	(0.02)	(0.02)
# of CBs = 2	-0.99^{***}	-0.97^{***}
	(0.05)	(0.04)
# of CBs = 3	-0.68^{***}	-0.68^{***}
	(0.03)	(0.03)
# of CBs = 4	-0.63^{***}	-0.63^{***}
	(0.03)	(0.03)
# of CBs = 5	-0.50^{***}	-0.49^{***}
	(0.03)	(0.03)
Select Large Credit Union Value Shifters		
# of LBs	0.14^{***}	0.14^{***}
	(0.03)	(0.02)
Pres of SCUs	-0.28^{***}	-0.29^{***}
	(0.07)	(0.07)
# of CBs	0.01	0.03
	(0.03)	(0.02)
# of LCUs = 2	-1.13^{***}	-1.13^{***}
	(0.05)	(0.05)
Log Likelihood	-3,903.96	-3,903.72
Number of Markets = 1,771		

Note: *,**, and *** represent p-value $\leq$ 10%, 5%, and 1%, respectively.

Table 1.7: Comparison of endogenous entry model estimates using rural markets

	Community Banks Move First	Large Credit Unions Move First
	(1)	(2)
Select Community Bank Value Shifters		
# of LCUs	-0.05	-0.07
	(0.10)	(0.12)
Pres of SCUs	0.09	0.08
	(0.06)	(0.10)
# of LBs	-0.22^{***}	-0.22^{***}
	(0.04)	(0.04)
# of CBs = 2	-0.94^{***}	-0.94^{***}
	(0.05)	(0.08)
# of CBs = 3	-0.73^{***}	-0.73^{***}
	(0.06)	(0.06)
# of CBs = 4	-0.63^{***}	-0.63^{***}
	(0.03)	(0.05)
# of CBs = 5	-0.51^{***}	-0.51^{***}
	(0.05)	(0.05)
Select Large Credit Union Value Shifters		
# of LBs	0.18^{***}	0.18^{***}
	(0.05)	(0.05)
Pres of SCUs	-0.36^{***}	-0.36^{***}
	(0.13)	(0.13)
# of CBs	0.02	0.03
	(0.05)	(0.06)
# of LCUs = 2	-1.11^{***}	-1.11^{***}
	(0.09)	(0.09)
Log Likelihood	-1,244.50	-1,244.46

Number of Markets = 565

Note: *,**, and *** represent p-value $\leq$ 10%, 5%, and 1%, respectively.

Table 1.8: Comparison of model estimates derived using 2015 data

	Community Banks Move First	Large Credit Unions Move First
	(1)	(2)
Select Community Bank Value Shifters		
# of LCUs	-0.13^{**}	-0.16^{**}
	(0.06)	(0.07)
Pres of SCUs	0.10^{**}	0.09^{*}
	(0.06)	(0.06)
# of LBs	-0.24^{***}	-0.22^{***}
	(0.02)	(0.02)
# of CBs = 2	-0.87^{***}	-0.87^{***}
	(0.05)	(0.05)
# of CBs = 3	-0.67^{***}	-0.67^{***}
	(0.03)	(0.03)
# of CBs = 4	-0.62^{***}	-0.62^{***}
	(0.03)	(0.03)
# of CBs = 5	-0.48^{***}	-0.48^{***}
	(0.03)	(0.03)
Select Large Credit Union Value Shifters		
# of LBs	0.13^{***}	0.13^{***}
	(0.03)	(0.02)
Pres of SCUs	-0.22^{***}	-0.23^{***}
	(0.07)	(0.07)
# of CBs	−0.02	0.00
	(0.03)	(0.03)
# of LCUs = 2	-1.17^{***}	-1.16^{***}
	(0.05)	(0.05)
Log Likelihood	−4,026.86	−4,027.03
Number of Markets = 1,771		

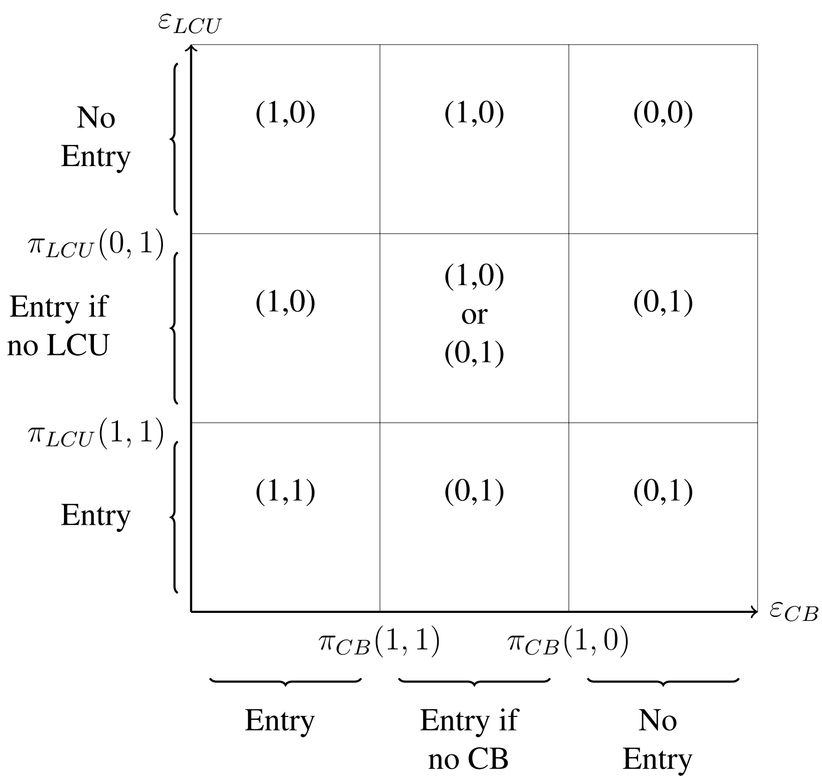
Note: *,**, and *** represent p-value $\leq$ 10%, 5%, and 1%, respectively.

Table 1.9: Product overlap's impact on market structure

	Base	No Product Overlap
Average		
Community Banks	2.78	2.85
Large Credit Unions	0.46	0.48
Total		
Community Banks	4,916	5,040
Large Credit Unions	806	842
Percent Change		
Community Banks		0.02
Large Credit Unions		0.04

Note: The above table displays predicted numbers of firms, as well as changes under counterfactual assumptions on entry decisions.
Equilibrium entry predictions are based on the parameter estimates in Table 8. The Base case corresponds to the demographics used in estimation; in the data, the observed number of firms averages to 2.78 and 0.46 for community banks and large credit unions, respectively.
Columns (3) illustrates market structure outcomes under the absence of product overlap between large credit unions and community banks.

Figure 1.1: Multiplicity problem for a 2 by 2 game



CHAPTER 2
FOCAL POINTS, MARKET POWER, AND TACIT COLLUSION IN LOCAL PAYDAY LENDING MARKETS

2.1 Introduction

In the United States and many other countries, payday loans are notorious for their high interest rates relative to other credit products.[1] Given these high rates, many countries have established inquires into whether any feature or combination of features in payday loan market distorts competition.[2] Lately, the preponderance of payday lenders in the United States to charge fees near the regulated limit has drawn the criticism of consumer advocacy groups and regulators. Critics point to the drastic differences in fees charged by lenders in states with high and low fee caps.[3] Given that over 19 million households use payday loans in the United States, efficient and competitive payday loan pricing is a critical societal issue. This study empirically investigates the if non-binding fee caps can be used as

[1]"A $300 cash advance on the average credit card, repaid in one month, would cost $13.99 finance charge and an annual interest rate of almost 57%. By comparison, a payday loan costing $17.50 per $100 for the same $300 would cost $105 if renewed one time or 426% annual interest."- Consumer Federation of America (2017)

[2]Notably, in 2013 the Competition and Market Authority investigated competition in United Kingdom payday lending markets. The commission found that "...entry by new firms into the payday lending market does not appear to have resulted in existing lenders facing an effective constraint when setting their prices."

[3]'Pews research indicates that a states limit on interest rates is the key factor driving loan pricing. The four largest payday lenders in the United States charge similar prices within a given state, with rates set at or near the maximum allowed by law. But in states with higher or no interest rate limits, the same companies charge comparable borrowers far more for essentially the same small-loan product." Pew Charitable Trusts (2014).

focal points by payday lenders in the United States to facilitate tacit collusion in 1,978 local markets.

Knittel and Stango's (2003) seminal study on credit pricing and price ceilings revealed that usage of focal points as a facilitator of tacit collusion, and larger profit margins, is more common in less competitive markets. On the surface, the features of the payday lending industry are inconsistent with characteristics that may facilitate a systemic collusive environment. There is little evidence exists to suggest significant barriers to entry or exit, high sunk costs of entry or scarcity of production inputs are issues in the industry. Payday loans are close to a homogeneous good and the nearly 18,000 stores in the United States suggest low barriers to entry. Also, empirical evidence indicates that profit margins in the payday lending industry are smaller than those of other credit products (Flannery and Samolyk, 2005). Despite these characteristics, this study finds evidence of tacit collusion at focal points in payday lending markets as the results suggest that payday lenders earn higher profits in markets with sufficiently high, non-binding fee caps.

Yet, a regime of tacit collusion can be broken by a sufficient number of competitors. Knittel and Stango (2003) find that tacit collusion at a focal point is less frequent in markets with more firms. Perhaps if tacit collusion occurs only in markets with an inadequate number of lenders, then the problem may be just in small markets. However, the results imply that in markets with one to five payday lenders and non-binding fee caps, tacit collusive regimes continue to persist. Hence, the problem of tacit collusion may be found in both markets with modest and robust numbers of payday lenders.

Unlike most studies of focal points as a facilitator of tacit collusion, significant payday loan price or profit margin data at the market level for a substantial number of markets are unavailable. Although these data are not available, this study uses structural techniques that do not require prices to make inference on how non-binding fee caps impact profit margins and how those profit margins relate to the number of lenders in a local market. Empirical models of endogenous entry, first used by Bresnahan and Reiss (1991), allow for identification of how market structure impacts profit margins and thus provides for inference on how market structure relates to competition, using only information on locations of firms and market sizes. Because profits must be at least greater than zero for a firm to choose to enter a market, market characteristics effects on the decision to enter reveal how market structure affects profits. Moreover, how minimum market sizes needed for entry or entry threshold respond to market structures can reveal how competition affects profit margins. If competition reduces profit margins, firms require a larger volume of sales to cover entry costs, so the minimum market size needed for entry expands.

The predictions of entry thresholds can also determine when a price ceiling is binding or non-binding and the qualitative differences in profit margins across price ceiling regimes. The first approach is constructed from the notion that a price ceiling is binding when profit margins in markets with price ceilings at a certain level are smaller than those in markets without price ceilings. In other words, the price ceiling value that equates profits in markets with and without price ceilings is near the upper-bound value that results in a binding price ceiling. The second approach comes from the concept that if entry thresholds are significantly smaller than those in markets without price ceilings, then profit margins are more significant in markets with non-binding price ceilings. Hence, if entry thresholds of payday lenders in markets with non-binding fee caps are smaller than those in markets without fee caps, then there is evidence of tacit collusion at focal points in the market.

Using payday lender location data acquired from yellowpages.com in 2017, this study finds evidence that supports the notion that non-binding fee caps can be used by payday lenders to tacitly collude. First, the full sample model predicts that payday loan fee caps tend to be binding at a 556 annual percentage rate. Controlling for local demand and cost characteristics, a fee cap of 780 percent in markets, as in Louisiana, leads to 7.14 percent more payday lenders than in markets without fee caps. A more considerable magnitude of entry into these markets suggests that markets with non-binding fee caps are more profitable than markets without fee caps, implying that they can be used as focal points to facilitate tacit collusion.

Second, differences in entry thresholds between the average market with binding fee caps and the average market without fee caps are economically significant. Binding fee caps at low levels significantly affect payday lender entry. For example, a fee cap rate of 156 percent, as in Oregon, reduces the number of lenders relative to a market without fee caps by roughly 11 percent. At binding levels, the results show that fee caps may minimize payday lender profitability.

Next, models estimated with three sub-sample groups for each fee cap regime show that entry thresholds are smaller in markets with non-binding fee caps compared to those in markets without fee caps. Payday lender entrants in markets with non-binding fee caps require on average roughly 29 percent smaller market size, or about 7,000 fewer consumers per entrant, than lenders in markets without fee caps. Also, lenders entering binding fee caps require on average approximately 14 percent greater market size, or around 4,000 more consumers per entrant, than lenders in markets without fee caps. These findings further imply that payday lenders use non-binding price ceilings as focal points for tacit collusion and binding fee caps reduce a payday lender's profitability.

Lastly, the competitive effect of entry is constant in markets with non-binding fee caps as well as markets with other fee cap regimes. Calculated entry threshold ratios reveal that the competitive outcomes of entry are negligible in all types of payday loan markets. These effects suggest that tacit collusion could occur in markets from one to five lenders as well as the potential for market power in general payday lending markets. Moreover, the results suggest that decreases in the number of firms due to binding fee caps will not result in reductions to competition.

The rest of this paper is organized as follows. The second section presents an overview of the theoretical and empirical background of focal points as a facilitator of tacit collusion. The third section discusses an overview of the payday lending industry. The fourth section describes an empirical model of endogenous entry in local payday lending markets. Next, the fifth section presents an overview of the market level data as well as the web-scrapping procedure used to collect lender location data. Next, the sixth section reports the estimated parameters of the payday lender profit function as well as calculated values and patterns of entry thresholds. This section also presents values and trends of the entry thresholds for payday lenders in markets without fee caps and with binding and non-binding fee caps. The seventh section concludes.

2.2 Focal points and tacit collusion

Tacit collusion often requires successful coordination. Firms can address the coordination problem through many mechanisms. One mechanism is the use of focal points. For example, suppose two people attempt to meet in New York City without first proposing where to meet. Given that there are a significant number of possible meeting points, the likelihood that they encounter are small. However, if both choose to go to a prominent location in the city, such as the Statue of Liberty or Grand Central Station, the probability they successfully meet becomes higher. In scenarios where firms set prices, it is often implied that the "agglomeration" of prices occurs at specific focal points (e.g., recommended retail prices).

As discussed by Scherer (1967), focal points may assist firms in tacit collusion and lead to supra-competitive prices. There are many explanations to why firms can take advantage of focal points. One possibility is that market power allows firms to cooperate. In a market where firms have elastic residual demand, the incentive to undercut a rival may be too strong to coordinate. For example, in markets where cooperation is difficult to maintain, such as markets where products are very similar (Chang, 1991), the presence of focal points may have little effect on prices. Alternatively, when firms possess significant market power such as in markets with switching costs (Klemperer, 1987), focal points may lead prices above the competitive outcome.

Several empirical studies examine the issue of focal points as a facilitator of tacit collusion. Knittel and Stango (2003) find that non-binding price ceilings can serve as a focal point of collusion in the credit card industry, as they lead to higher prices than markets without price ceilings. Danzon and Chao (2000) find that price regulations in pharmaceutical markets decrease competition. Busse (2000) proposes that cellular telecommunications firms competing in multiple markets used price schedules from other markets as a focal point to maintain supra-competitive prices. Lewis (2013) determines that odd-numbered pricing points can be used as focal points to facilitate tacit collusion. DeYoung and Phillips (2013) find that payday loan prices in Colorado rose after the imposition of a price ceiling, consistent with price ceilings as focal points of collusion. These studies find evidence that tacit collusion at a focal point is more likely when firms have greater market power.

2.3 The payday lending industry

Payday loans are small amounts of credit loaned at high rates of interest on the agreement that they will be repaid when the borrower receives their next paycheck. Payday loans typically range from \$100 to \$500 and are repayable in no more than two weeks. Finance fees, the price of a payday loan, are conditional on the size of the loan and typically range from \$15 to \$30 for every \$100 loaned. On a $100 loan repaid in two weeks, this amounts to an annual percentage rate of roughly 391 to 782 percent. In most cases, to be issued a payday loan, a typical potential borrower must show proof of residence, identification, employment and a checking account, and must meet a minimum level of monthly income. If they qualify, borrowers provide the lender with a postdated check for the amount of the loan plus the finance fee (or provide authorization to their checking account). Lastly, the process does not involve a standard credit check, and borrowing activity is not reported to the national credit bureau.

2.3.1 Payday loan regulation

The price of a payday loan is usually not labeled as "interest". Alternatively, payday lenders label their charges as "fees." With this classification, lenders can avoid violating state usury laws which limit the amount of interest that can be charged on a personal loan. However, many states have also passed laws and installed regulations that target payday lenders and place limits on these fees. Across states, regulations can span from effective bans on payday lending to few and no restrictions. Many states impose usury regulations on payday loans. A common usury regulation is fee caps, which limit the amount a payday lender can charge on a payday loan. The differences across states in fee caps is considerable. Fee caps can range from 45 to 1,500 percent. Also, the market fee for a payday loan in many states tends to equal the fee cap. For example, the average market fee for a payday loan and regulated fee cap on a payday loan in North Dakota are both 520 percent. The average market fee for a payday loan and regulated fee cap on a payday loan fee cap and average finance fee in nearby Nebraska is 459 percent (Pew Charitable Trusts, 2014). Given the propensity of lenders to charge close to the fee cap and the variation in fee caps across states, it is plausible that some states have binding fee caps while others have non-binding fee caps.

Since average fee charges in states without fee caps are higher than states with fee caps, critics asset they are an efficient mechanism to reduce payday loan costs (Pew Charitable Trust, 2014). However, the effectiveness of fee caps to negatively affect payday lenders is questionable. Standaert and Weed (2010) find that payday lenders reclassify themselves as brokers to charge the state fee caps plus a "broker fee". Also, there is empirical evidence that shows that fee caps have an insignificant effect on payday lender entry. Ramirez (2013) indicates that payday lender entry does not significantly decrease when a fee cap is imposed in a market. Paradoxically, these fee caps may be used by payday lenders to increase fees. DeYoung and Phillips (2013) find that average payday loan fees gravitated towards a newly installed fee cap in Colorado. Since average fee charges in states without fee caps are higher than states with fee caps, critics asset they are an efficient mechanism to reduce payday loan prices.

2.3.2 Competition in payday lending markets

Payday lending markets possess many features that may promote competition. Payday loans are reasonably homogeneous goods, input goods are not scarce, and there are few barriers to entry and exit in the industry. A few studies have found evidence of competition in the payday lending industry. Melzer and Morgan

(2015) determine that the presence of payday lenders decreases overdraft prices at conventional financial institutions. Moreover, DeYoung and Phillips (2013) find a positive correlation between market concentration and payday loan fees in Colorado.

As in other credit markets, competition may affect non-pecuniary aspects of payday lending which may not reduce prices but may reduce profit margins. If competition pressures lenders to make riskier loans, loan loss rates will increase, and profit margins will decline. Keeley (1990) provides evidence that the increased competition produced by relaxation of state branching restrictions in the 1980s caused large U.S. bank holding companies to improve their risk profiles, as proxied by estimates of market capital-to-asset ratios and actual interest costs on large certificate of deposits.

Payday loans are riskier than other credit products. Montezemolo and Wolff (2015) found that approximately half of all borrowers default on a payday loan within their first two years of borrowing. Loan loss rates can explain why prices are high and profit margins are low in the industry. Flannery and Samolyk (2005) find evidence that payday loan finance fees capture the cost of loan loss associated with the payday lending consumer base. Standard financial models predict that an interest rate needed for a lender to receive an expected positive return rise as the borrower's credit risk increases.

Ausebel (1991) argues that adverse selection, switching costs, and consumer irrationality may diminish the role of competition in credit rates. Adverse selection has been well documented in the payday lending industry. Dobbie and

Skiba (2013) find evidence of adverse selection as borrowers who choose to take out more significant first-time loans are more likely to default. Because the industry does not widely use credit checks, borrowers may have more significant private information on their credit risk. If payday lenders have difficulty separating bad (defaulting) and good (eventually repaying) borrowers, they may be less likely to engage in activities that disproportionately draw in bad borrowers.

Switching costs may make it costly for good borrowers to shop for a new payday lender. Since industry participants view repeat business as a critical component of profits, many payday lenders offer loyalty programs and rewards cards. These mechanisms encourage borrowers to become repeat customers with offers like: "if you pay your interest five times in a row on time, you get your sixth interest payment at half price."[4] The process of taking out an additional loan to cover a portion of a previous loan is known as "rolling over". Evidence suggests that the practice of rolling over increases payday lender profitability. Stegman and Faris (2003) find that the conversion of one time borrowers to chronic borrowers increases payday lender profitability. With these market implications in mind, lenders may provide disincentives for good borrowers to shop for a different payday loan provider.

With switching costs, the pool of consumers looking for a payday lender may be disproportionately bad borrowers. Skiba and Tobacman (2006) find that 1 percent of accepted first-time applicants go to a different store for their second loan application, while 6 percent of failed first-time applicants go to a different

[4] See Martin (2010).

location for their second application. If payday lenders reduce their loan fees to attract consumers from rival stores, they may draw more bad than good borrowers. Hence, the cost of dealing with bad borrowers may reduce the incentive for a new payday loan store to lower prices to steal rivals' borrowers.

Moreover, if borrowers discount the future costs of payday loans, they may not react to lower cost loans offered by nearby payday lenders. Bertrand and Morse (2013) find evidence of the relationship between borrowing and cost insensitivity as they determine that after consumers become more aware of the adding-up dollar fees incurred when rolling over payday loans, payday loan usage declines by 11%.

2.4 An empirical model of endogenous entry decisions in the payday lending industry

Oligopoly models of dynamic interactions show that firms can sustain prices above the static competitive level by using the threat of future punishment to support co-operation. Many studies assume that collusion will occur at the monopoly price level since it provides symmetric firms the highest possible profits in a collusive regime.[5] Regrettably, according to the "Folk Theorem", any price between the competitive level and some maximum sustainable price will be an equilibrium in a dynamic game. The nearly infinite number of possible equilibrium outcomes make it difficult for economists to construct tests of collusive behavior.

To accomplish this problem, this study uses techniques similar to those

[5] See, for example, Porter (1983), Ellison (1994), and Genesove and Mullin (1998)

developed by Bresnahan and Reiss (1991) that can determine and contrast market conduct in markets with and without focal points. In particular, this study develops a discrete choice model relating the number of lenders in a market to demand and cost characteristics of that market that allows for identification of market conduct without the need of profit margin data. Moreover, this method can determine the values that lead to binding fee caps. This value is the fee cap in a market that results in lenders earning fewer profits than lenders operating in markets without fee caps. Thus, this study can determine the economic significance of market conduct in markets with and without focal point prices.

A lenders entry decision depends on the profits that it expects to earn following entry, given the entry decisions of other potential lenders in the market, the nature of post-entry competition, and demand and cost characteristics. Let the long-run profit of a lender i in a market k be a function of the number of incumbent lenders in the market and demand and cost characteristics of the market. Strictly speaking, profits are given by $\Pi(Y_k, N_k, X_k, W_k)$ where Y_k is a scalar representing market size, such as total population or income, N_k is the number of lenders in a market, and X_k and W_k are vectors of variables denoting demand and cost characteristics. This expression is a reduced-form, equilibrium long-run profit function that captures the outcome of competition between lenders in market k.

In an ideal world, the model would include product and other store level characteristics. These characteristics, such as productivity and brand recognition, would allow for heterogeneous profit functions across payday lenders in the data. However, in reality, these data are not available in this study. Hence, the inclusion of a stochastic, unobserved component of profit ϵ_k is necessary in order to identify the effects of the variables that affect observed profit $\pi(Y_k, N_k, X_k, W_k)$. Also, the unobserved and observed component of profits must be common for all lenders in a market k. In other words, a shift in demand for payday loans in market k has an equal effect on all lenders in the market. These conditions result in long-run equilibrium profits

$$\Pi(Y_k, N_k, X_k, W_k) = \pi(Y_k, N_k, X_k, W_k) + \epsilon_k. \tag{2.1}$$

Although these assumptions are restrictive; they have useful implications. If observed profits decline in the number of lenders, the assumption that profit is only affected by market-specific characteristics implies that the standard Nash equilibrium of the entry game results in firms entering until it becomes unprofitable. In other words, the equilibrium number of incumbent payday lenders in a market is the maximum number that the market can profitably sustain. Thus, this assumption suggests that inequality conditions on profit describe the equilibrium number of lenders in a market.[6] The equilibrium number of firms in market k,

[6]In order to facilitate estimation, the maximum number of payday lenders is limited to five.

denoted N_k^*, is given by

$$N_k^* = \begin{cases} 0 & \text{for } \pi_k^1 + \varepsilon_k < 0; \\ 1 & \text{for } \pi_k^1 + \varepsilon_k \geq 0 \text{ and } \pi_k^2 + \varepsilon_k < 0; \\ 2 & \text{for } \pi_k^2 + \varepsilon_k \geq 0 \text{ and } \pi_k^3 + \varepsilon_k < 0; \\ \vdots & \\ 5 & \text{for } \pi_k^5 + \varepsilon_k \geq 0, \end{cases} \tag{2.2}$$

where $\pi_k^N = \pi(Y_k, N_k = N, X_k, W_k)$. Another useful implication of the form of long profits is the normality of the unobserved portion of profits. Because the stochastic, unobserved component of profits is i.i.d. normal across markets, the probabilities of observing N firms in market k are

$$P(N_k = N) = \begin{cases} 1 - \Phi(\pi_k^1) & \text{for } N = 0; \\ \Phi(\pi_k^1) - \Phi(\pi_k^2) & \text{for } N = 1; \\ \Phi(\pi_k^2) - \Phi(\pi_k^3) & \text{for } N = 2; \\ \vdots & \\ \Phi(\pi_k^5) & \text{for } N \geq 5, \end{cases} \tag{2.3}$$

where $\Phi(\cdot)$ is the distribution of a standard normal random variable with the variance of the stochastic, unobserved component of profit normalized to one.

Following Bresnahan and Reiss (1990), assume that payday lenders' unobserved profits can be broken down into variable profits and fixed costs. Variable profits are linear in market size and the slope of profits in market size may vary across market structures. Assume that fixed costs may also differ over market structure due to barriers to entry or differences in efficiency. Strictly speaking, if lenders must invest in multiple outlet locations to steal an incumbent's consumers by offering better convenience to consumers, entry costs will be higher for additional lenders. Unobserved profits for a firm in market k are

$$\pi(Y_k, N_k, X_k, W_k) = V(N_k, X_k)Y_k - F(N_k, W_k). \tag{2.4}$$

Furthermore, for simplicity, assume that variable profits and fixed costs are composed of a linear combination of the number of lenders and demand and cost characteristics, respectively. For a market k with N firms, variable profits are

$$V(N_k, X_k) = \sum_{i=1}^{N} \alpha_i + \alpha_X X_k \tag{2.5}$$

and fixed costs are

$$F(N_k, X_k) = \sum_{i=1}^{N} \gamma_i + \alpha_W W_k. \tag{2.6}$$

Substituting (5)-(6) into (4), yields

$$\pi(Y_k, N_k, X_k, W_k) = (\sum_{i=1}^{N} \alpha_i + \alpha_X X_k)Y_k - (\sum_{i=1}^{N} \gamma_i + \alpha_W W_k). \tag{2.7}$$

The dummy variables for market structure's effect on variable profits and fixed costs add up as new lenders enter the market. For example, the observed profit for the payday lender monopolist is $\pi(Y_k, N_k = 1, X_k, W_k) = (\alpha_1 + \alpha_X X_k)Y_k -$

$(\gamma_1 + \alpha_W W_k)$ and the payday lender duopolist is $\pi(Y_k, N_k = 2, X_k, W_k) = (\alpha_1 + \alpha_2 + \alpha_X X_k)Y_k - (\gamma_1 + \gamma_2 + \alpha_W W_k)$. To identify the estimates within the profit function, the parameter attached to market size is set to one.

To identify the binding fee cap rate, the profits of lenders in markets without fee caps are set to profits of lenders in markets with fee caps. Any fee cap rate that results in lenders' profits in markets with fee caps being smaller than lenders' profits in markets without fee caps is likely binding. Formally, after setting profits equal and rearranging terms, the fee cap rate R^* that equates lenders' profits in markets with and without fee caps is

$$R^* = \frac{\gamma_{NoFeeCap}}{\gamma_{FeeCap}} \tag{2.8}$$

where $\gamma_{NoFeeCap}$ and γ_{FeeCap} are the effects of being in a market without fee caps and the impact of an additional unit of fee cap on lenders' profits. Hence, a market with fee caps higher than R^* has a non-binding fee cap, while any market with fee caps less than or equal to R^* has a binding fee cap.

The probabilities of observing market structures as defined in Equation 3 produces a maximum likelihood function described in Equation 7. The empirical model takes a similar form of that of an ordered probit. In order to determine the robustness of the estimates to different definitions of market size, the model is estimated using the market's total population and the total income in place of Y_k.

Payday lenders' profit function reveals the market sizes needed to support a given number of entrants, or entry thresholds. Since the Nash Equilibrium of the entry game predicts lender entry until profit is at least zero, one could obtain the minimum market size needed to support entry of N lenders by setting the profit function π^N equal to zero and solving for Y. For the minimum profit needed to support entry of N lenders into the average market, where $E(\pi(Y_k, N, X_k, W_k)) = \pi(Y_N, N, X, W)$, the average minimum market size needed for entry is

$$Y_N = \begin{cases} \frac{\gamma_1 + \alpha_W W}{\alpha_1 + \alpha_X X} & \text{for } N = 1 \\ \frac{\gamma_1 + \gamma_2 + \gamma_W W}{\alpha_1 + \alpha_2 + \alpha_X X} & \text{for } N = 2 \\ \vdots & \\ \frac{\sum_{i=1}^{5} \gamma_i + \gamma_W W}{\sum_{i=1}^{5} \alpha_i + \alpha_X X} & \text{for } N \geq 5 \end{cases}. \tag{2.9}$$

where the coefficients are estimated using maximum likelihood.

As described in the Introduction, the pattern of entry thresholds needed to support entry reveals the nature of competition in the market. If more significant competition reduces prices, leads lenders to make more sunk cost investments in quality, and encourages lenders to make riskier loans, then profit margins will decline, and lenders must need more borrowers to sustain entry. Since in oligopolistic competition the competitive effect of entry converges to some limit, entry thresholds will converge to some number as N approaches a large amount. These conditions suggest that the entry thresholds rise in a concave, exponential manner.

However, if payday lenders interact in a monopolistic or collusive setting, the entry threshold will behave differently than in the oligopolistic case. If switching costs, adverse selection, or consumer irrationality leads payday lenders to set finance fees and loan offerings regardless of the number of lenders in the market, profit margins will not decline with new entry. Non-decreasing profit margins imply that the entry threshold needed will not rise and remain relatively constant as the number of lenders approaches a significant amount.

With these conditions in mind, the model allows for inferences about the competitive effects of new lenders without the presence of data such as price-cost margins. By estimating the link between market structure and market characteristics one can identify the ramifications of additional lenders on the intensity of competition by examining the market features needed to support further lenders across markets with and without focal points. However, the methodology cannot determine the extent of collusion or market power within a market. In other words, the model cannot predict the size of price markups as a result of cooperation. However, the model can determine the change in market conduct concerning market conduct and test this study's question.

2.5 Data

The payday loan industry presents an ideal environment in which to implement the techniques described in the previous section. An advantageous aspect of the payday lending industry is that borrowers tend not to travel far for payday loan services. Studies that examine payday lending behavior find that local demographics are critical to entry decisions.[7] Moreover, nearly three-quarters of payday loan

[7] See Prager (2009).

borrowers obtain loans from physical locations.[8] Hence, local market characteristics are likely to affect the profits of local payday lenders.

Estimation of the model described in the previous section requires information on the presence of payday lenders in the sample markets as well as demand and cost characteristics of the market, including details on fee caps. Areas with large populations may have many submarkets. To ensure the sample is composed of isolated markets, this study defines a market as a contiguous US county or parish in 2017 that satisfies the following criteria: (i) the total market population, is less than 100,000 and (ii) payday lending is not effectively banned. Figure 1 depicts a map of lender locations in an example market within the sample: Oconee County, South Carolina. Payday lenders in this sample market agglomerate in the highest density area, Seneca, South Carolina. This example demonstrates the benefit of sampling from small counties; payday lending markets are likely to be isolated from other markets. The final sample includes 3,466 unique to the market, payday lenders. States with active payday loan bans include: Arizona, Arkansas, Connecticut, Georgia, Maine, Maryland, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Vermont, and West Virginia.[9] After removing markets that fail these criteria, 1,978 mid-sized markets compose the sample. Figure 2 displays a map of the locations of markets in the sample.

Information on the locations of payday lending firms in 2017 was obtained from yellowpages.com. The web scrapping procedure was performed using the

[8] See Pew Charitable Trusts (2013).

[9] With the exception of Georgia, these states essentially ban payday loan rates by setting fee caps below 36 percent.

following method. First, a search query was entered into yellowpages.com for outlets that offer payday loans in a zip-code from a set of counties with a population less than 100,000. Next, the program collected the names of payday lenders that operate within the entered zip code. After storing the data, the web scrapping process was performed again until the entire set of zip codes were entered and the data stored about 15,000 times. Finally, after finishing the procedure, the program eliminated duplicate firms operating in the same market from the sample.

The final sample composes firms that offer payday loan services. Provided that they make payday loan services, firms in the sample could also offer title loans, checking services, pawn services. Moreover, this study treats lenders with more than one outlet as precisely one lender. The model cannot predict the entry decisions of outlets into markets. Payday lenders are unlikely to cannibalize profits of incumbent stores by adding more stores. Counting outlets as firms would likely lead to an underestimation of the competitive effects. However, this implication is not a serious concern, as markets with multiple stores constitute forty-three percent of markets with at least one lender.

Table 1 presents an overview of the definitions and sources of variables included in this study. Table 2 shows descriptive statistics on market structure, market size, demand, and cost variables in the sample markets. Variables within the sample are at the county level for the year 2016. Fifty-one percent of the sample markets have at least one payday lender. The distribution of payday lenders is right-skewed. To ensure parameter identification, it is necessary to truncate the lender count distribution in estimation to provide a sufficiently large number of market structure observations for each realized lender count. In other words, there are not enough observations to identify the individual markets structure effects of beyond five operating lenders. With these considerations, there are 279 markets with one payday lender, 180 with two, 130 with three, 100 with four, and 268 markets with five or more payday lenders.

Markets with a more substantial population ($Population$) and total income ($Income$) are more likely to have a more significant number of payday lenders. Hence, as required in a standard entry model, the descriptive statistics support the notion of a monotonic relationship between market structure and market size.

The profit function consists of demand variables income per capita ($IncomePerCap$), poverty (Pov), African American population ($BlackPop$), and food insecurity ($FoodInsec$) as well as cost variables median rent ($Rent$), annual percentage rate of payday loan fee caps ($FeeCap$), and the state's maximum loan amount allowed by law ($MaxLoan$). The demand variables control for market specific shifters in payday loan demand. For example, since payday loans may be an inferior good, the demand for them may be more significant in markets with lower incomes. Moreover, since African Americans historically have had less access to credit than many racial groups (e.g., Blanchflower et. al, 2006), markets with high $BlackPop$ may have greater demand for alternative credit. Ideally, one would also include a measure of financial instability when modeling the determinants of payday loan profits. However, if a household is experiencing financial instability, it may have difficulty in subsistence goods, such as food. Hence, $FoodInsec$ proxies for financial instability in the payday lender profit function. $Rent$ is also included to control for the effect of local factor prices on profitability. However, it may be difficult to determine the impact of $Rent$ on profitability as it is likely correlated with variables in the profit function.

Other variables that affect fixed costs include regulatory controls $FeeCap$ and $MaxLoan$. The $FeeCap$ is the max annual percentage rate of a fee on a \$100 payday loan allowed by the market's state government.[10] The average $FeeCap$ in a sample market is 402 percent. To ensure correct identification of the effect of $FeeCap$ and $MaxLoan$ on payday lender profits, an indicator function for the presence of a fee cap interacts with these covariates. The profit function contains a dummy variable $NoFeeCap$ to capture the effect of operating in a market without a fee cap. States without fee caps include Delaware, Idaho, Ohio, Texas, Utah, and Wisconsin.[11] $MaxLoan$ identify the maximum a loan amount a payday lender is allowed to offer a borrower.

Table 3 displays summary statistics for market by fee caps regime. Fee cap regimes, represented by columns 4-6, include no fee cap, non-binding fee cap, and binding fee cap. On the surface, there appears to be little differences in the mean demand and cost variables in each regime. However, the average county population share of African Americans in markets with non-binding fee caps is larger than the average sample mean. Moreover, the average number of payday lenders in markets with non-binding fee caps is larger than the sample mean. However, hypothesis tests reject the notion that differences in these means

[10] The fee cap rate is calculated by $FeeCap = \frac{Fee \times \frac{365}{14}}{100}$.

[11] Ohio has a payday loan fee cap, but, as affirmed in *Ohio Neighborhood Fin., Inc. v. Scott.*, lenders are not bound by them if they classify as mortgage lenders.

are statistically significant.[12]

2.6 Results

Table 4 consists of the estimates from the single equation entry model, analogous to the entry model of Bresnahan and Reiss (1991). To reiterate from the previous sections, this method is equivalent to a discrete choice model where one regresses factors, such as market structure and demand and cost shifters, on the dependent variable, the number of lenders, to expose characteristics of underlying profitability. This approach yields consistent estimates and entry thresholds as long as the stochastic, unobserved portion of profit ε is normal, and an ordered probit with contributions to the likelihood function as described in Equation 3. In columns 1-3, market size Y_k is defined as total county population $(Population)$, while in columns 4-6 market size is set as total county income $(Income)$. Market size is the sole explanatory variable in columns 1 and 4, while columns 2 and 5 contain demand and cost characteristics and columns 3 and 6 add regulatory components.

Consistent with the entry literature, the estimates α_2 to α_5 and γ_2 to γ_5 measuring market structure's effect on profitability have the expected signs. Additional lenders appear to cause variable profits to fall, as the estimates of α_2 to α_5 are negative, and lead fixed costs to rise, since the estimates of γ_2 to γ_5 are positive. In contrast with most oligopoly models and with the results presented by Bresnahan and Reiss (1991), the magnitude of the effect of entry on variable profits does not decrease and is constant as lenders enter the market. In other words,

[12] T-tests can be made available upon request.

lender entry does not have a smaller incremental impact on conduct as the number of lenders increases. However, fixed costs rise as more lenders enter the market. In context to market behavior, incumbent lenders either utilize more efficient resources (e.g., better locations) or are subject to barriers to entry (e.g., new entrants must establish more outlets to match an incumbent's quality).

The effects of demographic factors Pov, $BlackPop$, $FoodInsec$ on variable profits are positive and statistically significant, although $IncomePerCap$ is statistically insignificant in a few specifications. The average marginal effects calculated from specification 3 reveal that a one percent increase in $BlackPop$ leads to on average a 14.70 percent increase in the likelihood of observing a market structure of five or more firms. One explanation for these results is that people in poverty and African Americans may lack access to conventional financial services and, thus markets with more individuals in these groups have a higher demand for payday loans. Poverty also has an economically significant positive effect on payday lender entry as a one percent increase in Pov leads to on average a 39.20 percent increase in the likelihood of observing a market structure of five or more firms.

Markets with greater factions of individuals who have difficulty in satisfying a subsistence level of consumption, as measured by $FoodInsec$, also have a higher demand for payday loans. If these factors affected supply-side conditions, one would expect a negative sign. Intuitively, the risk of not collecting a loan should rise with the income uncertainty of the borrower. However, the results suggest that the markets which have more consumers who are financially insecure, impoverished, and credit constrained, the higher the profitability of payday lenders. Hence, more substantial profits accruing from greater demand for payday loans outweigh the cost of making loans to a riskier group of borrowers. Regarding the demand characteristics, financial insecurity tends to have the most significant economic effect on entry as a one percent increase in $FoodInsec$ leads to on average a 45.02 percent increase in the likelihood of observing a market with five or more payday lenders.

Estimates of the effects of $Rent$, $MaxLoan$, and $APRcap$ on payday lending profitability suggest positive increases in these factors lead to adverse supply-side effects. A rise in factor prices, such as $Rent$, leads to higher fixed costs. However, $Rent$ could also capture demand-side characteristics. For example, previous results suggest that the demand for payday loans is more elevated in impoverished markets and if rental prices correlate with household income, the $Rent$ estimate may capture the relationship between household income and payday loan demand. The signage of the effect of $FeeCap$ on profit margins shows that a decrease in the fee cap rate leads to fewer payday lenders in a market. For example, a fee cap rate of 156 points to an 11 percent decrease in the number of entrants relative to entrants in markets without fee caps. At sufficiently low levels, the estimates of the effect of fee cap rate on profitability suggest that fee caps may reduce payday loan prices at the cost of fewer firms. Also, estimates of the $MaxLoan$ effect on profit are negligible and suggest that differences in profitability in markets with and without max loan limits are insignificant.

The estimated market sizes needed to support a monopoly, duopoly, and oligopoly, namely Y_1 to Y_5 are reported in the first section of Table 5. The numbered column headings in Table V relate to the specifications reported in Table 4. As outlined in previous sections, the break-even market size, or entry threshold, for a given market structure is calculated by setting the appropriate expected profit function equal to zero. In each condition, entry thresholds were computed with all the covariates taken at their sample means. The computations imply that a county with a population of 22,000, or aggregate income of 800 million, is required to support a monopolist. A population of approximately 33,000, or a total income of around 1.25 billion, is needed to support a duopolist. After the duopolist, new lender entrants require about ten thousand more people or nearly 300 million in income. Hypothesis tests reveal that these entry threshold estimates are statistically different from each other at the 99 percent confidence level.

As discussed in previous sections, per lender entry thresholds can reveal the nature of how competition functions within the market. The second section of Table 5 presents the calculated ratio of per lender entry thresholds, where $y_N = \frac{Y_N}{N}$. To reiterate, in an oligopolistic market, per lender entry thresholds ratio beginning above one and converging to one imply that lenders require exponentially larger market sizes as competition reduces variable profits exponentially. However, calculated per lender entry threshold ratios reveal the opposite effect; the duopolist and oligopolist require a smaller market size than the monopolist to enter. A duopolist requires a market size nearly 25 percent smaller than a monopolist and an oligopolist tends to require a market size five percent smaller than the duopolist. Also, hypothesis tests at the 99 percent confidence interval reject the null that the estimated per lender entry threshold ratios are greater than one for each market structure and specification. These results show that entry has an insignificant economic effect on payday lending profit.

To reiterate the rates at which fee caps are binding are found by setting the profits of lenders in markets with caps to the profits of lenders in markets without caps. The reported estimates of $FeeCap$ effects on payday lending profitability yield some intriguing results. First, fee caps reduce payday lenders profits below a value of approximately 556 percent.[13] This value is in the neighborhood of the average fee rates charged in states without fee caps. For example, the average fee rate in Texas, Nevada, and Idaho are 454, 521, and 582 percent.[14] Fee caps below this rate are likely to be binding and caps above it are expected to be non-binding.

Second, firms operating in markets with non-binding fee caps earn higher profits than in markets without fee caps. For example, after controlling for local demand and cost characteristics, a fee caps rate of 780 percent, which is also the cap in Louisiana, results in 7.14 percent more payday lenders than in markets without fee caps. This finding suggests that entry is economically greater in markets with non-binding fee caps, implying that profit margins are larger in markets with non-binding fee caps and evidence of tacit collusion at focal points in the industry.

[13] The 90 percent confidence interval of values which result in a binding fee cap is between 424 and 689 percent.

[14] See Pew Charitable Trusts (2013).

2.6.1 Non-binding fee caps as focal points for tacit collusion

In order to further test the question if focal points lead to higher profit margins for payday lenders, and thus evidence of tacit collusion at focal points, this study calculates entry thresholds and threshold ratios for lenders in markets without fee caps and with binding and non-binding fee caps. To identify these effects, the sample is split into three groups using the fee cap value previously identified: markets without fee caps and with binding non-binding fee caps. A market at and above a fee cap of 520 percent is a non-binding fee cap market and a market below the cap is a binding fee cap market. Next, three models were estimated similar to the specification described in column 2 of Table 2.[15] Finally, the entry thresholds and threshold ratios were calculated from the estimates.

Figure 3 displays the mean entry thresholds and their 95 percent confidence interval for markets without fee caps and with binding and non-binding fee caps. For each given fee cap regime in Figure 3, the confidence intervals for every market structure show that entry thresholds are statistically different. In a given market structure, the differences in entry thresholds for a lender in a market without fee caps and with non-binding fee caps are statistically significant, except for market structures at and above four payday lenders. Also, the differences in entry thresholds for lenders in markets with non-binding fee caps and without fee caps are statistically different.

The results suggest that all else equal, profit margins are higher in markets

[15]The other specifications were tried, and the results were similar.

with non-binding fee caps than markets with different fee cap regimes. The mean estimated entry thresholds are 29 percent smaller for lenders in markets with non-binding fee caps compared to lenders in markets without fee caps. Evidence of lower entry thresholds in markets with non-binding fee caps relative to markets without fee caps is consistent with the notion that payday lenders earn higher profit margins in markets with focal points. Since higher profit margins in markets with focal points suggest tacit collusion, the results indicate that non-binding fee caps facilitate tacit collusion in payday lending markets. Moreover, because tacit collusion at a focal point in a market is tantamount to the presence of market power, market power may allow payday lenders to engage in anti-competitive behavior.

Intuitively, binding price ceilings result in lower profit margins for firms. Entry thresholds of payday lenders displayed in Figure 3 reveal that the average binding fee cap in the sample has an economic effect on entry and profits. Binding fee caps appear to put pressure on payday lenders entry decisions and operations. On average, in order for a payday lender to enter a market with binding fee caps, they must have 4,000 more consumers than the average market without fee caps. Although binding fee caps may reduce profits, the results do not show that binding fee caps reduce payday loan prices for consumers. Payday lenders may pass through the costs of navigating around binding fee caps to consumers through additional fees, such as a broker fee. This change may reduce the quantity demanded of payday loans, leading to fewer stores. Nevertheless, binding fee caps seem to put downward pressure on payday lenders' profits.

Although profit margins are higher in markets with non-binding price ceilings; market conduct is strikingly similar across markets without fee caps and with non-binding and binding fee caps. Figure 4 displays the estimated entry threshold ratios and their confidence intervals. All the entry threshold ratio in each subgroup sample model and specification are statistically less than one. Moreover, the differences between the estimated entry threshold for each market structure produced from each segmented sample are statistically insignificant. These entry threshold ratios demonstrate that the competitive effect of entry is similar in markets without fee caps and with non-binding and binding fee caps. Since the competitive effects of entry are identical across each type of market, there does not appear to be a significant effect of fee caps on the competitive impact of entry.

In models of tacit collusion, collusion may break down as more firms enter the market. An endogenous entry model would predict constant and non-decreasing entry threshold ratios below one, or constant profit margins, up to some number of firms where collusion is stable. At the market structure where cooperation breaks down, entry threshold ratios would rise above one and begin to decline towards one as the market converges to the competitive outcome. In the case of payday lenders, it does not appear that tacit collusion breaks down even with five payday lenders in the market. The competitive effects of entry in markets with non-binding fee caps remain below one. Given that tacit collusion is stable even up to five payday lenders, there may exist a mechanism in the market which gives payday lenders market power and facilitate tacit collusion.

2.7 Conclusion

The efficiency of the market to guide payday loan prices to a competitive outcome is the heart of regulatory issues in the industry. In a market where many consumers rely on payday loans to meet subsistence needs, market failures in the industry can lead to significantly perverse outcomes. Mechanisms that allow payday lenders to engage in higher market power would be most damaging to an economically vulnerable part of society. The results of this study suggest payday lenders use non-binding fee caps as focal points for tacit collusion. Payday lender entry is more significant in markets with non-binding fee caps compared to other markets, suggesting that profit margins are higher in these markets. Moreover, this issue could be present in both small and large markets. A more significant level of incumbent payday lenders does not significantly change the decisions of the next entrant. These results demonstrate the paradoxical effects of specific regulation intended to reduce costs for payday loan borrowers.

Although the analysis presented in this study finds evidence of tacit collusion at non-binding fee caps in local payday lending markets, it did not identify the source of market power in the industry. Potential causes of market power in the industry include adverse selection, switching costs, and consumer irrationality. Many industry observers suggest that the industry use credit reports similar to other credit markets to solve the adverse selection problem. Indeed, these measures may lead to competitive pricing in the industry. Given the potential welfare gains of achieving a competitive outcome, future research should identify the mechanism of market power within the industry.

Many industry observers argue that more payday lenders, and hence competition, are the solution to lowering payday loan prices. However, the results of this study suggest that, given additional incumbents do not affect the next lender's entry decision, increasing the number of participants will not lead to more competitive pricing. Proponents of lower pricing in payday lending should focus their attention on aspects of payday lending unrelated to the market structure when looking to promote competition in the market.

Similar to Knittel and Stango (2003), this study's results suggest that focal points as facilitators of tacit collusion are a potential explanation for larger profit margins for payday lenders in markets with non-binding fee caps. Regulators should take care when instituting and setting the level of a fee cap. If regulators establish a fee cap above the binding rate, consumer welfare may decline.

Figure 2.1: Locations of payday lenders in a sample market: Oconee County, South Carolina

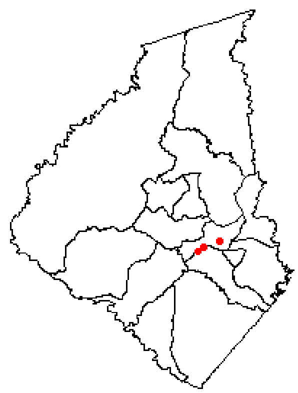


Figure 2.2: Markets in the sample

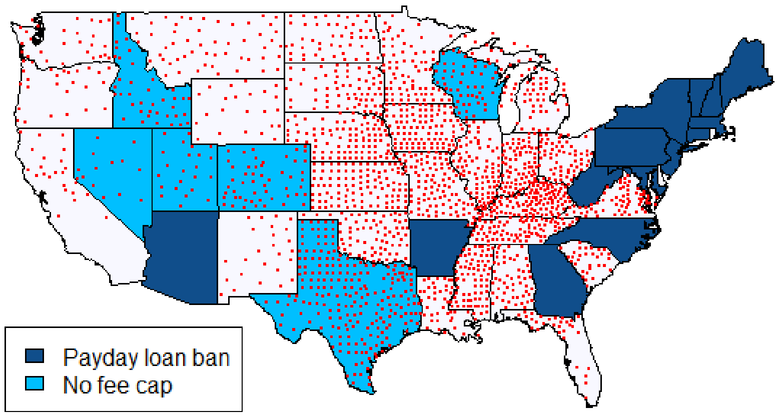
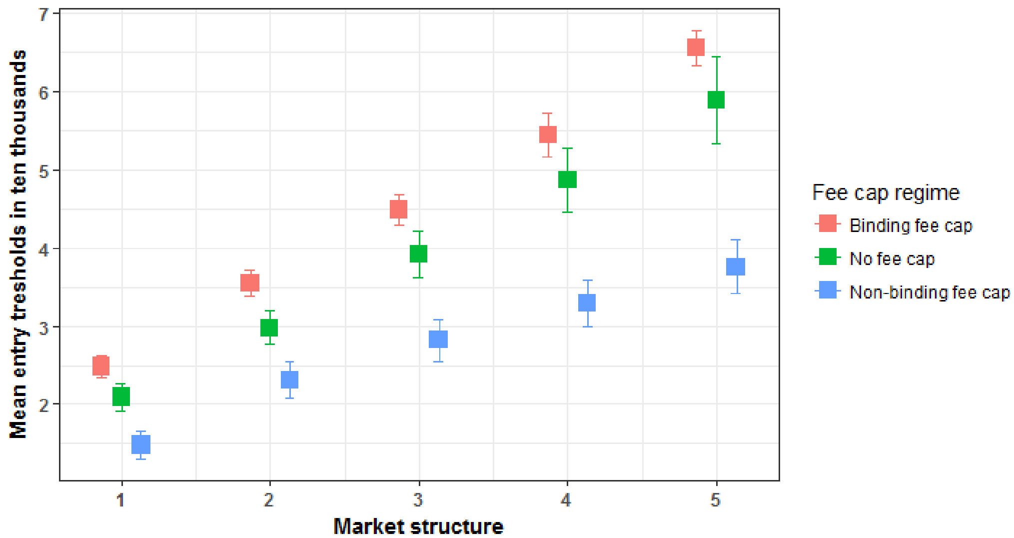
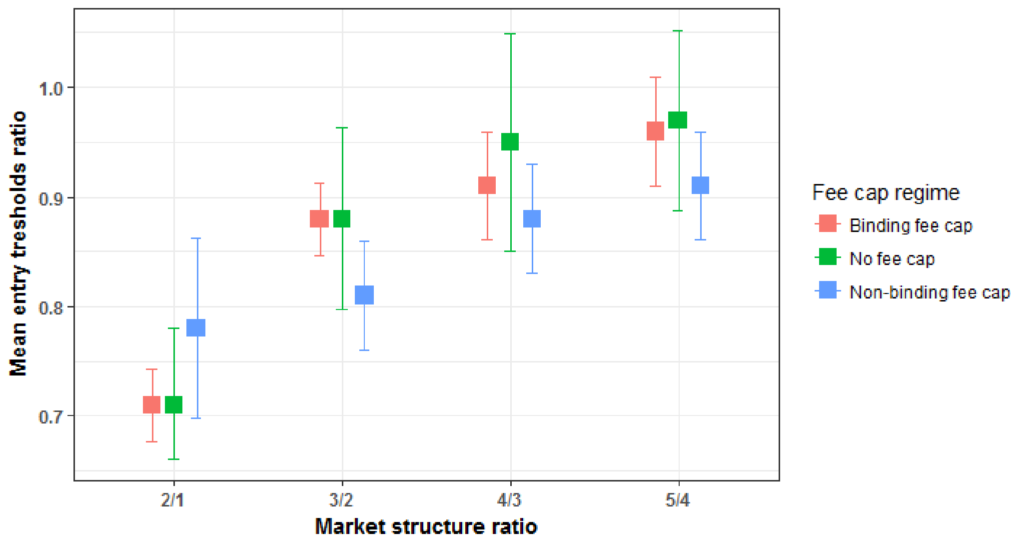


Figure 2.3: Payday lender entry thresholds



Payday lender entry threshold for three fee cap regimes. Boxes indicate the mean entry threshold for the corresponding market stucture. Error bars indicate the 95% confidence interval of the mean entry threshold.

Figure 2.4: Payday lender entry threshold ratios



Payday lender entry threshold ratios for three fee cap regimes. Boxes indicate the mean entry threshold ratio for the corresponding market stucture. Error bars indicate the 95% confidence interval of the mean entry threshold ratio.

Table 2.1: Variable definitions

Variable	Definition	Source
$Population$	Total county population in ten-thousands.	US Bureau of Labor Statistics
$Income$	Total county income in billions.	US Bureau of Labor Statistics
Pov	Share of county population in living in poverty.	US Economic Research Service
$IncomePerCap$	Income of average individual in a county in tens of thousands.	US Bureau of Labor Statistics
$BlackPop$	Share of county population that is black.	US Census
$FoodInsec$	Share of county population that lack access to enough food for an active, healthy life.	US Economic Research Service
$Rent$	Median housing cost expenses for renters.	US Census
$FeeCap$	Maximum annual percentage rate of a finance fee on a $100 payday loan allowed by law.	Consumer Federation of America
$MaxLoan$	Limit of loan amount a payday loan borrower may take out in one transaction.	Consumer Federation of America

Table 2.2: Summary statistics for sample markets

			Number of payday lenders					
Variable		Sample	0	1	2	3	4	5+
Count		1,978	1,011	279	180	130	100	268
$Population$	mean	2.43	1.89	2.61	3.24	3.93	4.34	5.22
	std. dev	2.16	1.17	1.70	1.76	1.72	2.25	2.14
$Income$	mean	1.26	0.49	0.90	1.26	1.45	1.67	1.95
	std. dev	0.92	0.54	0.73	0.91	0.82	0.99	0.95
Pov	mean	0.16	0.15	0.17	0.16	0.16	0.16	0.18
	std. dev	0.06	0.06	0.06	0.06	0.06	0.05	0.05
$IncomePerCap$	mean	3.99	4.24	3.74	3.77	3.85	3.76	3.67
	std. dev	1.09	1.29	7.66	7.88	1.77	6.13	5.88
$BlackPop$	mean	0.07	0.05	0.10	0.07	0.09	0.09	0.14
	std. dev	0.14	0.12	0.15	0.11	0.13	0.14	0.18
$FoodInsec$	mean	0.15	0.14	0.16	0.15	0.16	0.16	0.17
	std. dev	0.04	0.04	0.04	0.03	0.03	0.03	0.04
$Rent$	mean	648	623	673	677	693	676	676
	std. dev	130	136	118	116	138	108	91
$Feecap$	mean	402	353	452	432	431	387	514
	std. dev	417	369	457	455	440	383	510
$MaxLoan$	mean	1,152	1,510	778	830	541	535	501
	std. dev	5,649	7,075	3,568	3,710	390	369	362

Table 2.3: Summary statistics for sample markets by fee cap regime

Variable		Sample	No fee cap	Non-binding fee cap	Binding fee cap
Count		1,978	394	353	1,231
Number of Payday Lenders	mean	1.75	1.35	2.64	1.60
	std. dev	2.73	2.36	3.76	2.43
$Population$	mean	2.43	2.03	2.27	2.55
	std. dev	2.16	2.06	1.91	2.23
$Income$	mean	1.26	0.81	0.88	0.98
	std. dev	0.92	0.84	0.89	0.90
Pov	mean	0.16	0.15	0.18	0.15
	std. dev	0.06	0.05	0.07	0.06
$IncomePerCap$	mean	3.99	4.20	3.85	3.97
	std. dev	1.09	1.34	1.35	0.93
$BlackPop$	mean	0.07	0.04	0.18	0.05
	std. dev	0.14	0.06	0.21	0.11
$FoodInsec$	mean	0.15	0.15	0.16	0.15
	std. dev	0.04	0.04	0.06	0.03
$Rent$	mean	648	708	645	631
	std. dev	130	158	149	111

Table 2.4: Estimated parameters of payday lender profit function

Coefficient	Specification					
	(1)	(2)	(3)	(4)		
α_1	0.50***	0.23***	0.25***			
	(0.02)	(0.08)	(0.05)	(0.03)	(0.19)	(0.22)
α_2	−0.00	−0.00	−0.01	−0.00	−0.00	−0.02
	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.05)
α_3	−0.05***	−0.05***	−0.07***	−0.09***	−0.11**	−0.14***
	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)	(0.05)
α_4	−0.05***	−0.06***	−0.07***	−0.06**	−0.13***	−0.18***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.05)	(0.05)
α_5	−0.03***	−0.04**	−0.04**	−0.06**	−0.10**	−0.11***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.05)
α_{Pov}		1.01***	1.27***		4.81***	5.71***
		(0.27)	(0.31)		(0.71)	(0.72)
$\alpha_{BlackPop}$		0.58***	0.48***		2.00***	1.65***
		(0.10)	(0.13)		(0.30)	(0.37)
$\alpha_{FoodInsec}$		1.50***	1.47***		2.60***	5.56***
		(0.41)	(0.42)		(1.01)	(1.26)
$\alpha_{IncomePerCap}$		−0.01	−0.01		−0.14***	−0.15***
		(0.01)	(0.01)		(0.03)	(0.02)
γ_1	1.14***	0.87***	1.22***	0.83***	0.71***	1.09***
	(0.05)	(0.17)	(0.20)	(0.05)	(0.17)	(0.20)
γ_2	0.55***	0.61***	0.61***	0.49***	0.61***	0.62***
	(0.05)	(0.06)	(0.07)	(0.04)	(0.05)	(0.06)
γ_3	0.27***	0.31***	0.29***	0.27	0.34***	0.33***
	(0.06)	(0.07)	(0.08)	(0.05)	(0.06)	(0.07)
γ_4	0.16***	0.18***	0.17***	0.22***	0.26***	0.23***
	(0.06)	(0.07)	(0.08)	(0.05)	(0.07)	(0.07)
γ_5	0.20***	0.24***	0.24***	0.21***	0.26***	0.26***
	(0.06)	(0.08)	(0.09)	(0.06)	(0.07)	(0.08)
γ_{Rent}		0.73***	0.64***		−0.64	0.94***
		(0.28)	(0.29)		(0.80)	(0.33)
$\gamma_{MaxLoan}$			0.00***			0.00***
			(0.00)			(0.00)
γ_{FeeCap}			−0.05***			−0.05***
			(0.01)			(0.01)
$\gamma_{NoMaxLoan}$			−0.05			−0.02
			(0.12)			(0.12)
$\gamma_{NoFeeCap}$			−0.26***			−0.27***
			(0.12)			(0.11)
LogLik	−2,291.05	−2,125.76	−2,070.67	−2,463.08	−2,140.44	−2,083.27

N = 1,978

Notes: standard deviations in parentheses. ***significant at the 1% level, **significant at the 5% level, and at the *significant at the 10% level

Table 2.5: Estimated parameters of payday lender profit function

Coefficient	Specification					
	(1)	(2)	(3)	(4)	(5)	(6)
α_1	0.50***	0.23***	0.25***	0.92***	0.87***	1.06***
	(0.02)	(0.08)	(0.05)	(0.03)	(0.19)	(0.22)
α_2	−0.00	−0.00	−0.01	−0.00	−0.00	−0.02
	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.05)
α_3	−0.05***	−0.05***	−0.07***	−0.09***	−0.11**	−0.14***
	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)	(0.05)
α_4	−0.05***	−0.06***	−0.07***	−0.06**	−0.13***	−0.18***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.05)	(0.05)
α_5	−0.03***	−0.04**	−0.04**	−0.06**	−0.10**	−0.11***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.05)
α_{Pov}		1.01***	1.27***		4.81***	5.71***
		(0.27)	(0.31)		(0.71)	(0.72)
$\alpha_{BlackPop}$		0.58***	0.48***		2.00***	1.65***
		(0.10)	(0.13)		(0.30)	(0.37)
$\alpha_{FoodInsec}$		1.50***	1.47***		2.60***	5.56***
		(0.41)	(0.42)		(1.01)	(1.26)
$\alpha_{IncomePerCap}$		−0.01	−0.01		−0.14***	−0.15***
		(0.01)	(0.01)		(0.03)	(0.02)
γ_1	1.14***	0.87***	1.22***	0.83***	0.71***	1.09***
	(0.05)	(0.17)	(0.20)	(0.05)	(0.17)	(0.20)
γ_2	0.55***	0.61***	0.61***	0.49***	0.61***	0.62***
	(0.05)	(0.06)	(0.07)	(0.04)	(0.05)	(0.06)
γ_3	0.27***	0.31***	0.29***	0.27	0.34***	0.33***
	(0.06)	(0.07)	(0.08)	(0.05)	(0.06)	(0.07)
γ_4	0.16***	0.18***	0.17***	0.22***	0.26***	0.23***
	(0.06)	(0.07)	(0.08)	(0.05)	(0.07)	(0.07)
γ_5	0.20***	0.24***	0.24***	0.21***	0.26***	0.26***
	(0.06)	(0.08)	(0.09)	(0.06)	(0.07)	(0.08)
γ_{Rent}		0.73***	0.64***		−0.64	0.94***
		(0.28)	(0.29)		(0.80)	(0.33)
$\gamma_{MaxLoan}$			0.00***			0.00***
			(0.00)			(0.00)
γ_{FeeCap}			−0.05***			−0.05***
			(0.01)			(0.01)
$\gamma_{NoMaxLoan}$			−0.05			−0.02
			(0.12)			(0.12)
$\gamma_{NoFeeCap}$			−0.26***			−0.27***
			(0.12)			(0.11)
LogLik	−2,291.05	−2,125.76	−2,070.67	−2,463.08	−2,140.44	−2,083.27

N = 1,978

Notes: standard deviations in parentheses. ***significant at the 1% level, **significant at the 5% level, and at the *significant at the 10% level

Table 2.6: Market threshold estimates

Variable	Specification					
	(1)	(2)	(3)	(4)	(5)	(6)
Estimated entry thresholds						
Y_1	2.27	2.20	2.19	0.90	0.81	0.81
	(0.07)	(0.06)	(0.06)	(0.04)	(0.02)	(0.02)
Y_2	3.39	3.22	3.20	1.43	1.18	1.17
	(0.09)	(0.07)	(0.06)	(0.05)	(0.03)	(0.02)
Y_3	4.33	4.09	4.08	1.91	1.51	1.50
	(0.10)	(0.09)	(0.07)	(0.06)	(0.03)	(0.02)
Y_4	5.28	4.95	4.95	2.37	1.84	1.83
	(0.13)	(0.13)	(0.09)	(0.08)	(0.04)	(0.02)
Y_5	6.27	5.91	5.91	2.88	2.21	2.19
	(0.18)	(0.18)	(0.11)	(0.12)	(0.06)	(0.03)
Estimated per lender entry threshold ratios						
$\frac{y_2}{y_1}$	0.74	0.73	0.72	0.80	0.73	0.72
	(0.03)	(0.08)	(0.02)	(0.04)	(0.02)	(0.05)
$\frac{y_3}{y_2}$	0.86	0.85	0.86	0.89	0.85	0.85
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)
$\frac{y_4}{y_3}$	0.92	0.91	0.92	0.91	0.91	0.93
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)
$\frac{y_5}{y_4}$	0.96	0.97	0.97	0.97	0.96	0.98
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.06)

N = 1,978

Notes: standard deviations in parentheses.

CHAPTER 3
DO INTEREST RATE SWAPS AFFECT MORTGAGE LENDING? EVIDENCE FROM THE US CREDIT UNION INDUSTRY

3.1 Introduction

Since the 1980s, traditional financial intermediaries have gathered a significant stake in the interest rate derivative market, as the notional amount of all interest rate contracts in the US banking industry reached \$1.3 quadrillion at the end of 2017 (FDIC, 2017). As interest rate derivatives help financial intermediaries mitigate interest rate risk, they may have profound implications for lending decisions by financial institutions.

A derivative is an independent contract, agreed upon between two parties, that specifies, based on the condition of an asset or liability, when payments are to be made between the parties. The largest component of the global derivative market, representing roughly 52.4% of the global market in 2017, are interest rate swaps (Bank for International Settlements, 2017). A vanilla interest rate swap is a contract between two parties that allows one party to exchange a fixed-rate payment obligation for a floating-rate one, typically the London Interbank Offered Rate (LIBOR). For financial intermediaries that are end users of swaps, interest rate swaps allow buyers to insure against the re-pricing risk that arises from rate mismatches between assets and liabilities. This mismatch is typically a results of financial intermediaries using short term shares (such as deposits) to fund long term loans and investments.

The impact of interest rate derivatives on the supply of credit has been widely discussed and acknowledged in the literature. Since the advent of interest rate derivatives in the financial intermediary markets, they have consistently been in the spot light of financial regulators, as interest rate derivatives may have a profound effect on lending decisions and risk held by financial intermediaries. On one hand, interest rate derivatives can lead to a transfer of risk from financial intermediaries to other firms in the financial market, leading to reduced costs in lending and, perhaps, an expansion in the supply of credit. On the other hand, interest rate derivatives could be used by financial intermediaries to attempt to earn greater revenue through speculation, resulting in increased risk. Since the US government insures deposit accounts up to $250,000 for most domestic financial intermediaries, a decision by a financial intermediary that results in a greater probability of insolvency could have significant impact on federal government expenditures.

In this paper, I test how access to interest rate swaps affects financial intermediaries lending decisions. In particular, I examine how the use of interest rate swaps impacts growth in fixed-rate and variable-rate mortgage lending by US credit unions. Although this question has been addressed in the literature (e.g., Brewer et al. 2000), to the best of my knowledge, my study is the first to identify this effect using a difference-in-differences approach, in which I exploit a rule change as a source of variation, as opposed to using balance sheet items as instrumental variables. Since the use of interest rate swaps and lending decisions are endogenous, an econometric technique that ensures a causal effect is necessary to establish proper identification. To the best of my knowledge, my study is the first to identify the effects without relying on the assumption of the exclusion restriction that comes with instrumental variables.

In 2014, as part of the National Credit Union Association's (NCUA) strategy for helping credit unions manage interest-rate risk, credit unions with assets over $250 million were allowed limited access to financial derivatives, which includes interest rate swaps, interest rate caps, interest rate floors, basis swaps, and Treasury futures. By the fourth quarter of 2017, 18 credit unions held interest-rate swaps with a notional value of $3.6 billion. A feature of the NCUA's regulation and policy of credit unions is that they cannot deal interest rate swaps to other financial intermediaries. This aspect is ideal for this study, since I do not have to consider entities that take the fixed-rate position on a interest rate swap, which may occur in the banking industry, in my sample.

My sample represents all NCUA-insured credit unions with total assets greater than $250 million as of January 2011 that hold mortgage loans in their portfolio. Using this sample, I create models that explain growth rates in total, fixed-rate, and variable-rate mortgage loans that include a measure of a credit union's use of interest rate swaps. I find a statistically significant and positive relationship between total and fixed-rate mortgage loan growth and the use of interest rate swaps for US credit unions. Credit unions that use interest rate swaps experience roughly 0.5 percent points greater mortgage loan growth than credit unions that do not use them. However, I find a statistically insignificant relationship between variable-rate mortgage loan growth and use of interest rate swaps.

The positive correlation between interest rate swap use and mortgage loan growth is consistent with the notion that derivatives markets allow financial intermediaries to increase lending at a larger rate than without them. In particular, my results suggest that the use of interest rate swaps allows intermediaries the ability to hedge against the risk associated with making a loan with a fixed-rate return. However, it is also possible that other factors that specifically affect credit unions that would choose to use interest rate swaps that occur around the time that the rule change went into effect, thus introducing bias to my estimates. To account for this, I use a matching procedure to pair my treatment credit unions, those that use interest rate swaps, with select control credit unions, those that do not use interest rate swaps, that have similar financial characteristics to the treated group. My main results remain when I use a matched sample.

In general, my results suggest that mortgage lending of US credit unions that use interest rate swaps experience greater growth, particularly in fixed-rate loans, than credit unions that do not use swaps. Thus, regulations that restrict the use of interest rate swaps may result in decreased lending growth. Since fixed-rate mortgage loans are popular in the US, these regulations may have a profound effect on domestic housing markets.

3.2 Institutional background

Before describing my sample and empirical methodology, I explain the interest rate risk associated with fixed rate mortgages, and present vital institutional details regarding US credit unions and the NCUA's policy on financial derivatives, which is the basis of my identification strategy.

3.2.1 Risks associated with mortgage lending

In the US, the interest rate on a first mortgage real estate loans is typically set at a fixed- or variable-rate . A fixed-rate mortgage in the US is a mortgage with fixed nominal monthly payments over the term of the loan, typically 30 years. A variable-rate mortgage, also known as an adjustable rate mortgage, is a mortgage that involves a period of fixed-rate monthly payments that transitions to a floating-rate payment that is subject to change, typically in response to changes in interest rates. When a change occurs, the monthly payment is "adjusted" to reflect the new interest rate. Over the last few decades, U.S. borrowers have increasingly favored fixed-rate mortgages over variable-rate mortgages (Aragon et al., 2010). At the end of 2018, the market share for variable-rate mortgages was roughly four percent of all mortgages sold (Ellie Mae, 2018).

Interest rate risk is risk that arises when the absolute level of interest rates change. Fixed-income securities are particularly susceptible to interest rate risk. As a fixed-rate mortgage is a type of fixed-income security, it is significantly more susceptible to interest rate risk than a variable-rate mortgage. In addition, mortgage lenders are particularly susceptible, since lenders' short-term funding costs, such as deposits and short-term wholesale financing, are susceptible to interest rate changes. Mismatches in fixed revenue stream and floating short-term funding costs have serious implications for a lenders financial health, as holding a significant amount of fixed-rate mortgage in their portfolio will expose the lender to losses in a rising interest rate setting. This mismatch was a significant cause of US savings and loan failures during the early 1980s (White, 1991).

Another form of risk related to interest rates and mortgage loans is prepayment risk. Prepayment risk is the risk of borrowers refinancing mortgage loans when interest rates fall. Prepayment risk affects fixed-rate mortgage as mortgage borrowers with fixed-rates made prior to a decline in interest rates are more likely to refinance to a lower rate after a decline in interest rates. Unlike interest rate risk, the relationship between interest rates and prepayments is less direct as housing turnover and credit conditions also affect the intensity of prepayments. These combination of factors makes it intractable to hedge prepayment risk. Gabaix, Krishnamurthy, and Vigneron (2007) find evidence that holding nondiversifiable prepayment risk is expensive and requires a positive premium.

In an ideal world, with frictionless capital markets imagined in Modigliani and Miller (1958), mortgage lenders would be indifferent to holding these risks, as the value of an unhedged mortgage loan is equal to the value of a hedged mortgage loan. However, corporate finance research assets that bearing undiversified risk is costly due to the presence of financing frictions (e.g., Smith and Stulz (1985); and Froot et al. (1993)).

Mortgage lenders typically deal with interest rate risk in two ways. First, lenders can reduce interest rate risk from its portfolio by selling fixed-rate mortgages on the secondary mortgage market, typically to government sponsored entities (GSE) such as Federal Home Loan Mortgage Corporation (Freddie Mac) and the Federal National Mortgage Association (Fannie Mae), allowing lenders to reduce interest rate risk and expand fixed-rate mortgage lending in the market (Vickery and Fuster, 2014). However, a GSE will not purchase mortgage loans for single-family homes with values that exceed $484,350, or $726,525 for high-cost areas. Mortgage loans that exceed this value are known as “jumbo loans”. Lenders can only sell to non-agency buyers, which tend to be less liquid than GSEs, on secondary markets. When non-agency buyers are illiquid, mortgage lenders tend to make fewer fixed-rate jumbo loans, suggesting that mortgage lenders are reluctant to retain the prepayment and interest rate risk associated with fixed-rate mortgages (Vickery and Fuster, 2014).

Second, mortgage lenders can hedge against interest rate risk by obtaining interest rate derivatives, such as interest rate swaps. In terms of notional value, interest rate swaps hold the largest share in the global over-the-counter (OTC) market, representing roughly 52.4 percent in total notional value of all contracts sold in 2017 (BIS, 2017). An interest rate swap is an agreement between two parties to exchange a stream if interest payments without exchanging the underlying debt. In a vanilla interest rate swap, one party exchanges a fixed interest payment on a notional principle to another party for a floating interest payment, typically the LIBOR rate. The economic rationale for interest rate swaps is based on the principle of comparative advantage (Bicksler and Chen, 1986). In Diamond’s (1984) model of financial intermediation with risk aversion, diversification increases the intermediary’s risk tolerance toward each loan, allowing the risk bearing necessary for incentive purposes to be less costly. Hence, using Diamond’s approach, interest rate swaps reduce the cost associated with interest rate risk on holding fixed-rate mortgages, resulting in mortgage lenders having a greater tolerance for holding fixed-rate mortgages. In the banking literature, studies have found that financial institutions that use interest rate derivatives tend to experience greater overall loan growth than institutions that do not (e.g., Brewer et al. 1999; Brewer et al. 2014).

3.2.2 The US credit union industry

A credit union is a mutual organization that provides deposit, lending, and other services to a membership defined by an common bond. Profits are re-payed to members through reinvestment in the credit union, dividends, or lower interest rates on loans (Bauer, 2007). At the end of 2017, there were 5,573 credit unions in the US, with a membership base of 111.3 million and total asset size of $1.38 trillion, roughly 8.3 percent of total assets held by US commercial banks.

Credit unions offer financial products to members defined by a common bond. For credit unions, a common bond could be a shared employer, shared geography, or other organizational affiliation such as a religious institution. The original design of the common bond was to allow members to substitute their shared knowledge of each others' creditworthiness for collateral. Historically, this common bond status allowed credit unions to make low risk, and thus at a reduced interest rate, small-value, uncollateralized loans (Walter, 2006).

The creation of nationwide credit bureaus, which provides information on the creditworthiness of most borrowers, and the rise of credit card lending as well as loan products that allow borrowers to affordably use real estate collateral for small loans, such as a home equity line of credit (HELOC), led to a less important need for small value loans from credit unions. In the presence of new competition, credit unions were forced to change from their original structure. As a result the credit union industry transitioned to offering primarily small value loans, such as automobile loans, to mortgage and, to a lesser extent, toward commercial lending.

After passage of the Credit Union Membership Access Act of 1998, credit unions were allowed to constitute a membership base with multiple common bonds. This policy has facilitated the growth of the average asset size of credit unions through mergers and acquisitions. While the number of credit unions declined from 10,628 in 1999 to 5,573 in 2017, the average credit union size increased more than sixfold over this period, from $39 million in 1999 to $250 million in 2017.

Since the early 1990's, credit unions' market share of residential real estate loans has risen (Disalvo and Johnston, 2017). As credit unions' share of the mortgage market rises, mortgage loans became a greater share of their total loans, as the proportion of mortgage loans to assets grew from 25.3 percent at the end of 2000 to 40.7 percent at the end of 2017 (NCUA 2000, 2017). Similar to other US mortgage lenders, the average US credit union's mortgage portfolio is mostly composed of fixed-rate mortgages as they represented 71.3 percent of mortgage loans at the end of 2017 (NCUA, 2017).

As mentioned in the previous section, fixed rate mortgages present interest rate risk for mortgage lenders. Since interest rate sensitive non-core deposits make up a significant portion of credit unions deposit share — interest rate sensitive deposits such as money market shares, share certificates, and non-member deposits represented 38.2 percent of total credit union deposits at the end of 2017 — the mismatch between fixed income earning assets and variable priced liabilities exist in the credit union industry. When interest rates rise, credit unions' investments may suffer losses on their investments.

Figure 1 shows the total quarterly accumulated unrealized gains or losses on available for sale securities for the credit industry and the quarterly 30 month LIBOR rate from 2003 to 2013. When the LIBOR rate was relatively high from 2004 to 2008, credit unions experienced losses on their investments. Recently, the asset-liability mismatch has caused concern among US regulators.[1]

Traditionally, the primary method credit unions use to mitigate interest rate risk is to offload fixed-rate loans. Regulators often encouraged credit unions to remove mortgage loans from their balance sheet.[2] As long-term interest rates plummeted in 2009 and again in 2011, credit unions found it increasingly important to sell fixed-rate mortgages to avoid locking in low earning assets for the long term. As a result, the share of loans sold almost doubled, to an average of 52 percent from 2009 to 2012, and as much as 58 percent in the first quarter of 2013 (United States. Cong. Senate. Committee on Banking, Housing and Urban Affairs, 2013). Figure 2 shows the relationship of credit unions' sales of secondary mortgages

[1]"Interest rates have recently started to rise. A rapid rise would rock the foundation of many credit unions' balance sheets. Thousands of credit unions would earn realize negative earning." Debbie Matz, former NCUA chairman (2013)

[2]"Real estate loans have come to comprise large parts of credit union balance sheets. Our concern is that as you put more fixed-rate assets on the books, it raises the bar on risk management." John Worth, former Chief Economist of the NCUA (2015)

and interest rates. From 2004 to 2008, credit unions sold a smaller proportion of their new mortgage loans than in the period of low interest rates, from 2008 to 2012, suggesting that credit unions are less willing to hold on to assets with fixed low rates.

On March 3, 2014, the NCUA Boards final derivatives rule went into effect and allowed federal credit unions to apply to use derivatives to reduce interest rate risk. Under the regulation, federal credit unions with assets of at least $250 million and a composite CAMEL rating of 1, 2, or 3 were allowed to apply to use derivatives. Approved federal credit unions have limited authority to invest in simple interest rate derivatives for balance sheet management and risk reduction, including interest rate swaps, interest rate caps, interest rate floors, basis swaps, and Treasury futures. At the end of 2017, 18 federally insured credit unions held interest rate swaps with a total notional value of $3.6 billion, representing roughly 40 percent of all derivatives held by US credit unions (NCUA, 2017).

3.3 Methodology

There are three major issues to consider when isolating and studying the causal effect of interest rate swap usage on lending decisions. First, an event that induces credit unions to use interest rate swaps to expand mortgage lending must be identified. Second, operational differences across credit unions must be controlled for. Third, differences in portfolio choice between credit unions that use and do not use interest rate swaps must be accounted for so that the causal effect of swap usage on lending decisions can be distinguished from other differences between these two types of credit unions.

The usage of interest rate swaps may be related to organizational factors that are correlated to lending decisions. Purnanandam (2007) finds that commercial banks with higher probability of financial distress manage their interest rate risk more aggressively with off-balance instruments. Credit unions that engage in significant mortgage lending may use interest rate swaps to avoid insolvency rather than to grow their lending activity. Hence, the endogeneity between the use of interest rate swaps and lending decisions may result in biased OLS estimators from a model of financial intermediation.

To identify the effect of interest rate swap use on loan growth, econometrician use an instrumental variables approach, where balance sheet items instrument for the propensity to use interest rate swaps. For example, Brewer et al. (2000) uses the log of bank assets, net-interest margin, a binary variable indicating whether the bank was a derivatives dealer, the capital-to-asset ratio, and the concentration ratio for each bank's primary market area as instrumental variables. The issue of this approach is that these variables likely directly, and not indirectly through use of interest rate swaps, influence lending decisions, thus violating the exclusion restriction.

Prior to March 3, 2014, US credit unions were not allowed access or usage of interest rate derivatives. During this time, credit unions that held significant amounts of mortgage loans in their portfolio may have desired access to interest rate swaps, but were not permitted access by the regulation of the time. Also, credit unions may have desired access to interest rate swaps in order to expand mortgage lending without incurring additional interest rate risk. In either case, the variation in the use of interest rate swaps before and after the rule change comes from the rule change itself. Hence, I can compare credit unions that use interest rate swaps with credit unions that do not and credit unions that were prevented from using them prior to the rule change. In other words, I can use the rule change to examine a treatment group (credit unions that use interest rate swaps) and a control group (credit unions that do not use interest rate swaps) in a difference-in-differences context.

In addition, I use a panel dataset of US credit unions from 2010 to 2017. By using a panel dataset, I can include firm and time fixed effects in the main specification. Firm fixed effects prevents assigning a false significance to a time-invariant credit union-specific factor, such as use of interest rate or asset size, due to an omitted variable. The time dimension also allows for the control of credit union-wide factors, such as macroeconomic factors, that change over time.

Difference-in-differences methods provide unbiased effect estimates if the trend over time would have been constant between the treatment and control groups in the absence of the policy. However, a concern with difference-in-differences models is that the treatment and control groups may contrast in way that would affect their trends over time. Credit unions that chose to use interest rate swaps after the policy change may have fundamental differences with those that do not. Other policies and market trends that occurred after the policy change may impact credit unions that use interest rate swaps differently than those that do not, violating the constant trend assumption.

Propensity score methods are typically used to deal with this type of confounding in difference-in-differences studies. Propensity score matching works by linking treatment to control observation with the same observed characteristics. Ideally, the only difference between the matching observations is the treatment status. Hence, I conduct a semi-parametric matching procedure developed by Ho et al. (2007) to match treatment and control credit unions by their balance sheet characteristics from Q1 2011.

3.4 Sample description and data source

The sample of credit unions includes NCUA-insured credit unions with total assets greater than $250 million. Of these entities, I remove credit unions that do not hold real estate loans. My sample starts with 721 credit unions in January 2011 and ends with 834 in December 2017. To avoid any possible selection bias, I include all credit unions with assets greater than $250 million that merged or were acquired from 2011 to 2017 in the sample. Balance sheet and off-balance sheet data come from the NCUA's Call Report Quarterly Data. I define mortgage loans to be all first mortgage real estate loans held on a credit unions balance sheet at the end of a given quarter.

Figure 3 shows the total notional value of interest rate swaps held by US credit unions and the total number of credit unions that use interest rate swaps from 2013 to 2017. Note that eight credit unions immediately began using interest rate swaps in Q4 2013 after the NCUA amended it's derivative policy.

Table 1 presents sample statistics for selected balance sheet items at the end of

2017. Selected balance sheet items include book value of assets, total mortgage loan growth, fixed rate mortgage loan growth, variable rate mortgage loan growth, the ratio of real estate loans to total assets, the ratio of deposits to assets, non-performing mortgage loans to assets, and the capital asset ratio. Growth variables are the difference between current and previous quarter book value of a type of loan on a credit unions balance sheet normalized by the previous quarter's total assets. The capital asset ratio, also known as the net worth ratio in the credit union industry, is the ratio of regular reserves and undivided earnings to total assets. Federal regulation stipulates that a credit union with a 6 percent net worth ratio is "adequately" capitalized.

Table 1 reveals some interesting differences between credit unions that use and do not use interest rate swaps. In terms of the book value of assets, credit unions that use interest rates swaps are about twelve times as large as credit unions that do not. These differences are statistically significant at the 10 percent level.

A similar pattern exists with regard to the ratio of real estate loans to total assets. The ratio of real estate loans to total assets for credit unions that use interest rate swaps are roughly twenty percentage points greater than those that do not. These differences are statistically significant at the 5 percent level. Discovering that credit unions that use interest rate swaps hold proportionally more real estate loans is an unsurprising result. Since mortgage loans hold more interest rate risk than consumer loans, such as automobile loans, it is reasonable to find that credit unions that hold interest rate swaps hold relatively more mortgage loans on average. However, it is still unclear if holding interest rate swaps motivates credit unions to make relatively more mortgage loans, as credit unions that hold more mortgage loans may prefer to use interest rate swaps to mitigate their interest rate risk.

There is no statistically significant differences between the capital asset ratio and the non-performing mortgage loans to assets ratio held be credit unions that use and do not use interest rate swaps.

Figure 4 shows fixed-rate mortgage loan growth from 2011 to 2017 for credit unions that use and do not use interest rate swaps. The graph demonstrates that after the rule change went into effect, credit unions that use interest rate swaps experienced greater growth in fixed-rate mortgages than credit unions that do not. Figure 5 shows growth in variable-rate mortgage loans from 2011 to 2017. The graph reveals no discernible difference in variable-rate mortgage loan growth between credit unions that use and do not use interest rate swaps.

3.5 Regression analysis

As mentioned in the methodology section, the analysis compares changes in mortgage lending decisions of credit unions that use and do not use interest rate swaps after the NCUA changed it's derivative policy on March 3rd, 2013.

One characteristics that complicates the econometrics of the analysis is that mortgage loans in a given quarter will impact the credit union-specific factors of future quarters. In other words, the dependent variable for a given quarter will be correlated with the credit union-specific control variables for future quarters. For example, loans are entered on balance sheets as part of bank assets, the typical measure of credit union size. Thus, when credit union size is controlled for by credit union assets, this measure includes loans that were issued in previous quarter but had a maturity beyond a year. Furthermore, credit unions are likely to adjust their current lending behavior conditional on their past funding levels. To account for the correlation of previous quarter's financial characteristics on current quarter's lending decisions, I assume the model for mortgage lending behavior by credit unions i in time t is

$$y_{it} = \boldsymbol{\beta x_{it-1}} + \lambda_1 PostRuleChange \times UsesInterestRateSwaps + \theta_t + \alpha_i + \epsilon_{it} \tag{3.1}$$

.

Where y_{it} is the change in mortgage loans relative to the previous quarters assets; x_{it-1} is a vector of financial characteristics; $PostRuleChange$ is a dummy variable that takes the value of one if the time is after the NCUA rule change; $UsesInterestRateSwaps$ is a dummy variable that takes the value of one if the credit union uses interest rate swaps; θ_t is a time fixed effect; α_i is a credit union fixed effect; and ϵ_{it} is an idiosyncratic error term assumed to be drawn from the normal distribution.

The standard errors are corrected for clustering at the credit union level to prevent possible bias in the standard errors while giving errors robust to credit union-level autocorrelation.

Primary regressions use the unmatched sample, which tracks all credit unions that hold assets with book value greater than $250 million from 2011 to 2017 or until their exit from the sample, and are shown in Table 2. All dependent variables are a credit union's difference in loans made in the current and previous quarter normalized by the previous quarter's assets. In Table 2, the first dependent variable located in the second column is all mortgage loans, the third column is fixed-rate mortgage loans, and the third column is variable-rate mortgage loans.

All the regressions include as explanatory variables the natural log of asset size in USD, the natural log of asset size in USD squared, the ratio of mortgage loans to assets, the ratio of deposits to assets, the ratio of non-performing mortgage loans to assets, and the capital asset ratio. These variables are from the previous quarter and assumed to be sequentially exogenous. Other variables are assumed to be exogenous and are as of the current quarter.

For the second column, the coefficient for the effect of interest rate swap use on all mortgage loan growth is positive and statistically significant; on average credit unions that use swaps experience roughly 0.4 percentage points greater mortgage loan growth than credit unions that do not use them. This result if the first confirmation that use of interest rate swaps leads to greater loan growth.

Statistically significant covariates in column 2 include the ratio of mortgage loans to assets, the ratio of non-performing mortgage loans to asset, and the capital asset ratio. Note that the impact of the capital asset ratio and deposits to assets on lending growth is positive and the effect of the ratio of mortgage loans to assets and the ratio of non-performing loans to assets is negative. These estimates indicate that credit unions in better financial condition have larger mortgage loan growth and that credit unions that hold significant mortgage loans on their balance sheet tend to have less significant growth in mortgage lending.

Estimates shown in the third column reveal that the use of interest rate swaps has a positive and statistically significant effect on the growth of fixed-rate mortgage loans. This estimate is slightly larger and more statistically significant than for all mortgage loans. Estimates shown in the fourth column reveal that the effect of use of interest rate swaps on variable-rate mortgage loan growth is statistically insignificant. As expected, the results demonstrate that interest rate swaps have a detectable impact on fixed-loan mortgage loan growth, but not on variable-loan growth, consistent with the notion that interest rate swaps encourage financial institutions to make more fixed-rate loans by reducing interest rate risk on assets with fixed-rate returns.

Using the matching procedure discussed earlier, I match treatment and control credit unions based on asset size, the ratio of mortgage loans to assets, the ratio of deposits to assets, the ratio of non-performing mortgage loans to assets, and the capital asset ratio one quarter prior to the policy change, in Q1 2014. Table 3 shows the summary statistics for the matched treatment and control credit unions. Notice that the difference in means of the financial characteristics are now statistically insignificant.

Table 4 displays the estimates of the parameters of the loan growth model using credit unions belonging to the matched sample from 2011 to 2017. Similar to the previous estimates from Table 2, the effect of using interest rate swaps on total mortgage loan and fixed-rate loan growth is positive and statistically significant, with similar magnitudes.

3.6 Conclusion

This paper provides empirical evidence about the influence of interest rate swaps on mortgage lending decisions by US credit unions. The paper focuses on the differences in lending decisions across fixed-rate and variable-rate loans. By comparing the different effects of interest rate swaps on mortgage loans with different rate structure, the analysis isolates the impact of swaps on assets with fixed and variable-rate returns. In addition, I exploit a policy change in the US credit union industry that impacts the use of interest rate swaps to identify the effect of swap usage on lending decisions. The results show that after a credit unions starts using interest rate swaps after the policy change, it's fixed-rate mortgage loan growth increases without a change in variable-rate growth. In total, the use of interest rate swaps leads to more total mortgage lending growth by a credit union. Furthermore, these results are robust after estimating the model with matching treatment and control credit unions.

As found in Brewer et al. (2000), I find that the use of interest rate swaps leads to greater loan growth, consistent with Diamond's (1984) theoretical prediction that hedging allows financial institutions to focus on their role as delegated monitors. My results suggest that policies that interfere or reduce financial institutions' access to interest rate swaps will reduce growth in fixed-rate loans. Given the popularity of fixed-rate mortgages in the United States, these policies may have significant impacts on the US housing market.

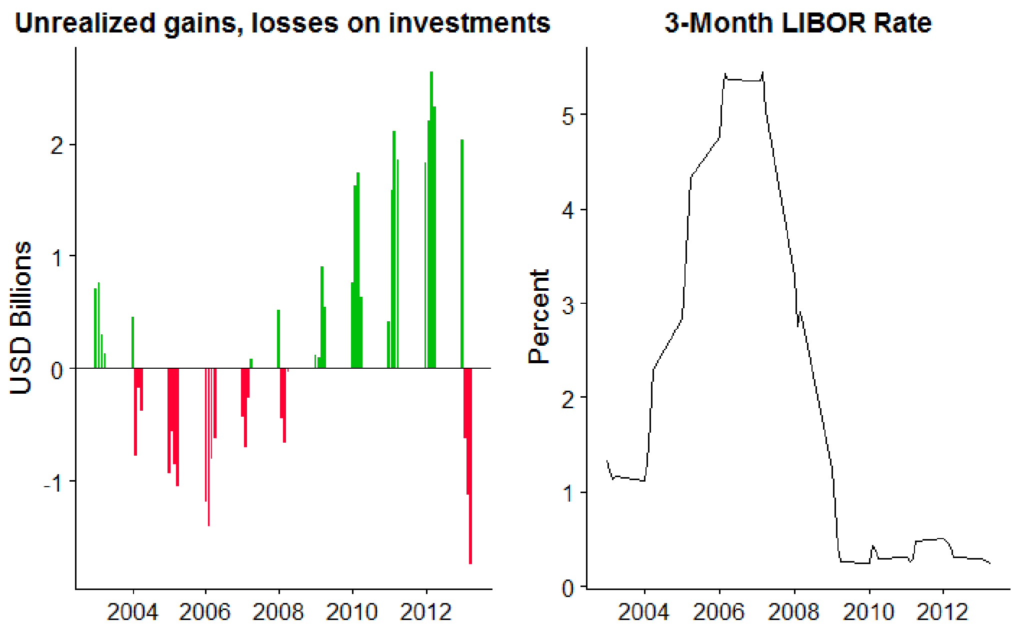


Figure 3.1: The quarterly return on credit unions' investments and interest rates from Q1 2003 to Q4 2013

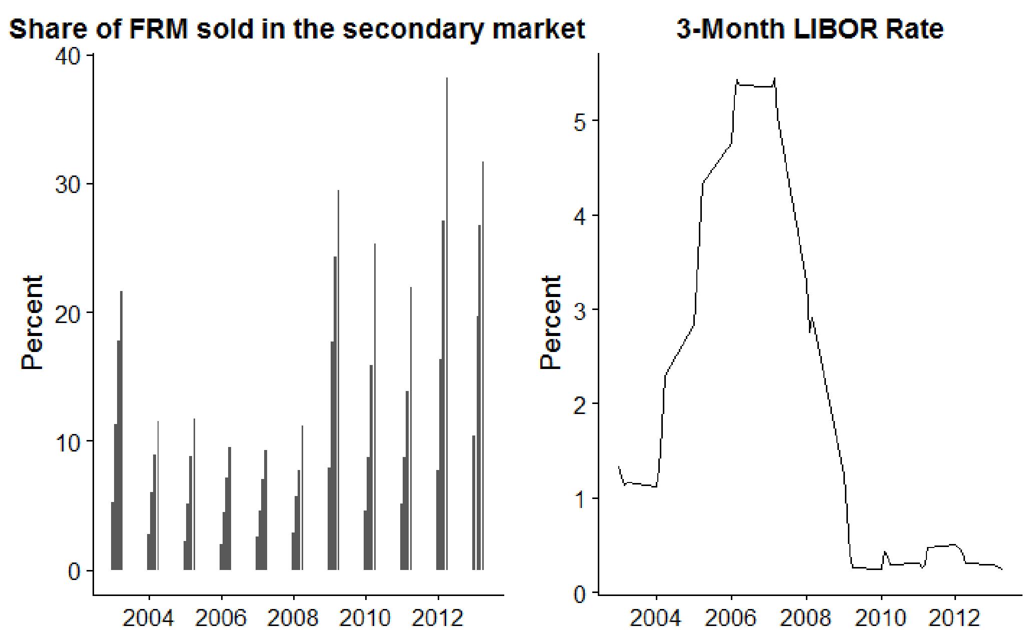


Figure 3.2: The share of all first mortgage loans which have been sold in the secondary market to all mortgages made year-to-date from Q1 2003 to Q4 2013

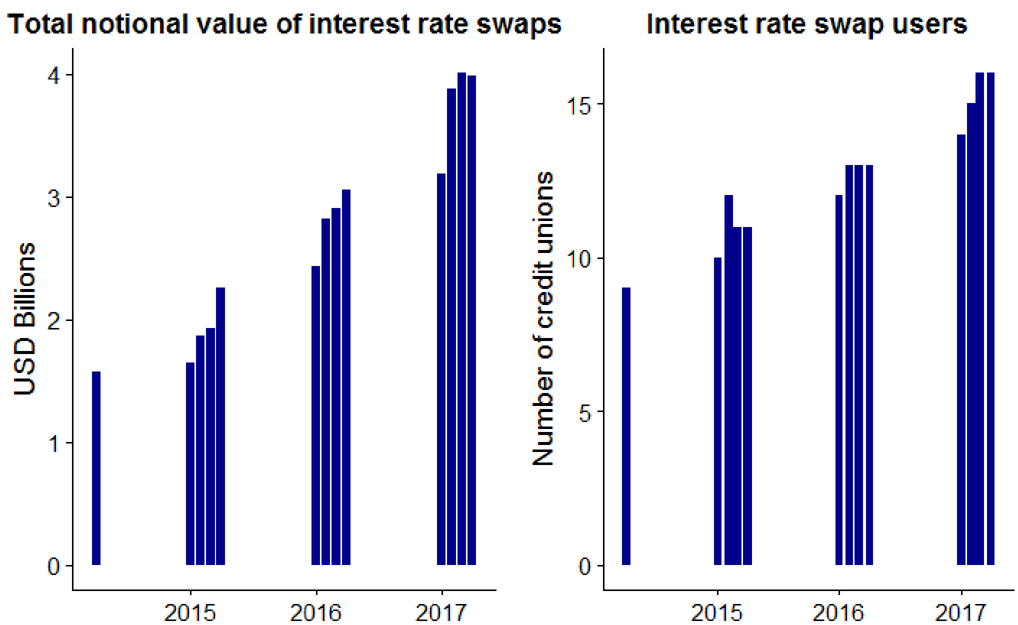


Figure 3.3: Total notional value of interest rate swaps and total number of interest rate swap users in the US credit union industry from Q4 2014 to Q4 2017

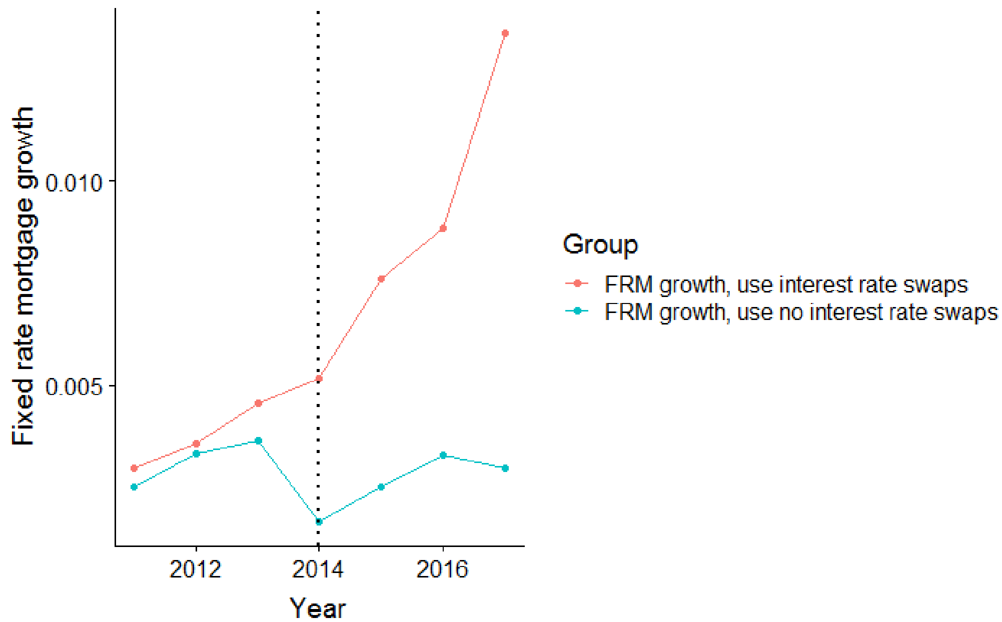


Figure 3.4: Fixed-rate mortgage loan growth for US credit unions from 2011 to 2017

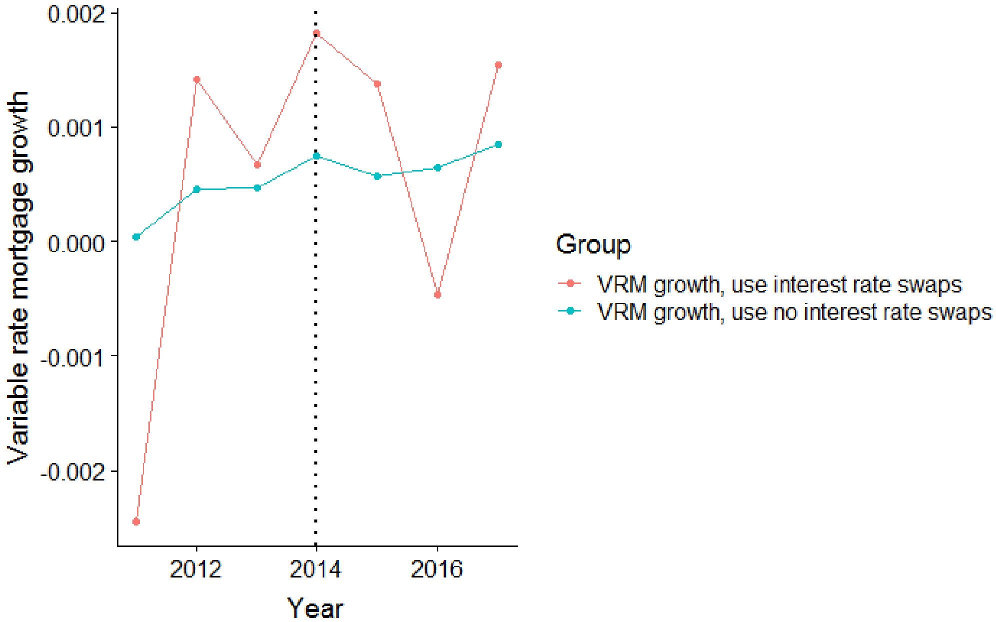


Figure 3.5: Variable-rate mortgage loan growth for US credit unions from 2011 to 2017

Table 3.1: Sample statistics for credit unions with asset sizes greater than \$250 million (Q4 2017)

		Uses Interest Rate Swaps	Control
	n	15	819
Asset size (in $B)	mean	12.2	1.15
	sd	22.7	1.85
	max	90.6	3.73
	min	0.6	0.2
Total mortgage growth	mean	0.021	0.005
	sd	0.041	0.011
	max	0.160	0.083
	min	−0.017	−0.059
Fixed-rate mortgage growth	mean	0.017	0.003
	sd	0.039	0.008
	max	0.157	0.078
	min	−0.011	−0.048
Variable-rate mortgage growth	mean	0.002	0.001
	sd	0.011	0.010
	max	0.038	0.131
	min	−0.011	−0.206
Mortgage loans / assets	mean	0.411	0.265
	sd	0.127	0.128
	max	0.712	0.699
	min	0.057	0.000
Deposits / assets	mean	0.818	0.856
	sd	0.059	0.049
	max	0.881	0.985
	min	0.679	0.533
Non-performing real estate loans / assets	mean	0.006	0.006
	sd	0.006	0.008
	max	0.023	0.127
	min	0.000	0.000
Capital asset ratio	mean	0.086	0.099
	sd	0.028	0.032
	max	0.117	0.389
	min	0.005	−0.051

Table 3.2: Regression results on the determinants of quarterly changes to mortgage lending relative to last quarter's total assets

Dependent variable	(All mortgage loans)	(Fixed-rate loans)	(Variable-rate loans)
PostRuleChange×UsesInterestRateSwaps	0.004^{*}	0.006^{***}	0.000
	(0.002)	(0.002)	(0.001)
Asset size $(\log)_{t-1}$	0.021	0.060	0.009
	(0.043)	(0.043)	(0.011)
Asset size squared $(\log)_{t-1}$	−0.000	−0.001	−0.000
	(0.001)	(0.001)	(0.000)
Mortgage loans / assets_{t-1}	-0.050^{***}	-0.036^{***}	-0.008^{***}
	(0.013)	(0.013)	(0.002)
Deposits / assets_{t-1}	0.040^{***}	0.028^{**}	0.002
	(0.013)	(0.013)	(0.004)
Non-performing mortgage loans / assets_{t-1}	-0.075^{***}	−0.027	-0.011^{**}
	(0.022)	(0.022)	(0.005
Capital asset ratio_{t-1}	0.126^{***}	0.069	0.014^{**}
	(0.045)	(0.045)	(0.007)
Time fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
N	21,858	21,858	21,858
R^2	0.017	0.016	0.003

Standard errors in parentheses. Two-tailed test.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3: Balancing Effect of the Matching Approach for Interest-Rate Swap Users

		Uses Interest Rate Swaps	Control
	n	15	15
Asset Size (log)$_{t-1}$	mean	22.2	21.8
	sd	0.98	1.2
Mortgage loans / assets$_{t-1}$	mean	0.337	0.361
	sd	0.166	0.142
Deposits / assets$_{t-1}$	mean	0.801	0.801
	sd	0.084	0.123
Non-performing mortgage loans / assets$_{t-1}$	mean	0.016	0.019
	sd	0.019	0.020
Capital asset ratio$_{t-1}$	mean	0.091	0.104
	sd	0.037	0.091

Table 3.4: Regression results on the determinants of quarterly changes to mortgage lending relative to last quarter's total assets

Dependent variable	(All mortgage loans)	(Fixed-rate loans)	(Variable-rate loans)
PostRuleChange × UsesInterestRateSwaps	0.004**	0.005***	0.001
	(0.002)	(0.002)	(0.002)
Asset size (log)$_{t-1}$	0.131**	0.261***	0.058
	(0.027)	(0.050)	(0.047)
Asset size squared (log)$_{t-1}$	−0.002*	−0.006***	−0.001
	(0.001)	(0.001)	(0.001)
Mortgage loans / assets$_{t-1}$	−0.024	−0.011	−0.008
	(0.017)	(0.013)	(0.012)
Deposits / assets$_{t-1}$	0.028	0.087***	−0.054
	(0.027)	(0.021)	(0.020)
Non-performing mortgage loans / assets$_{t-1}$	−0.122***	−0.068**	−0.008
	(0.042)	(0.033)	(0.031)
Capital asset ratio$_{t-1}$	0.151*	0.099	0.034
	(0.086)	(0.065)	(0.063)
Time fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
N	981	981	981
R^2	0.039	0.081	0.013

Standard errors in parentheses. Two-tailed test.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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