Essays on competition, regulation and innovation in the banking industry

Capera Romero, Laura

Publication date:
2020

Document Version
Publisher's PDF, also known as Version of record

Essays on Competition, Regulation and Innovation in the Banking Industry

Laura Capera Romero

December, 2020

Essays on Competition, Regulation, and Innovation in the Banking Industry

Proefschrift ter verkrijging van de graad van doctor aan Tilburg University, op gezag van de rector magnificus, prof. dr. W.B.H.J. van de Donk, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de Portrettenzaal van de Universiteit op maandag 7 december 2020 om 13.30 uur

door

Laura Marcela Capera Romero

geboren te Bogota, Colombia

PROMOTORES: prof. dr. J.H. Abbring
prof. dr. T.J. Klein

LEDEN PROMOTIECOMMISSIE: prof. dr. J. Boone
prof. dr. A. Gavazza
prof. dr. N. van Horen
dr. N. Pavanini

Acknowledgements

Undertaking this Ph.D. has been a life-changing experience for me, and it would not have been possible without the support and generous help of many people and institutions who I wish to acknowledge sincerely.

I would first like to I would like to acknowledge my indebtedness and express my deepest gratitude to my supervisors, prof. dr. Jaap Abbring and prof. dr.Tobias Klein, for giving me the fantastic opportunity to complete my Ph.D. thesis under their supervision, it has been truly an honor. I could never give them enough credit for their enormous contribution to my growth as a researcher. I was lucky to receive feedback from such brilliant mentors and always find a lot of humor and warm encouragement in each of our meetings. I am sincerely grateful for all their invaluable advice, ideas, moral support, and patience in guiding me through this dissertation's development. By following their guidance and example, I have learned to conduct quality research.

Jaap, your insightful feedback pushed me to sharpen my thinking and brought my work to a higher level. Your attention to detail and enlightening comments allowed me to identify and solve countless identification issues, improve my modeling and writing skills. After our meetings, I always left the office with a completely fresh perspective and a concrete plan of action when I was struggling. Special thanks for helping navigate through the challenges of the job market. During this critical time, your decisive support and timely advice allowed me to improve my research and gain the confidence to find a job in academia.

Tobias, your positive and pragmatic attitude allowed me to look to my research through an optimistic lens, even in the most challenging times of writing this thesis. Thank you for all our brainstorming meetings. They helped me find solutions when I got stuck and were the source of many of the ideas developed in these pages. Your untiring curiosity inspired me to develop new research interests and find connections

between my research and other fields. I also learned a great deal from you as a lecturer during my Research Master years and later as a teaching assistant. I always admired how you used each lecture, assignment, or exam to inspire and encourage students to think critically and stay curious. These lessons will accompany me on my own journey as a lecturer.

I would also like to express my gratitude to Dr. Nicola Pavanini for all his generous support during my Ph.D. journey. Nicola, your feedback allowed me to improve substantially the work presented in this dissertation and offered me a detailed perspective of the challenges and advantages of developing structural models applied to banking and financial intermediation. Our conversations shaped my research interests and helped me enormously during the job market. Thank you for offering me such thoughtful feedback and helpful advice during my time in Tilburg.

I wish to express my sincere gratitude to the other outstanding committee members who have assessed and approved this dissertation. Prof. Alessandro Gavazza, Prof. Neeltje van Horen and Prof. Jan Boone: thank you for sharing your knowledge and expertise and for letting my defense be an enjoyable moment. Your thoughtful feedback allowed me to improve significantly many specific parts of the dissertation that required further discussion and helped me articulate the chapters into a more cohesive research agenda.

I would also like to thank the Structural Econometrics Group -SEG- participants for the inspiring research discussions during the last four years. The innovative applications of structural econometrics to industrial organization, marketing, and health economics presented by its members were a constant source of inspiration for my own work and pushed me to broaden my interests. I benefited greatly from the thoughtful and constructive feedback provided by Prof. Bart Bronnenberg, Prof. Jeff Campbell, Dr. Martin Salm, and all other participants. Discussions on a wider range of research topics with Ittai Shacham, Suraj Upadhyay, Maciej Husiatyński, Ana Moura, Lei Lei, Marie Le Mouel, Mingjia Xie, Madina Kurmangaliyeva, and Renata Rabovic were always stimulating and inspiring.

I want to pay my special regards to Prof. Pavel Cizek, who was my education coordinator during my time as a Ph.D. student. His helpful advice allowed me to organize my work and set realistic goals. I would also like to recognize the invaluable help of dr. Bettina Siflinger, dr. Jochem de Bresser, dr. Nikolaus Schweizer and Prof. Arthur van Soest on the job market preparation. Their timely and helpful advice allowed me to improve my research, gain confidence in my abilities, and decide on

my future career path. Special thanks to dr. Patricio Dalton for his generous career advice during this critical time. It was also great to work with him as a student coordinator in the ENTER initiative. His compromise and enthusiasm were truly inspiring.

To dr. Marieke Quant: special thanks for your guidance and patience during the time I worked with you as a teaching assistant. Your exceptional skills in explaining mathematical concepts and engaging big audiences were an inspiration for me and helped me improve my own teaching style. I also learned a great deal from your superb organizational skills.

I am immensely grateful to Cecile de Bruijn for her efficient assistance in handling tons of applications during the job market and to Korine Bor for her timely and considerate help with several administrative tasks. Their kind assistance allowed me to participate in multiple academic events during my time as a Ph.D. I also want to recognize the excellent support of the secretaries of the EOR Department: Anja Heijeriks, Anja Manders-Struijs, Monique Mauer, and Heidi van Veen. To Aislinn Callahan-Brandt, Ank Habraken, and Corine Struis, thank you for always offering a smile and a helping hand.

During my Ph.D. I was fortunate to participate in the Graduate Student Association (GSS) Board. Thank you to all members for making life more enjoyable for all TiSEM Ph.D. students. Special thanks to Joris Berns: your leadership and hard work truly made a difference. To Daniel Karpati: it was a pleasure to organize the GSS Seminar Series with you. Thank you for all your patience and compromise, especially when I was too busy with the job market preparation.

I have been fortunate to come across many good friends who made my time in the Netherlands a marvelous and unforgettable experience. Dorothee, Mirthe, Oliver, Thijs, Sophie, and Aaron: thank you for all the enjoyable lunches and non-mandatory dinners. Your presence brightened many grey and cloudy days and brought me a lot of fun and relief in times when all I wanted was to throw my computer through the window. Oliver, I'll be thrilled to visit you and Maria in Brussels. In the meantime, I'll try to remember to take the stairs more often! Doro, I'm glad to count you among my lifelong friends. Your friendship has been a real blessing. I'm looking forward to sharing many Colombian recipes whenever we meet again in Amsterdam or in Brussels.

To my lovely office mates, Yi, Liz, and Rafael: it was a pleasure to share this journey with you. Yi, your hard work was always an inspiration. Thank you for all our entertaining and inspiring conversations and your cartoons. Liz, your attention to detail saved me countless times when I was trying to debug my code or dealing with my sloppy writing style. Thank you for all your kind advice; I hope we can find opportunities to meet soon. Rafael, you have my gratitude for all your great talks, comments,suggestions and your generous supply of chocolates (also for never complaining about having stolen your place near the window). I also want to extend my sincere appreciation to Lenka, Clemmens, Sebastian, Ricardo, Hanan, Manuel, Gulbike, Manwei, and other TiSEM colleagues with whom I had the pleasure to share enjoyable conversations.

Sara Osma, Catalina Velasquez, and Bibiana Martinez Camelo, I learned a lot from you, brave girls! The library was never the same without you. I'll always treasure our memories of our trips and look forward to meeting you back in Bogotá. Carlos Sandoval, thank you for all the karaoke nights, our long Messenger conversations, your great comments and suggestions on my research, and overall, for being a trustworthy and caring friend. Giovanni Castro, I'm so happy you are staying here in the Netherlands. I hope we find many occasions to meet and laugh together. To the other Colombians in Tilburg: Victor Gonzalez, Mauricio Rodriguez, Anderson Grajales, and Richard Jaimes: thank you for making me feel closer to home.

Now it is my time to thank all the people in Colombia who made this journey possible. First, I owe my deepest gratitude to Banco de la República for the generous support that allowed me to come to the Netherlands to pursue my training as a researcher. I commend their determination to contribute to the development of my beloved country through their scholarship program. I commit to continuing to put all my effort in developing relevant research that can be used to design more effective public policies in Colombia and elsewhere.

I am deeply grateful to Dairo Estrada for his unwavering support during the last ten years. Thanks for believing in me and giving me advice and countless opportunities to grow as a researcher. Your unwavering determination to improve the rural access to credit in Colombia has served as an inspiration for my research. I look forward to finding new opportunities to work together in the future. Special thanks to Esteban Gómez, Miguel Angel Morales, Nancy Zamudio, Mariana Laverde, Santiago Caicedo, Wilmar Cabrera, Juan Sebastián Lemus, Andrés Murcia, and the rest of the Financial Stability Department -DEFI- crew. I learned a lot from all of you, and I will be forever grateful for the phenomenal time we spent together.

I finish with my family in Colombia and my boyfriend. I could not have completed

this journey without their unconditional love and support; this recognition feels only right in Spanish...

Santiago, muchas gracias por todo tu cariño y tu compañía en estos años que hemos compartido juntos. Ha sido un placer y un privilegio enfrentar contigo todos los retos de nuestro viaje de doctorado. Soy muy afortunada de contar con el mejor confidente, el crítico más honesto, y el más incondicional de los amigos. Tu inagotable fe en mis capacidades y tu paciencia para lidiar con mis crisis existenciales han sido indispensables en este viaje.

Y por último, muchas GRACIAS a mi familia, por todo el apoyo incondicional que me han dado durante todos estos años. Papi, mami, peque, esta disertación es de ustedes. Es el fruto de todos los esfuerzos que han puesto en mi formación desde que era una niña. Gracias por enseñarme ser independiente y nunca rendirme, por darme la confianza para alcanzar mis sueños. Estos años han sido largos y han significado grandes esfuerzos, pero su paciencia, su buen humor, su comprensión y sus palabras de aliento siguen siendo la razón por la que me levanto a emprender nuevos retos y aventuras todos los días. Estoy segura de que en el nuevo capítulo encontraremos muchas más ocasiones para estar juntos.

Laura Capera Romero
September, 2020.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

The banking industry has experienced an upsurge of new business models and technological developments that have enhanced the use of alternative sources of information to determine borrowers' creditworthiness and reduced the cost of provisioning financial services in remote geographic locations. At the same time, policymakers have introduced regulatory changes intended to incentivize financial institutions to increase credit access in under-served areas while protecting consumers from predatory practices. Facilitating access to affordable credit has become a worldwide policy in recent decades, motivated by the premise that access to flexible and affordable funding allows individuals to develop productive projects and support the accumulation of productive assets and human capital, providing protection against unexpected shocks, and leading to an improvement in their socio-economic conditions.[1]

These developments have made it possible for large segments of the previously under-served population to gain access to formal credit alternatives. Yet the effects of public and private initiatives intended to promote financial inclusion differ substantially across locations and groups of consumers. This dissertation examines how the differences in the competitive response of incumbent lenders can contribute to explain these disparities, and proposes counterfactual exercises to illustrate how taking them into account can improve the efficiency of some widely used policy interventions.

Chapters 2 and 3 of this dissertation focus on the microfinance industry. Mi-

[1] Cull et al. (2013), Beck et al. (2007) and Donou-Adonsou and Sylwester (2017) present extensive reviews on the evolution of financial inclusion in recent years and its impact on development outcomes and economic growth.

crofinance institutions have differentiated from traditional banks by implementing alternative screening and monitoring methods that allow them to determine the creditworthiness of potential borrowers, typically small entrepreneurs with no collateral or permanent source of income who do not have access to financial services offered by traditional banks. These innovations have allowed them to scale up their operations, transforming from small non-profit organizations into large supervised financial institutions that compete with mainstream banks to attract both clients and investors. In the second chapter of this dissertation I examine how these changes in the competitive interaction between these types of loan providers have important implications for the design of policies intended to facilitate financial access in isolated rural areas in Colombia.

In the last decades, the portfolio of financial services available for lower-income borrowers has broadened substantially as a result of technological innovation and strategic policy support. The design of a regulatory framework that promotes credit access while protecting individuals from the excessive market power of financial institutions requires a detailed understanding of the firms' competitive environment. It is a challenging task, given the simultaneous interactions of different types of loan providers across multiple market segments, the varied sources of product differentiation that they can exploit, and the information asymmetries that are typical of the banking industry. In this context, regulatory measures that are perceived as similar at a glance can lead to very different results. For example, Cuesta and Sepulveda (2019) find that tightening the limits on the interest rates charged for consumer loans in Chile reduces lending significantly, as loan providers cannot transfer to the borrowers the operational costs associated with the provision of this services, while Agarwal et al. (2014) and Galenianos and Gavazza (2019) find that the introduction of regulatory limits on credit card fees in the United States can generate important savings for borrowers without substantial reduction in the volume of credit. I find in Chapter 3 that the resulting balance between higher economic costs and improved credit access that followed a relaxation of interest rate limits applied to microloans in Colombia differed significantly across geographic markets.

A crucial element of the analysis presented in Chapters 2 and 3 is the existence of barriers that make it difficult for consumers in different locations to access the complete set of credit alternatives offered by all the financial institutions that operate in the country. In the context studied in these chapters, consumers can only choose among the financial institutions that administer a branch in their vicinity. Most of the potential clients are located in remote or underdeveloped areas with limited access to the internet and have informal occupations, which makes it difficult for financial institutions to obtain information about their payment behavior from conventional sources. Loan providers need to rely on the direct interaction with loan officers to collect information about the payment behavior of potential borrowers and monitor the performance of productive projects that have received funding. In consequence, the decisions of loan providers regarding their offices' location have a significant impact on the local availability of credit and the optimal pricing strategies implemented by financial institutions. Furthermore, the analysis proposed in these chapters recognize that even in urban or higher-income areas some segments of consumers may be prevented from accessing credit provided by local lenders due of regulatory barriers, inattention, lack of financial literacy or high search costs.

More recently, technological innovation has disrupted the banking industry even further with the development of cloud computing, internet application programming interfaces (APIs) and blockchain technology, increasing both the set of information available and the capacity of processing tools relevant in the provision of financial services, from loans to payment and transaction services (Vives, 2019). The broader availability of reliable internet, smartphones and mobile networks has led to the development of technological platforms that reduced the need for 'face to face' interaction between loan officers and customers. While this technology is still not widely used in the loan market in many developing countries, financial institutions in higher-income countries have reduced the role of traditional branches in the provision of other financial services, such as mortgages and consumer loans, with substantial effects on their pricing and geographical diversification strategies. With the introduction of mobile payment systems and online platforms, financial institutions have streamlined their branching networks, closing their offices in the least profitable locations and rethought the type of services that required physical interaction with clients. The fourth chapter of this dissertation explores some of these changes by studying the response of different kinds of incumbent lenders to the arrival of platform-based online lenders in the mortgage industry in the United States.

Across the different chapters of this dissertation, I use structural demand and supply models, as well as reduced-form estimation techniques to study the interaction of the firms and consumers in the banking industry, particularly in the sectors of microfinance and mortgage lending. In each chapter, I combine recent developments from the literature of empirical industrial organization in order to account for particular features of the microfinance industry, such as credit rationing, inattention, and unobserved price heterogeneity. Chapters 2 and 3 develop empirical strategies that use market-level data to analyze entry and pricing decisions of microfinance institutions, allowing for the quantification of consumer welfare gains associated with policy intervention. These models are also used to conduct counterfactual exercises to study the implications of alternative policies. Chapter 4 examines the effects of the advent of technological innovation in the U.S. mortgage industry.

1.1 Contributions

Chapter 4 explores the relation between MFIs and other types of loan providers that compete in the market of microloans. I examine the role of institutions specialized in microfinance at creating market expansion and how their presence in the market can influence the entry decisions of mainstream loan providers. To measure these spillovers, I use market-level information of small isolated markets in Colombia to estimate a structural model that identifies the effects of the presence of an additional competitor on the overall profit and the stock of loans provided by incumbents of different types.

The empirical strategy consists of an entry model similar to that in Berry (1994) that incorporates a revenue equation. This extension, first proposed by Schaumans and Verboven (2015) allows us to understand how entry affects both the market structure and the revenue of other competitors. I find positive and significant spillovers between banks and MFIs. Interestingly, these competitive effects are not symmetric among different types of loan providers. The presence of MFIs has a positive impact on the profit of mainstream institutions, which is partially explained by market expansion in the loans market. By contrast, MFIs seem to benefit less from the presence of mainstream institutions. This new insight about the competitive interaction among MFIs and other formal loan providers could help in the design of policies to promote investment in branching networks, particularly in small rural markets.

Chapter 3 explores the welfare implications of the relaxation of a regulatory ceiling applied to the interest rate of micro-loans in Colombia. The presence of usury ceilings can limit the availability of funding for some borrowers, with negative consequences for the availability of formal funding alternatives across regions, as it reduces the incentives to invest in branching networks, particularly in rural areas. On the other side, interest rate caps can be welfare improving, reducing the possibility of banks to price discrimination. Economic theory indicates that removing a price ceiling in the presence of third-degree price discrimination is not always welfare improving. The implications are largely determined by the degree of output expansion that takes place in the absence of the ceiling.

To measure these effects, I develop a structural model of the microcredit market in Colombia and estimate it using a unique data set that contains information on market shares and characteristics of financial institutions across geographic markets. My approach takes elements from the literature concerned with demand estimation in the presence of consumers' inattention (e.g. Ho et al., 2017; Abaluck and Adams, 2017), integrating them into the framework proposed by D'Haultfœuille et al. (2018) to account for potential market expansion and unobserved price heterogeneity. I use the variation of market outcomes across geographic locations before and after the policy change to identify the portion of consumers that gain access to formal loans as a consequence of the removal of the interest rate ceilings. I use the model to understand the implications of the regulation change in terms of the volume of loans and the optimal interest rate set by financial institutions in different market segments. With these elements, I can evaluate the policy's effects in terms of consumer and producer welfare across locations. I find that there is a loss in consumer surplus associated with an increase in the interest rates charged to all borrowers after the ceiling was relaxed. However, the welfare gains associated with the entry of financial institutions in new locations and the provision of financial services to borrowers who did not have access to formal loans before the policy change exceed these losses in most places. In a counterfactual scenario where I examine the effects of relaxing the usury ceiling in the absence of additional investment in branching networks, I find that the policy is still welfare improving at the national level, although in this case there is a significant number of locations, especially small markets, that would experience a loss in consumer surplus in the absence of additional branches.

Finally, Chapter 4 explores recent changes in the U.S. mortgage lending associated with the increased use of technological innovation in the provision of financial services. This industry has experienced a rapid transformation, with an increasing number of lenders adopting technological innovations that allow potential borrowers to complete their mortgage application process online, reducing the need for face-to-face interaction with loan officers. This chapter examines the response of incumbent mortgage lenders to the advent of this technology. I find that the increased availability of lenders providing online mortgages has had a differentiated impact on the volume of applications and loan originations for incumbent providers depending on their size. The results suggest that local lenders are better able to differentiate from FinTech institutions by offering services that are appealing to some segments of borrowers.

By contrast, mortgages provided by FinTech seem to be a closer substitute for the services offered by large financial institutions. As a result, these competitors have seen a reduction in their market share after FinTech entry.

1.2 Policy Implications

The results of Chapter 2 indicate that microfinance institutions can generate market expansion that benefits all competitors in the market, including traditional banks that focus on other types of financial services. Since their presence can lead to the entry of mainstream lending establishments in isolated markets, MFIs have the potential to contribute to consumer welfare by facilitating access to financial products beyond their loan portfolios. This new insight about the competitive interaction among MFIs and other formal loan providers can be used to improve the efficiency of subsidies designed to promote the opening of branches in rural locations.

Chapter 3 addresses the effects of interest rate caps on consumer welfare. The results indicate that the policy increased consumer surplus even in the absence of additional investments on branching networks. This is explained by the gains in consumer welfare of borrowers in existing locations who gained access to formal loans after the ceiling was relaxed. Nevertheless, additional investment in branching networks helped to compensate for the welfare losses associated with the increase in interest rates, particularly for safer borrowers who already had access to formal loans before the usury ceiling was removed.

The third chapter highlights the competitive advantages of small and large financial institutions in the U.S. market industry in the advent of a new type of competitor. The results suggest that online mortgage platforms are a closer substitute for services provided by large financial institutions, and contrast previous studies that have indicated that small and local lenders are more vulnerable to the arrival of platform-based competitors. Although the analysis presented here does not consider important differences in incumbent lenders' regulatory requirements, this insight could help us understand the effects of the development of online mortgage lending on credit access across geographic markets.

Recently, policymakers and industry experts have highlighted the benefits of partnerships between FinTech institutions and local lenders to expand the portfolio of services available for consumers, exploiting the competitive advantages of two different business models. While the effects of these alliances were still incipient during the period of analysis that I consider here, their role in shaping the competitive environment in the mortgage market industry should be considered in more detail in future research.

Chapter 2

The Interaction between Microfinance Institutions and Traditional Banks in Rural Markets. Evidence from Colombia

Abstract

In recent years, microfinance institutions (MFIs) in several developing countries have undergone a transition from non-profit organizations into regulated (for profit) financial establishments, transforming their competitive interaction with traditional loan providers. While the new scenario could be characterized by increased business stealing between the two types of competitors, the presence of rivals of the opposite type could also generate market expansion that benefits all incumbent lenders. I use a structural model to identify the effects of the presence of an additional competitor of either type on the overall profit and the stock of loans provided by incumbents in small isolated markets in Colombia. I evaluate different assumptions on the interaction across types of loan providers, finding positive and significant spillovers between banks and MFIs. I find that presence of MFIs has a positive impact on the profit of mainstream institutions, which is partially due to market expansion in the loans market. By contrast, MFIs do not seem to benefit significantly from the presence of mainstream institutions. This result is relevant for the design of policies that attempt to increase the supply of financial services in isolated markets.

2.1 Introduction

In recent decades, non-profit organizations, as well as regulated financial institutions, have developed a broad set of financial services designed exclusively for potential customers who find it difficult to access traditional financial services due to low income, lack of suitable collateral, or absence of reliable information about their payment behavior. Several studies have focused on the role of these specialized institutions at improving the living conditions of their clients; Cull et al. (2014) provides an extensive review of empirical studies that suggest that access to credit facilitates the accumulation of capital over time, as small entrepreneurs are able to start independent, productive projects as well as to overcome unpredictable situations that might put at risk the success of their ventures. Although evidence on long term effects of access to micro-loans is mixed (Banerjee (2013) provides a detailed review of empirical studies on the topic), governments in many countries have been enthusiastic at creating strategies to facilitate the provision of financial services for the low-income population segments, which has resulted in an increase of the number of non-profit private organizations and regulated financial institutions specialized in this segment.

MFIs specialize in the supply of financial services for the poor. These institutions operate under different regulatory settings, ranging from non-profit informal platforms at a local level to well-established banks with operations in many countries. In recent years, some of the biggest MFIs have transformed from non-profit organizations depending on external subsidies into specialized banks, able to provide funding to small entrepreneurs and low-income households, under profitability conditions required by investors and clients from the deposit market. Cull et al. (2009) compile evidence from a broad set of countries on the transition of non-profit microfinance institutions into regulated banks, free from subsidies, and how this process has affected the supply of microcredit. They find that MFIs that have undergone this transformation tend to offer products that are more comparable to those provided by mainstream loan providers.

As this transition allows MFIs to use deposits from the public as additional funding to expand their loan portfolio, increased interaction with mainstream financial institutions is expected. There are several reasons why the entry of an MFI is likely to have a different effect on the profit of mainstream financial institutions: first, as discussed by Banerjee (2013), the amount of learning involved in the credit relationship, both by the customer and the MFI, and the extent to which others can use this knowledge competitors in the market configure a potential externality. Second, inefficiencies in the loan supply might arise if there are barriers that tie borrowers to a particular provider for an extended period of time. Since these externalities can ultimately determine whether a financial institution enters or exits a market, it is important to examine whether MFIs contribute to expanding the portfolio of financial products available for consumers in local markets by facilitating the entry of other loan providers. This question turns out to be particularly relevant in the design of policies to increase access to financial services in isolated locations where few competitors are willing to enter. Furthermore, accurately measuring these interactions among MFIs and mainstream institutions at a local level adds to the understanding of the nature of competition in the microfinance sector at the national level.

Financial institutions are more likely to enter markets where they perceive favorable demand conditions as well as a milder competitive response from incumbents and other potential entrants. This simultaneous determination of entry and market structure, as well as the fact that some of the market/loan-provider characteristics that make entry profitable are likely correlated across different types of financial institutions and are often unobservable to the econometrician, create an endogeneity problem that needs to be addressed in order to obtain accurate measures of the spillovers that MFIs generate on incumbent institutions. In this paper, I estimate a structural model where the observed local market configuration is interpreted as the equilibrium outcome of the competitive interaction among different types of potential entrants. Taking elements from industrial organization models that have been used to examine competition in retail sectors, I propose a static entry model with revenue equation, similar to the one developed by Schaumans and Verboven (2015) to identify the effects of entry on market expansion for different types of competitors in the retail banking industry. This model uses the variation in the number of competitors across locations to obtain measures of effects of the presence of MFIs on other loan providers. Their approach extends the model proposed by Bresnahan and Reiss (1990) with information about the local revenues, to disentangle the impact of entry on market power and market expansion.

Using an approach similar to the one developed Mazzeo (2002), I introduce heterogeneity among loan providers and evaluate empirically different assumptions on the type of strategic interactions among MFIs and mainstream banks. My approach is closely related to the one developed by Fernandez (2016), who investigates the presence of positive (bilateral) spillovers between bars and cafeterias and the consequences for urban planning.

Exploring the competitive interaction in the banking industry is a challenging task due to the complex structure of the profit of financial institutions and their dual role in the deposits and loan markets. In this paper, I abstract from some of the elements that have been recently discussed in the literature concerning the spatial interaction across branches in the banking industry (Aguirregabiria et al., 2012; Ho and Ishii, 2011; Huysentruyt et al., 2013, e.g.), by modeling the local market structures as the result of entry decisions that are independent of those taken at other locations, and restricting my empirical analysis to small, geographically isolated markets. The cost of this decision is the impossibility of extending the conclusions obtained here to other types of markets, such as big urban centers. Nevertheless, analyzing the competitive interaction of lenders in these locations turns out to be particularly relevant from a policy point of view because the decision to open a branch in those locations has a high impact on the portfolio of financial services that become available for vulnerable clients.

Market structure is determined by entry and exit decisions of individual firms, and these are affected by expectations of future profits, which, in turn, depend on the degree of competition by potential entrants and incumbents within the market. Given the static nature of the approach that I propose here, no inference can be made about the competitive process that gave origin to the market structure observed in different locations in 2014. A dynamic framework could provide further insights on the short and long term effects of recent regulatory and technological changes on market structure and the mechanisms behind the potential spillovers among different types of loan providers. Introducing these dynamic considerations involves solving a dynamic game with large state space, which results in substantial computational challenges and requires additional information on entry and exit flows across locations. The extension of the model in this direction is left, therefore, for future research[1]

Dynamic considerations are particularly important in industries where there is a substantial difference between the incumbents' fixed cost of operation and the sunk costs faced by potential entrants. This distinction helps to rationalize simultaneous flows of entering and exiting firms. In the case of the retail banking industry, few studies have studied entry decisions using a dynamic framework. de Elejalde (2009) argues that the sunk costs associated with the opening of a branch in a rural location

[1]de Elejalde (2009) uses a dynamic framework to analyze competition in a context of rapid expansion of branching networks in the US banking industry, after the introduction of the 1994 Riegle-Neal Act, which permitted banks and holding companies to operate in multiple states. Although he is able to provide an estimate of the entry costs for different types of financial institutions, the results in terms of the competitive effect associated to the presence of rivals are qualitatively similar to those obtained by other authors using static models, such as Cohen and Mazzeo (2007).

in the United States are associated mainly with investments in advertising, licensing and other expenses that single market *de novo* banks need to face in order to start their operations, but do not seem to be very important for multi-market banks that are already operating in the industry. The retail banking industry in Colombia, and in particular, the microfinance sector, experienced a period of expansion during 2011 and 2012 that was characterized by an increase in the number of branching networks of existing financial institutions, rather than by the entry of new competitors at the national level. The absence of 'de novo' competitors at the national level suggests that the presence of sunk costs might not have a significant impact on the entry decisions of financial institutions at the local level.

After the branching network expansion observed in 2011-2012, there has been no change in terms of the number of financial institutions available in most the locations included in my sample, with exit of lenders occurring very rarely.[2] Also, there was no change in the number of competitors of both types at the national level between 2011 and 2014. As a result, a continuous competitive interaction between mainstream institutions and MFIs has taken place for at least two years in most of the locations. The stability in the market structure of the locations included in the sample and the overall favorable and stable macroeconomic environment observed in Colombia around the period studied here, allows us to interpret our estimates as the effects of sustained competitive interaction among incumbent lenders.

One of the advantages of the approach used here is that it does not rely on confidential individual data. Instead, I estimate a structural model that captures the strategic interaction among different types of loan providers using information on the number of competitors and the composition of the loan portfolio across small geographically isolated markets in Colombia in 2014. This country provides an interesting setting to evaluate the effects of entry of MFIs in the local retail banking industry because the conditions of microloans, such as the type of liability, the frequency of payments and the total amount borrowed, are closer to the ones of the products offered by mainstream financial institutions. The similarities across the characteristics of the loans provided by banks and MFIs, the regulatory framework under which both types of institutions operate, as well as the level of information sharing among the two types of loans providers via credit score agencies, suggest that the interaction between banks

[2] In During the period 2012-2014, there was no exit of MFIs in any of the markets analyzed, while exit of mainstream lenders occurred in 12 locations out of 498. After 2014, there have been reductions in the number of branches of the most prominent financial institutions, but they have all taken place in urban areas and have not translated into significant changes in the number of competitors.

and MFIs is likely to be significant.

I find that the presence of both mainstream banks and MFIs had a strong positive impact on the volume of loans of incumbent lenders, even after controlling for a broad set of unobservable and observable local factors that could have influenced the demand for loans for both types of lenders. Banks exhibited a higher outstanding value of the loan portfolio per capita in markets where there was at least one microfinance institution. Interestingly, the volume of loans provided by MFIs also increased in those markets where there was at least one mainstream bank, although to a lesser extent. There is, nevertheless, intense competition among loan providers of the same type. Banks' profits reduce to 43% of the monopolist level if there is a new bank in the market, while in the case of MFIs, the profit in markets with at least one competitor of this type becomes just 25,8% of the monopolist level.

This paper continues as follows: Section 2.2 contains a brief review of the literature. Section 2.3 outlines the essential features of the MFIs and other financial institutions that compete in the retail banking industry in Colombia and shortly summarize recent regulation changes that have had a significant impact on the development of microfinance. Section 2.4 provides summary statistics of the data and Section 2.5 and presents the econometric strategy. Sections 2.6 and 2.7 present the results of the structural model and counterfactual exercises. Section 2.8 contains the concluding remarks.

2.2 Literature Review

This paper contributes to a growing literature that studies the interaction of MFIs and other loan providers in local markets. Furthermore, it relates to a broad number of studies that investigate the intensity of competition among loan providers in the retail banking industry.

Several studies have focused on the competition dynamics among institutions specialized in providing services for the poor. Most of this research has made use of data of non-profit institutions that offer group-liability loans using private donations or government resources as a primary source of funding. These institutions typically target the poorest segments of the population, whose only alternative source of financing are informal lenders. Demont (2016) analyzes the impact of entry of MFIs on informal sources of lending in rural villages in India using a model where MFIs use joint-liability contracts while informal moneylenders offer standard individual loans.

By contrasting the predictions of the model with a panel household survey for India, he finds that MFIs can worsen the informational problems faced by traditional lenders, leading them to increase the interest rate charged to low-income clients. Kaboski and Townsend (2012) find similar evidence on interest rates increments in Thailand; they interpret these changes as an indication of the financial constraints of the households. These findings are consistent with a model where MFIs attract better borrowers from the moneylender and where fixed costs are essential in informal lending, such as the one proposed by Mookherjee and Motta (2016). Other studies have focused on the competition among MFIs. McIntosh et al. (2005) studies the effects of rising competition among the incumbent MFIs by examining the dropout and repayment rates of a sample of clients of one of the most prominent microfinance institutions in Uganda, as it abandons its position as local monopolist in the supply of micro-loans. The identification strategy relies on group-level changes in outcomes that occurred after the entry of a new competitor in the market.

Only in the last decade have studies directly addressed the effects of entry of MFIs on other loan providers that participate in local loan markets. In recent years, the business model of many MFIs has undergone structural changes aiming to achieve greater independence from donors while maintaining the rate of expansion of their portfolio. While the majority of MFIs today are still non-profit, several have already transformed into banks or other kinds of regulated financial institutions. Regulated MFIs include regional leaders such as Banco Compartamos in Mexico, Banco FIE in Brazil or Bandhan, and SKS in India, which are among the largest MFIs in the world (D'Espallier et al., 2017). The transition process implies the adoption of a shareholder ownership structure, and most often, it also includes becoming subject to prudential regulation by national banking authorities. These changes may translate into increased tensions between higher profit and outreach (Hermes and Lensink, 2007), as well as stricter competition among MFIs both in terms of attracting new clients and obtain funding from donors (Ly and Mason, 2012).

As noticed by Cull et al. (2009), while regulated MFIs continue to provide services to segments of the population without access to traditional banking, the characteristics of their products have become more similar to the ones offered by traditional financial institutions. For example, D'Espallier et al. (2017) and Cull et al. (2014) find that regulated MFIs tend to increase the size of their loans and to serve a lower percentage of women. Meanwhile, the majority of their loan portfolio has individual, rather than group, liability. Few studies have explored the effect of these transitions on the competitive interaction MFIs and mainstream financial institutions. Descriptive evidence is provided by Cull et al. (2009), who examine the impact of the presence of banks on the profitability and outreach of commercially oriented MFIs. They find that greater bank penetration in the overall economy is associated with more entry of commercial banks specialized in microcredit in poorer markets.

This paper provides new insights into this question by incorporating elements from empirical industrial organization models that have been used to study competition in other retail sectors. I extend the model proposed by Schaumans and Verboven (2015) and Fernandez (2016) to account for the differences between the loan providers that interact in local markets. To include the possibility that competitors belong to different types, I use the framework proposed by Mazzeo (2002), who analyzes entry decisions in the context of firms heterogeneity. In later work, Cohen and Mazzeo (2010) uses a similar approach to analyze competition for deposits in the retail banking industry in the United States.

In addition, this paper relates to several studies that examine the competitive interaction among different types of financial institutions using information from the market configuration observed across different locations. My approach is similar to the one proposed by Cohen (2004), who tests empirically different hypotheses about competitive interaction among banks and thrifts.

Competition among different types of financial institutions have been studied using spatial models that explicitly account for the consumer disutility from a distance traveled as in Ho and Ishii (2011) and Huysentruyt et al. (2013). This approach has been used to study competition in the banking industry urban locations where cannibalization across branches of the same bank is more likely, or when banks with large networks face competition from single-market financial institutions (e.g. Dai and Yuan, 2013; Adams et al., 2007). Other studies have tried to capture externalities among the nodes of the same branching network related to geographical diversification of risk and liquidity considerations (see: Aguirregabiria et al., 2012; Clark et al., 2017). In contrast with these studies, I model the decision of entry in each market as independent from the decisions taken in other locations. I argue that local profits, rather than the aggregate profit across markets, are the main determinant of these entry decisions. This assumption seems suitable to model entry in remote geographically isolated markets, where spillovers towards neighboring markets might not be very significant and where financial institutions tend to open only a reduced number of branches per market.[3]

[3]de Juan (2003) finds evidence in support of the independence of sub-markets, using information from small towns in Spain. He concludes that banks decide to enter the markets mostly based on

My work complements previous studies that have studied competition in the retail banking industry in Colombia, such as those by Salamanca (2005) and Rozo et al. (2008), by taking into account the heterogeneity among loan providers, and measuring the potential spillovers that MFIs can generate on other financial institutions in terms of market expansion. By exploring the competitive interaction among these loan providers, this paper offers new insights about the role of MFIs at facilitating access to banking services in isolated locations, that can be used in the design of future policy interventions.

2.3 Background: The Colombian Banking Industry

In this section, I provide a summary of the characteristics of MFIs and other loan providers that interacted in the retail banking industry in Colombia as of 2014, focusing first on the general economic and regulatory environment, and later on the particular characteristics of MFIs and other lending institutions.

Colombia experienced favorable macroeconomic conditions that were accompanied by a significant expansion of the demand for loans in the period between 2006 and 2014, particularly in the households' sector. After a deep financial crisis at the end of the 1990s that motivated stricter regulation concerning risks management and capital requirements for financial institutions, the banking industry underwent a process of consolidation that resulted in a relatively concentrated market, where commercial banks with extended branching networks throughout the national territory represented a significant share of the market portfolio. The segments that experienced higher growth were the ones related to the provision of financial services towards households and micro-entrepreneurs. The potential for growth in Colombia in the niche of microcredit is thought to be still high, given the levels of poverty, inequality, and financial restrictions faced by a significant portion of the population. According to Estrada and Rozo (2006), these restrictions are even more acute in rural areas, where a public bank had exclusively provided financial services and often tied to the existence of a productive project in the agricultural sector.

local conditions of demand.

2.3.1 Microfinance institutions in Colombia

Microfinance institutions in Colombia started operations at the end of the 1980s. Before their entry, loans for low-income entrepreneurs were provided exclusively by the government through development agencies. According to Barona (2004), during the 1990s, most of these institutions were non-profit organizations that funded their loan operations with donations from private individual donors or international development agencies. Only after the effects of a deep financial crisis that the country experienced at the end of the 1990s attenuated, the number of non-profit organizations that offered loans to poor clients started to increase. Between 2000 and 2010, the number of institutions increased, while the biggest MFIs transitioned from non-profit organizations into specialized banks.

According to Banca de las Oportunidades, the government agency in charge of implementing the national strategy to promote financial access, there were 18 no profit MFIs and nine regulated financial institutions specialized in microfinance (Banca de las Oportunidades, 2014) as of December of 2014. Besides, there was one public bank that intermediated government resources to provide funding for productive projects in the agricultural sector. The share of this bank in the total outstanding portfolio of microloans reached 42% in 2014. The public bank was present in all banks where private banks were active in 2014. This bank opened its branches long before the entry of any private bank in all the locations included in the sample. Historically, the network of this bank was used by the government to distribute currency in rural locations, and many public subsidies in rural areas are distributed using its branching network. There has been little change in the number of locations where this bank is active; it has not exited any market, and it has only experienced a few closures in big cities where it had several branches. The stability of its networks indicates that the development of private banks has had little impact on its operations.

Among the private institutions that provided this type of loan, the most important institutions were banks specialized in microfinance (27%) and non-profit MFIs (31%). These institutions registered sustained growth in previous years, both in terms of their number of clients and the size of their portfolio. Between 2007 and 2014, the number of clients nearly tripled, rising from almost 600.000 clients to 1,8 million, while the share of the total portfolio of loans (including commercial loans and mortgages) increased from 0.7% to 3%.

MFIs in Colombia offer different types of loans depending on the characteristics of the client, such as their credit record collateral availability. The vast majority of them are individual loans, rather than group liability loans, and they comply with the legal definition of microcredit, introduced by the government in 2007. This definition specifies i) a maximum amount that can be borrowed by a single client (around 7500 USD), ii) a cap on the total debt that the client can have with the financial system (nearly 36000 USD) and ii) all costs (different from the interest rate) and commissions that financial institutions can charge for the product. According to Fernandez (2014) the average amount of a microloan in 2014 was around 2170 USD . Most of these loans have a monthly frequency of payments.

While some of these characteristics are similar to those observed for loans given to higher-income households by mainstream financial institutions, the interest rate of this type of loan was significantly higher in 2014 (34% effective annual for micro-credits vs. 19% effective annual for other unsecured consumer loans, on average). [4] Furthermore, there are essential differences in the ways that MFIs value the available collateral and their methods of monitoring clients. To maintain low levels of default and reduce associated losses, MFIs rely on higher provisions and close monitoring of the productive projects of the clients, often including additional services for entrepreneurs, such as guidance on management skills and accounting. Branching networks are often complemented with mobile agents to reach clients in isolated locations, where there is a limited supply of financial services by mainstream lenders. In consequence, microloans are the type of loan with greater geographical diversification. In 2014, 62% of these loans were given to clients in locations different from the 13 biggest cities in the country, while only 5% of the loans in other categories were given to clients outside these locations.

MFIs in Colombia operated in the beginning as non-profit organizations that did not have legal authorization to capture deposits from the public. Once they transitioned into regulated financial institutions, they became legally able to capture deposits from the public and gained access to deposit insurance. However, they did not start capturing deposits from the public to a large scale after they became regulated financial institutions. Nowadays, many of them have relatively low levels of deposits compared with their volume of loans. As of 2014, they all maintained low levels of deposits even when they could legally capture deposits from the public. Their scarce participation in the deposits market could be explained by the lack of demand for these services in their market niche (small entrepreneurs in rural areas make all transactions using cash due to the lack of financial infrastructure, and low levels of

[4] These numbers correspond to nominal interest rates. The inflation rate in Colombia has remained in single digits since 2000. In 2014 the annual inflation rate was 2.91%.

financial literacy), the presence of sunk costs and entry barriers, both at the national and the local level (expansion of ATM and payment terminals, commercial agreements, etc), and the existence of sufficient and cheap funding obtained through other sources.

2.3.2 Other financial institutions

Commercial banks are the most relevant agents in the retail loan market in Colombia, both in terms of market share and size, representing more than 90% of the total provided to the private sector. These institutions have a diverse portfolio that includes services for business clients, households, and micro-entrepreneurs. The highest share of their portfolio corresponds to commercial loans (58% on average), followed by non-collateral consumer loans and mortgages. Microcredits account for less than 5% of their total stock of loans. However, there is significant heterogeneity in the composition of the loan portfolio of these institutions, with some smaller banks focusing on non-collateral loans to households or commercial loans, exclusively. Banks rely heavily on their activity in the retail credit market. Loans represented 65,7% of their assets in 2014, while net interest obtained from loan operations accounted for 62% of their total revenue.

Other institutions that compete in the retail loan market include loan providers regulated by the financial supervisory authority (Superintendencia Financiera de Colombia), and several organizations that offer loans to particular groups of the population such as credit unions and employees associations. These institutions exhibit a higher degree of specialization, both in terms of their geographic location and the range of products they offer, concentrating their operations in urban markets. The financial supervisory authority does not regulate employee associations and other credit unions, as these organizations are not allowed to capture deposits from the public. Since formal employment is often a requirement for membership, they are not considered as a source of funding for independent entrepreneurs with low income.

2.4 Data and descriptive statistics

I use a cross-sectional data set that contains information from 953 cities and towns in Colombia (from a total of 1102) in December 2014. The number of branches and the loan portfolio of all financial institutions are published by Superintendencia

Financiera, while the demographic variables per market are taken from the Municipalities Panel Data Set from Universidad de Los Andes, which contains information from several official sources.

I define a market as a group of administrative municipalities that fulfills two characteristics: its population is below 150.000 inhabitants, and the distance to the closest urban center is bigger than 40 kilometers[5]. If two or more municipalities are less than 25 kilometers apart from each other, they are considered as a single market, whenever the total population is below 150000. I obtained 498 markets. These markets account for 4,8% of the total outstanding value of loan portfolio in the country and 52,2% of the value of the microloans portfolio of regulated financial institutions. Furthermore, this sample of markets concentrates a significant proportion of the Colombian population (30.3%).

This definition of geographic market attempts to include the possibility that potential borrowers demand financial services from financial institutions located in neighboring municipalities. The distance that a borrower is willing to travel in order to access financial services differs greatly depending on the context and the type of products required. Brevoort and Wolken (2008) show that the distance between small businesses in the United States and their most frequently used depository institution was 6.4km in the median and 122.2km on average in 2003, while Degryse and Ongena (2005) find smaller estimates for the Belgian banking industry (between 4.8 to 8 km). By type of product, Brevoort and Wolken (2008) find that the median distance between a firm headquarters in the United States and the financial institutions that provides them with equipment or motor vehicle loans was 30.4km and 38.4km in 2003, respectively. By contrast, the distance to access asset services like checking accounts was just 3.2km. All these studies include urban areas densely occupied by banks, which explains the skewness of the distance distribution.

An estimate in a context more comparable to the Colombian one is provided by the National Committee for Financial Inclusion of Mexico, who found that the average distance between borrowers and brick-and-mortar branches in rural areas was 28.2km in 2017 (Comité Nacional de Inclusión Financiera de México, 2018). This measure is based on the geometric distance between coordinates; therefore, it does not necessarily correspond to the actual distance that borrowers need to travel in order to approach to a branch in person. The threshold used to define geographic markets here (40km) attempts to reflect the state of the road infrastructure in rural areas in Colombia,

[5]This distance corresponds to the shortest path between towns using the current road network, provided by Open Source Routing Machine Project.

and is, therefore, based on the shortest path between towns using the current road networks.

Table 2.1: Number of loan providers per type - December 2014

Market structure	Count	Loan portfolio per capita	
		Mainstream institutions	MFIs
$\{N_b = 0, N_m = 0\}$	316	0.00	0.00
$\{N_b = 0, N_m = 1\}$	10	0.00	81.40
$\{N_b = 0, N_m > 1\}$	0	0.00	0.00
$\{N_b = 1, N_m = 0\}$	66	354.94	0.00
$\{N_b > 1, N_m = 0\}$	51	344.77	0.00
$\{N_b = 1, N_m = 1\}$	6	301.60	46.56
$\{N_b > 1, N_m = 1\}$	34	305.31	69.33
$\{N_b = 1, N_m > 1\}$	0	0.00	0.00
$\{N_b > 1, N_m > 1\}$	17	218.26	52.19

Notes: Based on information published by Superintendencia Financiera de Colombia. Values expressed in US dollars (PPP-2014).

Table 2.1 presents the market configurations observed in the sample and the average value of the loan portfolio divided by the market population. There is at least one competitor in 36.5% of the markets. Within those markets, market structures with one or more mainstream institutions and no MFIs are the most frequent. The value of the loan portfolio per capita diminishes in markets with more competitors; in the case of banks, it is lower in markets where there is at least one MFI compared to markets where only banks operate. As it will be explained in further detail in Section 2.7, the econometric strategy used to measure the competitive interaction of loan providers compares market structures and loan volumes across geographic markets. The presence of many competitors of both types in a particular location can be indicative of complementarity among loan providers, but it can also indicate that the market is particularly profitable for the two types. In order to distinguish the effects related to presence of different types of loan providers it is necessary to control for all observable and unobservable characteristics that make a location attractive for both types of competitors. This is done by making specific assumptions on the distribution of the unobservables and incorporating information of all markets, including those where there is only one competitor or even those where there are no competitors at all. These markets are relevant in the estimation because the absence of lenders in those locations indicates that the potential profit obtained there in case of entry would be smaller than that of the outside option. In Section 2.7, I use these estimates I can to assess whether it is more likely to see the a mainstream institutions or an MFI opening a new branch locations where there are no incumbent lenders, and to provide a measure of the subsidies needed to achieve entry in locations that are currently under-served by loan providers.

Table 2.2: Summary statistics of markets - December 2014

	Mean	SD	Min	Q1	Median	Q3	Max
Mainstream financial institutions	0.86	1.73	0.00	0.00	0.00	1.00	13.00
MFIs	0.17	0.49	0.00	0.00	0.00	0.00	3.00
Public bank (dummy variable)	0.79	0.41	0.00	1.00	1.00	1.00	1.00
Total population	26736.76	26231.39	984.00	9333.00	17575.50	33937.00	143193.00
Population in rural areas (%)	0.61	0.19	0.07	0.50	0.63	0.76	0.96
Distance to closest urban center	122.37	225.80	40.50	68.50	99.88	138.68	4920.70
Population in poverty conditions (%)	0.49	0.19	0.09	0.34	0.46	0.61	1.00
Number of firms	207.59	359.07	1.00	34.00	92.50	219.00	3526.00
Oil extraction fields	2.73	6.84	0.00	0.00	0.00	0.00	23.82
Coca plantations (dummy variable)	0.14	0.35	0.00	0.00	0.00	0.00	1.00
Attacks of armed illegal groups*	0.33	1.49	0.00	0.00	0.00	0.00	23.82
Robbery of commercial establishments*	1.13	2.21	0.00	0.00	0.00	1.58	29.28

Notes: 498 markets in the sample. *Number of incidents per 100000 inhabitants. Based on information published by Superintendencia Financiera de Colombia.

I include in the model some variables that may help to predict the size of the market and individual demand for credit, such as population, distance to the closest urban center, share of population under in poverty condition, number of firms, and presence of oil extraction fields. In addition, I considered some measures of the level of violence experienced in each location, such as the number of attacks by illegal armed groups, the presence of coca plantations, and the number of robberies to commercial establishments. Table 2.2 presents summary statistics of the main variables in 2014.

2.4.1 Competitors

Based on the composition of the loans portfolio and the regulation that applies for each financial institution I classify loan providers into two categories: i) mainstream banks and other regulated financial institutions and ii) MFIs.[6] The last category includes all private regulated institutions whose share of microcredit loans exceeds 40% of their loans portfolio[7]. While, public institutions are important providers of funding in small isolated markets, their entry decisions and the amount of loans that they are able to provide depends to a greater extent on national policies and fiscal considerations, rather than on current local market conditions. Furthermore, they focus on a segment of the market (rural productive projects) that is less targeted by private financial institutions. Hence, I consider their presence as exogenous of the market structure represented by the number of private banks or MFIs in the market.

Financial institutions have only one branch per market in 89.8% of locations. Transaction terminals such as post offices and retail stores that offer banking services in agreement with banks (known as banking correspondents) are not taken into account to define entry because it is not possible for new clients to ask for loans or opening standard savings accounts. Furthermore, since financial institutions use existing branching networks from other firms, the decision on opening a new BC in a particular location is not strictly based on the local profit for the financial institution. The presence of transaction terminals helps reducing travel costs for the customers of financial institutions; however, potential clients are required to complete the applica-

[6]Financial institutions that do not participate in the retail loan market are excluded, as well as government development agencies, credit unions, and other associations that provide loans.

[7]I include these two institutions because the size of their portfolio is similar to that of the banks specialized in microcredit. Furthermore, these institutions share information with credit score agencies and offer similar products to those offered by regulated institutions specialized in this niche. Other institutions that are not included due to lack of comparable information provide less than 8% of microcredits.

tion process for the acquisition of different financial services by approaching in person to a traditional branch. As of 2014, the number of requests of saving accounts received via banking correspondents (BCs) was extremely low, with most of the clients using those terminals to make payments to third parties and transfers. In addition, it is often the case that retail chain stores have agreements at the national level with multiple financial institutions at the same time, which partially dilutes the individual competitive advantage that a single financial institution could derive from the presence of a transaction terminal. In those agreements, financial institutions do not have to make any investment at the local level; instead, commercial establishments arrange the terminal and obtain a commission for each transaction. Finally, since the commercial establishment is obliged to deposit in a nearby branch all the resources captured from the public in a regular basis, it happens only very rarely that BCs are located in markets where there is no branch of the financial institution nearby.

There were 44 mainstream financial institutions and 5 regulated MFIs in Colombia in 2014. Table 2.3 presents some descriptive statistics of those institutions that entered at least one of the small isolated markets considered in this paper. There are important differences between the types in terms of their branching network and loan composition. MFIs operate in a greater number of markets and have more branches on average than mainstream institutions. In contrast, most mainstream institutions are available only in a reduced number of markets. The loan portfolio differs significantly among mainstream institutions and MFIs, with the first group focused mainly on consumer loans and the second almost exclusively in microloans. Finally, the differences in the average interest rate and the default rate across types reveals that MFIs are able to charge a higher interest rate for this type of loan without incurring in higher default risk.

Table 2.3: Summary statistics of competitors - December 2014

	Type	Mean	SD	Min	Q1	Median	Q3	Max
Total markets	Mainstream	49.04	49.20	4.00	15.00	30.00	58.00	179.00
	MFI	80.00	40.34	43.00	58.50	74.00	98.50	123.00
Markets (in sample)	Mainstream	20.91	30.27	1.00	3.50	8.00	18.50	107.00
	MFI	36.00	28.16	12.00	20.50	29.00	48.00	67.00
Branches (in sample)	Mainstream	26.91	40.83	1.00	4.00	8.00	22.50	135.00
	MFI	38.00	28.16	14.00	22.50	31.00	50.00	69.00
Share of consumer loans (own portfolio)	Mainstream	0.68	0.31	0.00	0.54	0.77	0.93	1.00
	MFI	0.02	0.03	0.00	0.00	0.00	0.03	0.06
Share of microloans (own portfolio)	Mainstream	0.04	0.08	0.00	0.00	0.00	0.05	0.32
	MFI	0.89	0.17	0.69	0.84	0.98	0.99	1.00
Interest rate of microloans	Mainstream	0.29	0.07	0.19	0.24	0.27	0.34	0.41
	MFI	0.37	0.00	0.37	0.37	0.37	0.37	0.38
Default risk of microloans	Mainstream	0.07	0.10	0.00	0.00	0.06	0.11	0.45
	MFI	0.08	0.02	0.07	0.07	0.07	0.09	0.11

Notes: 498 markets in the sample. Statistics based on institutions with at least one branch in the sample. Interest rates are national averages reported to the financial supervisory authority. *Number of incidents per 100000 inhabitants. Based on information published by Superintendencia Financiera de Colombia.

2.5 Methodology

The model used here to estimate the competitive interaction between banks and MFI follows closely the approach proposed by Schaumans and Verboven (2015) and later extended to the case of two types of competitors by Fernandez (2016). Similar to the framework developed by Bresnahan and Reiss (1990), this model uses the variation in market structure across locations to obtain measures of the toughness of competition. Furthermore, the model incorporates information about the value of the loans in each location to identify the effects of the presence of rivals on market expansion in the loans market.

2.5.1 Assumptions on banks and markets

A key assumption of the model is that the observed market structure in each particular location is an equilibrium outcome that results from the interaction between incumbents and potential entrants in the industry. The existence and uniqueness of such equilibrium requires the fulfillment of a set of assumptions on firms and markets: i) banks and FMIs are able to operate in multiple markets. ii) Their type, either mainstream bank (b) or MFI (m), cannot be chosen after entry in each particular market, therefore it is the same across geographic locations.[8] iii) There is a fixed number of geographic markets M where banks can decide to enter, and banks can operate simultaneously in all of them if it is profitable (there are no capacity constraints). iv) Decisions about type and entry are irrevocable. Furthermore, I assume entry decisions are based mainly on the particular conditions of each location. MFIs and mainstream banks included in the sample have been operating in Colombia for more than 10 years as of 2014. These institutions define the characteristics of their portfolio, their business model, risk management and advertising strategies at the national level, and there are clear differences among these types that are perceived by potential borrowers. In this context, it is reasonable to assume that it would not be possible for them choose a different type in each location, or to change at their convenience after entry.

The last assumption, which states that entry decisions are based mainly on local conditions might be problematic in a context of multi-market competition. Financial institutions obtain funding for their loan operations either by capturing deposits in

[8] Microloans represent more than 80% of the total loan portfolio in all the markets considered in the sample, whereas this share is lower than 30% for mainstream banks.

other markets, or via the interbank market. In both cases, this might create some dependence among the nodes of the branching networks, as entry decisions could be affected by liquidity shocks that affect the overall capability of the loan providers to make this type of investment. Furthermore, loan providers could choose the locations of their branches in order to optimally diversify geographic risks, as shown by Clark et al. (2017). The presence of branches in nearby markets can serve for advertising purposes even if only few clients are willing to travel among geographic locations to demand their services, and their performance can help loan providers to learn about regional conditions that might be relevant for their potential operation in neighboring markets. Other externalities related to the costs of recruitment and training of human capital, and the development of technology that can be used in multiple nodes of the networks could make local entry and exit decisions dependent across geographic markets. These externalities play an important role in big urban locations, where entering the market requires a significant investment in equipment, human capital and advertising, and the mobility of potential customers creates competitive pressure among the nodes of the same branching network. Nevertheless, I expect operation costs in the banking industry to be affected to a lesser extent by the size and location of other nodes of the branching network, compared to other industries such as retail chain stores, where those features can translate into substantial changes in distribution and storage costs (see for example Holmes (2011)).

All financial institutions included in the sample have large branching networks across multiple regions. MFIs had 188 branches while mainstream banks had 583 in the median, as of 2014. The overall size of the branching networks and the decision of focusing only in small isolated locations makes the financial effort related to the entry in a single location less significant in relation to the overall resources of the institution. This reduces the dependence of local entry/exit decisions to liquidity shortages at the national level and makes it less likely that local shocks on the demand for loans or on the deposits supply have significant effects on the volume of loans provided in other markets. Furthermore, given that the loan providers maintain operations across different regions, it is reasonable to assume that they are relatively well known by potential customers all across the territory. In addition, I expect that the dependence across nodes to become less important in rural areas, where potential consumers tend to restrict their selection to the loan providers that have branches in their vicinity due to higher transportation costs. In the context studied here, clients need to approach personally to a branch in order to ask for a loan, since many of them still do not have the possibility of performing this type of operation using virtual or mobile platforms.

Although internet access was available in most of the cities and towns in Colombia as of 2014, a significant share of the population in those places did not have internet access at home at the time. As a result, many borrowers were not familiar with the use of virtual platforms to make transactions and preferred to approach a traditional branch since they perceived this transaction channel as safer and more reliable. Furthermore, clients might not demand loans from nearby towns, due to higher travel expenses and lower probability of obtaining funding (monitoring costs for banks also increase with distance, particularly for financial institutions offering microcredits).

2.5.2 Entry conditions

The market structure in location j is described by the number of mainstream institutions (N_{bj}) and MFIs (N_{mj}) and denoted by $N_j = \{N_{bj}, N_{mj}\}$. Let $\hat{N}_{ij} = \{N^b_{ij}, N^m_{ij}\}$ be a tuple that contains the number of competitors of type b (mainstream institutions) and m (MFIs) in market j, from the perspective of a lender of type $i \in \{b, m\}$. The number of competitors for a firm of type b is $\hat{N}_{bj} \equiv \{\hat{N}^b_{bj}, \hat{N}^m_{bj}\} = \{N_{bj} - 1, N_{mj}\}$, whereas $\hat{N}_{mj} \equiv \{\hat{N}^b_{mj}, \hat{N}^m_{mj}\} = \{N_{bj}, N_{mj} - 1\}$. The profit function of a bank of type i in a market j, can be written as follows:

$$\Pi_{ij}(N_j) \equiv \Pi_{ij}(\hat{N}_{ij}) = \left(r^l_{ij}(\hat{N}_{ij}) - r^d_{ij}(\hat{N}_{ij})\right) L_{ij}(\hat{N}_{ij}) +$$
$$(r^o_i - r^d_{ij}(\hat{N}_{ij})) \max\{D_{ij}(\hat{N}_{ij}) - L_{ij}(\hat{N}_{ij}), 0\} - F_{ij}(\hat{N}_{ij}),$$

where $r^l_{ij}(\hat{N}_{ij})$ is the expected return obtained from the current stock of loans, $L_{ij}(\hat{N}_{ij})$, $r^d_{ij}(\hat{N}_{ij})$ is the return of the deposits stock, and $D_{ij}(\hat{N}_{ij})$ that banks need to pay to their clients.

I assume that banks can make use of deposits obtained from an outside source to secure funding for their loan operations in case the local deposits are not enough to fund the local loan originations. In that case, those resources would be remunerated at the same rate as local deposits, $r^d_{ij}(\hat{N}_{ij})$. When there is a local surplus of deposits, banks can invest it in an outside option that has a return denoted by r^o_i. The expected local return rate, $r^l_{ij}(\hat{N}_{ij})$, may vary across markets depending on the ex-ante interest rates, the portfolio composition, and the materialization of credit risk, which in turn, may be affected by the market structure. Finally, the variable $F_{ij}(\hat{N}_{ij})$ captures the operative costs of the branch, which do not depend on the scale of the operation. Again, this variable might be affected by market structure if the presence of additional competitors generate spillovers on the development of necessary infrastructure for money transactions, such as ATM networks and debit/credit card payment terminals.

I consider a competitor as active in the market if there exists at least one "brick and mortar" branch in the market that reports non-zero stocks of deposits or loans. Therefore, $\hat{N}_{ij}$ is a vector that contains the number of competitors per type rather than the number of branches that each financial institution operates in each market. Hence, I am not able to capture the effect of competition among branches of the same competitor, or the relative advantage of competitors with more than one branch in the local market; this is likely not be a significant limitation since banks and other financial institutions operate just one office per market in most of the cases.

The profit function can be rewritten as follows:

$$\Pi_{ij}(\hat{N}_{ij}) = \mu_{ij}(\hat{N}_{ij})l_{ij}(\hat{N}_{ij})S_j - F_i(\hat{N}_{ij}), \tag{2.1}$$

where $l_{ij}(\hat{N}_{ij})$ is the value of the stock of loans per capita, $d_{ij}(\hat{N}_{ij})$ is the value of the local deposits per capita and S_j is the population of market j. The term $\mu_{ij}(\hat{N}_{ij}) = \Big((r^l_{ij}(\hat{N}_{ij}) - r^d_{ij}(\hat{N}_{ij})) + (r^o_i - r^d_{ij}(\hat{N}_{ij}))\max\{\frac{d_{ij}(\hat{N}_{ij})}{l_{ij}(\hat{N}_{ij})} - 1, 0\}\Big)$ captures other components of the profit, such as the markup obtained in the loans market and the profit obtained from operations in the deposits market. In the case of microfinance institutions, $\mu_{ij}(\hat{N}_{ij})$ could be interpreted directly as the expected return of the operations in the loan market, because of their scarce participation in the deposits/insurance markets. By contrast, mainstream institutions offer a wider portfolio of financial services, which allow them to capture deposits from the public. In these cases, the profit function captures the additional revenue obtained by the provision of those services.

If a financial institution decides to enter a location where it will face $\hat{N}_{ij}$ competitors, it must be because the profit of entering the market is greater than the outside option payment, which I normalize to zero. This condition can be written in logarithms using equation (2.1) as

$$\ln\left(\frac{\mu_{ij}(\hat{N}_{ij} + I_i)}{F_{ij}(\hat{N}_{ij} + I_i)}\right) + \ln l_{ij}(\hat{N}_{ij} + I_i) + \ln S_j > 0, \tag{2.2}$$

where the indicator vector I_i takes the value 1 if there is an additional competitor of type i in the market, and 0 otherwise. Both the overall profit and the volume of loans depend on the observed market structure, as well as of economic and demographic characteristics of the market such as income, distance to metropolitan areas, etc. I consider the following functional forms for these terms,

$$\ln\left(\frac{\mu_{ij}(\hat{N}_{ij})}{F_{ij}(\hat{N}_{ij})}\right) = \lambda_i X_j + \delta_i(\hat{N}_{ij}) + \eta_{ij} \tag{2.3}$$

$$\ln\ l_{ij}(\hat{N}_{ij}) = \beta_i X_j + \alpha_i(\hat{N}_{ij}) + \epsilon_{ij}, \tag{2.4}$$

where X_j is a vector that captures all the relevant demographic characteristics of market j, and ε_{ij} and η_{ij} are characteristics that vary across locations and types of competitors, unobservable to the econometrician. The effects of the presence of rivals on the volume of loans and other components of the profit of bank of type i in market j are captured by the functions $\alpha_i(\hat{N}_{ij})$ and $\delta_i(\hat{N}_{ij})$, defined as follows:

$$\alpha_i(\hat{N}_{ij}) = \alpha_i^{b1} I(\hat{N}_{ij}^b \geq 1) + \alpha_i^{b2} \max\{\hat{N}_{ij}^b - 1, 0\} + \alpha_i^{m1} I(\hat{N}_{ij}^m \geq 1) + \alpha_i^{m2} \max\{\hat{N}_{ij}^m - 1, 0\}$$

and,

$$\delta_i(\hat{N}_{ij}) = \delta_i^{b1} I(\hat{N}_{ij}^b \geq 1) + \delta_i^{b2} \max\{\hat{N}_{ij}^b - 1, 0\} + \delta_i^{m1} I(\hat{N}_{ij}^m \geq 1) + \delta_i^{m2} \max\{\hat{N}_{ij}^m - 1, 0\}$$

where $I(\hat{N}_{ij}^b \geq 1)$ and $I(\hat{N}_{ij}^m \geq 1)$ are dummy variables that indicate the presence of at least one competitor of type b or m, from the perspective of a firm of type i. The parameters $\{\alpha_i^{b1}, \alpha_i^{b2}, \alpha_i^{m1}, \alpha_i^{m2}\}$ and $\{\delta_i^{b1}, \delta_i^{b2}, \delta_i^{m1}, \delta_i^{m2}\}$ capture the effects related to the presence of rivals of each type on the overall profit and on the volume of loans provided by lenders of type i. This specification allows us to evaluate whether the competitive effect associated to the first competitor of each type is different from that related to the presence of additional firms.[9]

[9] Alternatively, the model was estimated using a linear specification on the number of competitors of each type and obtained qualitatively similar results (available upon request). Nevertheless, using a more flexible specification seems more reasonable, given that the the presence of the first rival is likely have a distinct impact on profits, compared to the presence of additional competitors. Using a specification that allows greater flexibility (such as using a dummy variable for each kind of market structure present in the sample) would result in very imprecise estimators due to sample size.

When analyzing the differences in market structure and the value of the loans across geographic markets an endogeneity problem arises because firms are more likely to operate in markets where they expect higher demand. Firms anticipate the impact of the presence of other incumbents and potential entrants on their profit when making their entry and credit supply decisions. Therefore, market structure variables and different observed outcomes are simultaneously determined. Furthermore, there is a potential omitted variables problem, since banks and MFIs might find some locations attractive due to variables unobserved by the econometrician. To correct for the potential bias caused by this correlation, an econometric model of equilibrium market structure is employed as a selection equation. If an incumbent firm of type i faces a number of competitors $\hat{N}_{ij}$, individual rationality indicates that its profits, given the market structure, should be greater than the outside option payment. Substituting equations (2.2) and (2.4) in (2.3), I obtain,

$$X_j\gamma_i + \ln S_j + \theta_i(\hat{N}_{ij}) - \omega_{ij} > 0.$$

Furthermore, any additional firm should obtain negative profits if it decides entering the market, otherwise, it should have entered the market already. Therefore,

$$X_j\gamma_i + \ln S_j + \theta_i(\hat{N}_{ij} + I_{ij}) - \omega_{ij} < 0.$$

If these conditions are met for all types of competitors, we can interpret the observed market structure as an equilibrium outcome. Therefore, the following conditions should be met at the equilibrium market structure described by $\hat{N}_{ij}$ for each type:

$$X_j\gamma_i + \ln S_j + \theta_i(\hat{N}_{ij} + I_{ij}) < \omega_{ij} < X_j\gamma_i + \ln S_j + \theta_i(\hat{N}_{ij})$$

where,

$$\begin{aligned}\gamma_i &= \lambda_i + \beta_i \\ \theta_i &= \alpha_i + \delta_i \\ \omega_{ij} &= \eta_{ij} - \varepsilon_{ij}.\end{aligned}$$

This is a simultaneous ordered probit and demand model, under the assumption that the entry of a new competitor always reduces profit of incumbents ($\theta_i < 0$). In markets where there are no competitors of type i, the volume of loans is not observed; hence, only one inequality must hold for that type:

$$X_j\lambda_i + \ln S_j + \delta_i(\hat{N}_{ij} + I_{ij}) < \omega_{ij}.$$

Instead, if there is at least one competitor of type i, the realization of the unobserved term ε_{ij} can be inferred for the particular values of the parameters β_i and α_i and the observed variables $l_{ij}(\hat{N}_{ij}, X_j)$ and X_j, Therefore, the two following conditions must be satisfied:

$$\ln l_{ij}(\hat{N}_{ij}, X_j) = X_j\beta_i + \alpha_i(\hat{N}_{ij}) + \varepsilon_{ij} \tag{2.5}$$

$$X_j\gamma_i + \ln S_j + \theta_i(\hat{N}_{ij} + I_i) < \omega_{ij} < X_j\gamma_i + \ln S_j + \theta_i(\hat{N}_{ij}). \tag{2.6}$$

Since the set market characteristics X_j enters both the profit and the revenue equation, an exclusion restriction is required in order to achieve identification. I use the population variable (S_j) as an exclusion restriction because it affects the overall profit, but it less likely to affect per-capita demand for loans.[10] This model can be estimated by maximum likelihood, under the assumption that the distributions of the unobservable terms η_{ij} and ε_{ij} are known.

2.5.3 Entry game for two types of competitors

As noted by Mazzeo (2002), when there are different types of competitors in the market, it is necessary to introduce additional assumptions that allow to interpret the distribution of firms across types as the result of a rational individual decision of potential entrants. Therefore, I impose some structure on the kind of interaction between financial institutions (mainstream banks (b) and MFIs (m)), such that the observed market structure can be interpreted as the outcome of an entry game under complete information.

[10] An OLS regression of the stock of loans per capita on demographic characteristics of the market reveals that after controlling for income and distance to closest market, population doesn't contribute to explain the variation of this variable across markets.

Similar to the investment game proposed by Mazzeo (2002), I assume there is a pool of potential entrants of the two types that make irrevocable decisions about entry. Potential entrants of the same kind are identical and play sequentially. Firms anticipate that subsequent firms will make decisions about entry and product type once they have committed to their choice. The last firm of each product type finds entry profitable, taking the number of competitors of each type that are active in the market as given. Additional entry, in either product type, is not profitable.

Different equilibrium market structures can be achieved depending on the type of interaction between mainstream institutions and MFIs. Cleeren et al. (2010) analyzes a case where competitors are substitutes, while Fernandez (2016) studies a situation where firms provide complementary goods, opening the possibility of bilateral positive spillovers. I also consider a third case, in which the relationship between the two types of competitors is not symmetric, resulting in one-sided positive spillovers. To see why this can be the case in the context of MFIs and mainstream banks, notice that limited business stealing between mainstream banks and MFIs is expected, particularly from the second group towards the first, since mainstream institutions offer relatively cheaper alternatives of credit for clients with lower default risk, and their share of microcredit in the loan portfolio is small. On the deposits side, many MFIs do not capture resources from the public, funding most of their operations with external loans. Positive spillovers for mainstream institutions, derived from the entry of a MFIs may occur instead since MFIs' clients might become eligible for accessing cheaper loans offered by mainstream institutions once they have build some credit history, amassed some collateral or become more aware of the benefits of formal financial services. To simplify notation, I will drop the sub-index j, to focus on the features of the interaction of competitors of types b and m in a given market.

Types are substitutes

If $\Pi_b(N_b, N_m + 1) < \Pi_b(N_b, N_m)$ and $\Pi_m(N_b + 1, N_m) < \Pi_m(N_b, N_m)$, then the types are substitutes. Furthermore, if the presence of a competitor of the same type reduces the profit of an incumbent more than a competitor of other type would, then a Nash equilibrium exists and can be represented by the pair $\{N_b, N_m\}$ for which the following inequalities hold:

$$\pi_b(N_b + 1, N_m) < \omega_b < \pi_b(N_b, N_m) \tag{2.7}$$

$$\pi_m(N_b, N_m + 1) < \omega_m < \pi_m(N_b, N_m), \tag{2.8}$$

where $\pi_i(N_b, N_m) = X_j\gamma_i + \ln S_j + \theta_i(\hat{N}_i^b, \hat{N}_i^m)$ for $i = \{b, m\}$. This equilibrium is not unique, however, as there is a sub-region of the area defined by inequalities above that is consistent with the outcome $\{N_b + 1, N_m - 1\}$. This sub-region is defined by the following inequalities:

$$\begin{aligned}\pi_b(N_b + 1, N_m) < \omega_b < \pi_b(N_b + 1, N_m - 1)\\ \pi_m(N_b + 1, N_m) < \omega_m < \pi_m(N_b, N_m).\end{aligned}$$

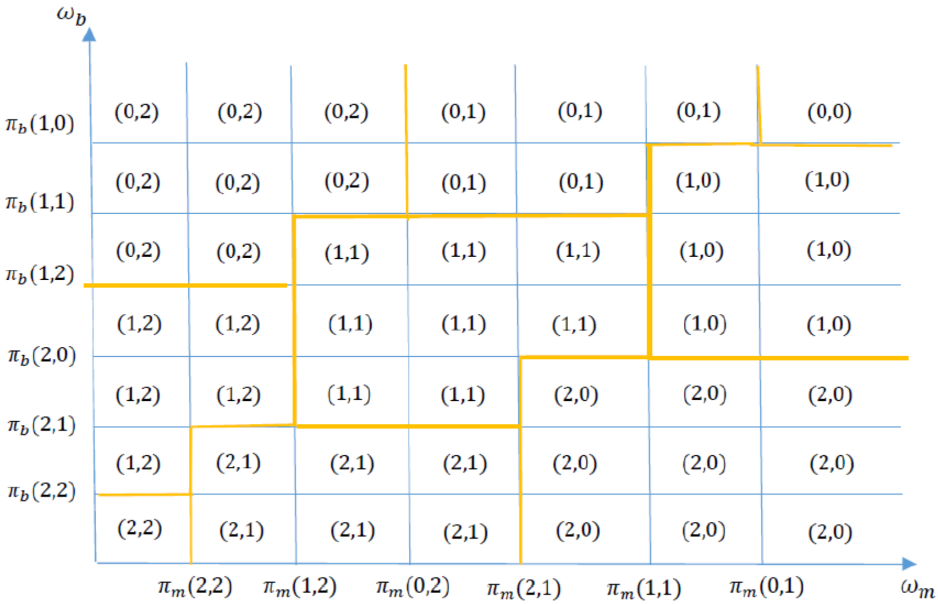
In order to obtain a unique equilibrium in terms of the number of firms of each type, Mazzeo (2002) introduces additional inequalities related to the optimal selection of types in each market. Given that types are given in the context of this paper, I assume instead that potential entrants of the type b (mainstream institutions) have a competitive advantage with respect to MFIs. This means that in markets that are attractive for both types, but where at most one additional competitor can operate profitably, the outcome $\{N_b + 1, N_m - 1\}$, rather than $\{N_b, N_m\}$ is obtained. This assumption is in line with the fact that traditional financial institutions have been active in the retail banking industry for a longer period and have more liquidity, which allow them to make investments in branching networks faster than MFIs. Given these assumptions, the resulting equilibrium is unique in terms of the number of competitor in each category, and the likelihood contribution of a market with $\{N_b, N_m\}$ competitors can be calculated as follows:

$$\begin{aligned}L(\{N_b, N_m\}) = &\int\limits_{\pi_b(N_b+1,N_m)}^{\pi_b(N_b,N_m)} \int\limits_{\pi_m(N_b,N_m+1)}^{\pi_m(N_b,N_m)} f(\omega_b, \omega_m) d(\omega_b, \omega_m) - \\ &\int\limits_{\pi_b(N_b+1,N_m-1)}^{\pi_b(N_b+1,N_m)} \int\limits_{\pi_m(N_b+1,N_m)}^{\pi_m(N_b,N_m)} f(\omega_b, \omega_m) d(\omega_b, \omega_m),\end{aligned}$$

where $f(\omega_{bj}, \omega_{mj})$ is the distribution function of the duplet (ω_b, ω_m).

Figure 2.1 presents an example with two players of each type. The delimited areas in the plane represent the set of values of $\{\omega_b, \omega_m\}$ that are consistent with each possible market outcome.

Figure 2.1: Substitutes case: equilibrium outcomes with two firms of each type



Notes: This Figure illustrates the values of the duplet (ω_b, ω_m) that are consistent each one of the possible market outcomes in an hypothetical scenario with two potential incumbents of each type, where the types are substitutes.

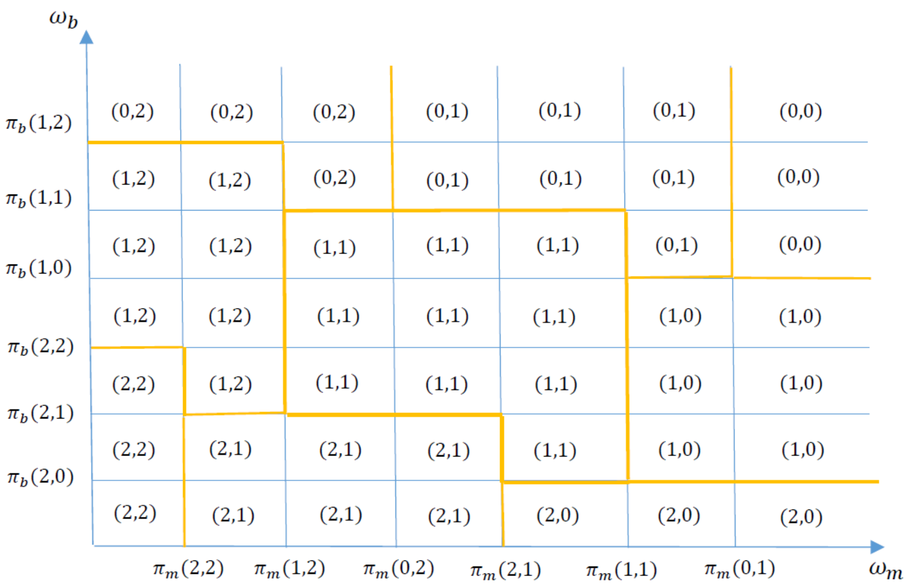
One-sided complementarity

Alternatively, if the effect of the presence of MFIs on market expansion is big enough such that $\Pi_b(N_b, N_m + 1) > \Pi_b(N_b, N_m)$, then the latter type of loan provider acts as complement of mainstream institutions. I consider a case where positive spillovers are one-sided, therefore, MFIs do not benefit from the presence of a mainstream loan provider ($\Pi_m(N_b + 1, N_m) \leq \Pi_m(N_b, N_m)$). A Nash equilibrium of the game exists in this scenario under the assumption that such spillovers on mainstream institutions are smaller than the effect related to another competitor of the same type: $\Pi_b(N_b + 1, N_m + 1) < \Pi_b(N_b, N_m)$ for all N_m. Figure 2.2 presents the predicted outcomes of the game for different values of (ω_b, ω_m) when there are only two competitors of each type. The outcome $\{N_b, N_m\} = \{1, 1\}$ is obtained in the area defined by the equations (2.7) and (2.8), but also in the area where the following inequalities hold:

$$\pi_b(2,0) < \omega_b < \pi_b(2,1)$$
$$\pi_m(2,1) < \omega_m < \pi_m(1,1).$$

In this area, an additional competitor of type b can only operate profitably in this market if there is at least one MFI, but the MFI would operate there if the type b does not. Since the presence of type b reduces the profit of the MFI to the point that it makes its operation not profitable, an additional competitor of its type cannot enter, and the result $\{1,1\}$ is obtained.

Figure 2.2: One-sided complementarity case: equilibrium outcomes with two firms of each type



Notes: This Figure illustrates the values of the duplet (ω_b, ω_m) that are consistent each one of the possible market outcomes in an hypothetical scenario with two banks and two MFIs, where there is complementarity among the two types.

Under this scenario, the likelihood contribution of a market with $\{N_b, N_m\}$ is:

$$L(\{N_b, N_m\}) = \int_{\pi_b(N_b+1,N_m)}^{\pi_b(N_b,N_m)} \int_{\pi_m(N_b,N_m+1)}^{\pi_m(N_b,N_m)} f(\omega_b,\omega_m)d(\omega_b,\omega_m) + \int_{\pi_b(N_b+1,N_m)}^{\pi_b(N_b+1,N_m+1)} \int_{\pi_m(N_b+1,N_m)}^{\pi_m(N_b,N_m)} f(\omega_b,\omega_m)d(\omega_b,\omega_m)$$

Two-sided complementarity

This case is described in detail by Fernandez (2016). She shows that in this case, an equilibrium exists, and it is unique, provided that the positive spillovers derived from the presence of a competitor of the opposite type do not exceed the losses derived from the competitive interaction with an additional loan provider of the same type. As Fernandez (2016) explains, while there can be multiple equilibria for particular values of the unobservable terms, only one of such outcomes is a sub-game perfect equilibrium, the one with the largest number of firms. Figure 2.3 presents the predicted outcomes of the game for different values of (ω_b, ω_m) when there are only two competitors of each type. The outcome $\{N_b, N_m\} = \{1, 1\}$ is obtained in the area defined by the equations (2.7) and (2.8), except for the sub-area where the following inequalities hold:

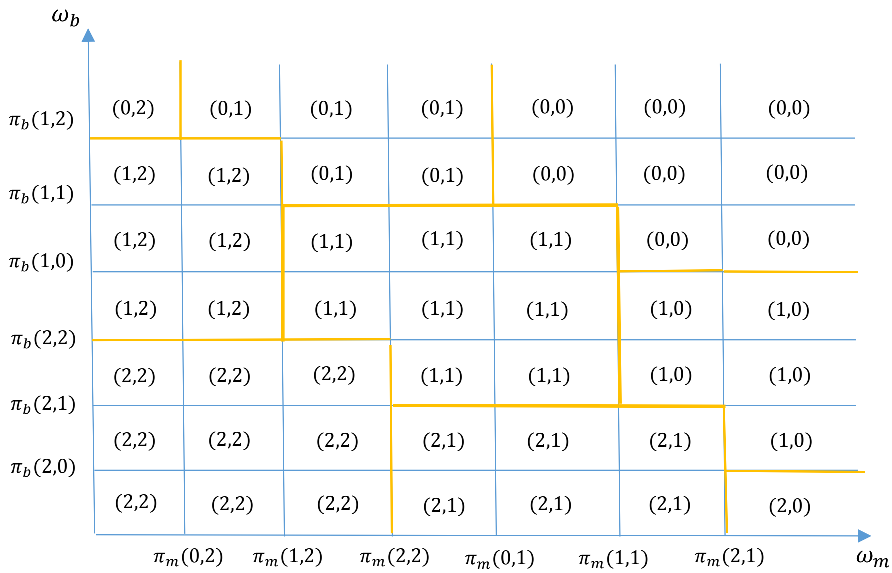
$$\pi_b(2,0) < \omega_b < \pi_b(2,1)$$
$$\pi_m(2,1) < \omega_m < \pi_m(1,1).$$

Under this scenario, the likelihood contribution of a market with $\{N_b, N_m\}$ is:

$$L(\{N_b, N_m\}) = \int_{\pi_b(N_b+1,N_m)}^{\pi_b(N_b,N_m)} \int_{\pi_m(N_b,N_m+1)}^{\pi_m(N_b,N_m)} f(\omega_b,\omega_m)d(\omega_b,\omega_m) - \int_{\pi_b(N_b+1,N_m)}^{\pi_b(N_b+1,N_m+1)} \int_{\pi_m(N_b,N_m+1)}^{\pi_m(N_b+1,N_m+1)} f(\omega_b,\omega_m)d(\omega_b,\omega_m)$$

As shown above, the assumptions on the strategic interaction among competitors of different types have consequences on the likelihood contribution attributed to each

Figure 2.3: Two-sided complementarity case: equilibrium outcomes with two firms of each type



Notes: This Figure illustrates the values of the duplet (ω_b, ω_m) that are consistent each one of the possible market outcomes in an hypothetical scenario with two mainstream institutions and two MFIs, where there is one-sided complementarity among the two types, i.e. mainstream institutions benefit from the presence of MFIs, but the opposite does not occur.

market outcome. Therefore, following the approach developed by Mazzeo (2002), I can compare the log-likelihood across models to decide which one captures better the observed strategic interaction in local markets.

2.5.4 Econometric Specification

The model is estimated by maximum likelihood, by imposing assumptions on the distribution of the unobservable variables ω_{ij} and ε_{ij}. I assume that these variables follow a joint normal distribution and can be correlated. Correlation is also possible across different types of banks that operate in the same market.

Hence, $(\varepsilon_b, \varepsilon_m, \omega_b, \omega_m) \sim N(0, \Sigma)$, where

$$\Sigma = \left[\begin{array}{c|c} \Sigma_{\varepsilon\varepsilon} & \Sigma_{\omega\varepsilon} \\ \hline \Sigma_{\omega\varepsilon} & \Sigma_{\omega\omega} \end{array} \right].$$

The individual likelihood contribution a market j where there are no competitors in the market is given by:

$$L_j(N_b, N_m) = \int\limits_{\pi_b(1,0)}^{\infty} \int\limits_{\pi_m(0,1)}^{\infty} f(\omega_b, \omega_m) d(\omega_b, \omega_m)$$

where the duplet $\{\omega_b, \omega_m\}$ is distributed normal with zero mean and variance equal to $\Sigma_{\omega\omega}$.

If there is a competitor of type $i \in \{b, m\}$ in the market, then it is possible to observe the value of the stock of loans; therefore, it is necessary to calculate the likelihood individual contribution of the market using the joint normal distribution of the duplet $\{\omega_b, \omega_m\}$, conditional on the realization of ε_{ij}. There are four different cases for the conditional variance matrix of the joint distribution function. As an illustration, I will consider here the case where types are substitutes, and the number of competitors is positive for all types.

When $N_b > 0$ and $N_m > 0$, the conditional distribution of the duplet $\varepsilon \equiv \{\varepsilon_{bj}, \varepsilon_{mj}\}$ can be inferred from equation (2.5), given the observed value of (l_{bj}, l_{mj}) and some parameter values β and α. Hence probability of a market structure described by (N_b, N_m) is given by the following expression if types are substitutes:

$$\begin{aligned} L_j(N_b, N_m) = f(\varepsilon_{bj}\varepsilon_{mj})(& \int\limits_{\pi_b(N_b+1,N_m)}^{\pi_b(N_b,N_m)} \int\limits_{\pi_m(N_b,N_m+1)}^{\pi_m(N_b,N_m)} f(\omega_b, \omega_m | \varepsilon_b, \varepsilon_m) d(\omega_b, \omega_m) - \\ & \int\limits_{\pi_b(N_b+1,N_m-1)}^{\pi_b(N_b+1,N_m)} \int\limits_{\pi_m(N_b+1,N_m)}^{\pi_m(N_b,N_m)} f(\omega_b, \omega_m | \varepsilon_b, \varepsilon_m) d(\omega_b, \omega_m)), \end{aligned}$$

The conditional probability density $f(\omega_b, \omega_m | \varepsilon_b, \varepsilon_m)$ is a multivariate normal density with mean equal to:

$$\mu(\omega_b, \omega_m|\varepsilon_b, \varepsilon_m) = \mu_\omega - \Sigma_{\omega\varepsilon}\Sigma_{\varepsilon\varepsilon}^{-1}\left(\varepsilon - \mu_\varepsilon\right),$$

where $\mu_\omega = \mu_\varepsilon = 0$, and variance $\Sigma_{\omega|\varepsilon}$:

$$\Sigma_{\omega|\varepsilon} = \Sigma_{\omega\omega} - \Sigma_{\omega\varepsilon}\Sigma_{\varepsilon\varepsilon}^{-1}\Sigma_{\omega\varepsilon}.$$

Identification of the elements of the variance-covariance matrix is possible, given the restriction on the population coefficient, which is set to be equal to one. I assume that the effect of the presence of an additional competitor of the same type on those components of the profit different from the volume of loans is always negative and larger than the effect of an additional competitor of the opposite type (which can be positive or negative).

2.5.5 Measures of competition intensity

Next, I calculate the changes in profit and loans supply generated by the presence of an additional rival of each type in the market, using equations (2.3) and (2.4). The competitive effects on the local supply of loans per capita can be estimated as:

$$\frac{l_{bj}(1,1)}{l_{bj}(1,0)} = \exp(\alpha_b(1,1) - \alpha_b(1,0)).$$

Similarly, the effects of the presence of an additional competitor on other components of the profit can be calculated as:

$$\frac{\mu_{bj}(1,1)/f_{ij}}{\mu_{bj}(1,0))/f_{mj}} = \exp(\delta_b(1,1) - \delta_b(1,0)).$$

Where $\delta_b(1,0) = \theta_b(1,0) - \alpha_b(1,0)$.

2.6 Results

Tables 2.4 and 2.5 present the detailed results of the estimation under the three sets of assumptions described in Section 2.5. While the estimated coefficients of control variables are similar across specifications, the value of the likelihood function is lower in the case of strategic substitutability and one-sided complementarity. Furthermore, the estimates of the parameters capturing the competitive interaction across types in these specifications seem to hit the constraints, which is suggestive of the incompatibility of these sets of assumptions with the type of competitive interaction observed in the data.[11] In consequence, I focus here on the results of the model that assume two-sided strategic complementarity. As expected, the share of the population in poverty conditions and the distance to the closest urban center and the number of attacks by illegal armed groups have a negative impact on the overall profit. Therefore, it is less likely that mainstream or microfinance institutions operate in poor, remote areas, with greater levels of illicit activity. Similarly, the estimates obtained for the equation for the volume of loans indicate that there is a positive impact of the variables that capture economic conditions, and a negative impact of crime and violence by illegal armed groups. The presence of the public bank is related to lower loan supply from mainstream institutions, while the effect has the opposite sign for MFIs.

In order to facilitate the interpretation of the coefficients that capture the competitive interaction across and within types, I present the estimated changes in the loan supply and the overall profit, relative to a monopoly scenario for different market structures (Table 2.6), after controlling for observed and unobserved market characteristics. By estimating the volume of loans' equation and the probit model jointly I am able to account for the selection bias generated by the fact that we are only able to observe the volume of loans of those competitors who are active in the market, and to provide an estimate of the correlation between the unobservable terms present in both equations, based the set of assumptions used to model the interaction of the competitors and the distribution of the unobservables. Failing to account for the correlation of unobservables across types would most likely result in overestimation of market expansion, since some markets may result attractive for both types due to the effect of variables unobserved by the econometrician.

The first section of Table 2.6 contains the changes in the value of the loan portfolio per capita related to the presence of an additional competitor of each type in the market. In the case of mainstream institutions, the presence of a competitor of the same type is associated to an increase in the volume of loans provided by incumbents

[11] In the case of strategic substitutes the parameters that capture the effect of MFIs on the profit of mainstream institutions are close to zero, while in the case of one-sided substitutability the estimated effect of a competitor of the opposite type is close to the effect of the entry of a competitor of the same type.

of 12.7% relative to the monopolist level if another mainstream bank is present in the market and of 21.1% if an MFI operates in the area. These results indicate that there is substantial market expansion associated with the presence of other financial institutions in the market. In the case of MFIs, these effects seem to be smaller in magnitude. The volume of loans is not significantly smaller than the monopolist level in markets with one competitor of the same type, and it reduces to 74,6% of the monopolist level in places with more than two competitors of this type. This is consistent with the fact that MFIs offer a narrower and more homogeneous portfolio of services than mainstream institutions. Finally, the volume of loans per capita of MFIs in markets with one mainstream loan provider is not significantly different from the one observed in places where they act as monopolists. This is an expected result, given that MFIs focus on potential clients that are often considered as not eligible by traditional banks.

Market expansion seems particularly strong in places where loan providers face only one additional competitor, either a mainstream institution or an MFI. There are several factors that might contribute to the low levels of business stealing among competitors in the loans market compared to other retail industries. First, competition among loan providers increases the pressure on banks to relax their credit standards by offering services towards clients with greater default risk. Second, the arrival of an additional competitor expands the financial infrastructure available in the market (number of ATMs, banking correspondents and commercial establishments accepting credit/debit cards), which increases the perceived benefits of the services offered by different loan providers, as well as the level of consumers awareness and financial literacy. Finally, as MFIs are able to create information about the payment behavior of clients, their presence contributes to expand the pool of clients that are eligible by mainstream institutions.

The second part of Table 2.6 presents the competitive effects on the overall profit (as explained in Section 3, these parameters also capture the effect of the presence of additional competitors in the deposits market). The results reveal important asymmetries in the competitive effects across types, with mainstream institutions obtaining substantially higher profits in markets where MFIs operate, while the opposite does not seem to occur. One explanation for this result is the presence of market expansion in the deposit markets. Micro-entrepreneurs who become clients of MFIs might begin to demand services offered by the mainstream institutions, such as saving accounts. On the other side, the results are suggestive of strong competition among competitors of the same type, especially in the case of MFIs. The drop in the overall profit of loan providers in places where there is at least one competitor of the same type indicates that they might need to incur higher costs in order to maintain a profitable level of operation, and is indicative of substantial competition in the deposits market.

Finally, Table 2.7 presents the estimated correlation between unobservables entering the profit and the volume of loans equation (η and ϵ). As expected, the correlation between the unobservables affecting the overall profit and the volume of loans of loan providers of the same type is positive for both types, indicating that those markets that are attractive for mainstream institutions are also profitable for MFIs. The variable ϵ captures local unobserved characteristics that have a direct impact on the volume of loans, while η captures the unobservable factors that have an impact on other components of the profit. I find that the correlation of these unobservable terms across types is positive and significant, which confirms the importance of modeling the entry and loan equations for both types. As seen in the Table, the covariance η and ϵ is larger for MFIs than for mainstream institutions. In addition, the covariance between ϵ_b and ϵ_m is positive and larger than the covariance between η_b and η_m. These results could be explained by the scarce participation that MFIs maintain the deposits market. While mainstream banks operate in some locations where the volume of loans is low, due to the possibility of capturing deposits from the public, the presence of MFIs is closely linked to the local demand for loans.

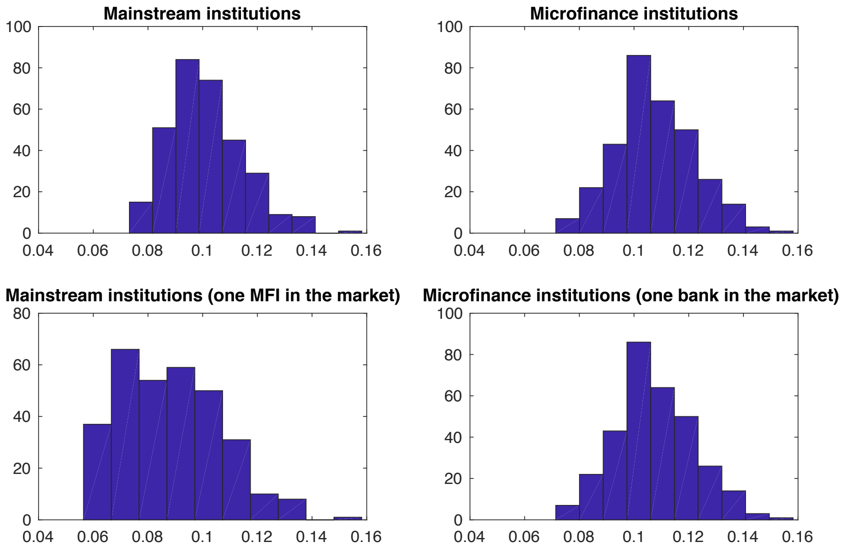
In summary, the results of the structural model confirm the presence of spillovers among mainstream and microfinance institutions and reveal important asymmetries in the competitive interaction of these types of loan providers. While mainstream banks benefit in general from the presence of MFIs, spillovers in the other direction are not significant. Furthermore, the estimates reveal that the positive spillovers generated by the presence of MFIs on the overall profit of mainstream institutions are not necessarily due to market expansion in the loans market, although the effects on the volume of loans are positive and significant. This could be related to the role of MFIs in creating demand for services provided by mainstream institutions in the deposit and insurance markets. In order to get a better understanding of the mechanisms behind the profit increase for mainstream institutions, more detailed information about local interest rates for both loans and deposits, default rates, and other costs is required.

2.7 Policy implications

It is the interest of many governments in developing countries to facilitate access to financial services to all segments of the population, particularly in remote zones where the lack of funding is cited as one of the main difficulties for the success of small scale production projects. One relevant question in the design of policies that facilitate entry in small distant markets is where should the government provide additional incentives for entry. Recognizing the existence of positive spillovers across mainstream and microfinance institutions might change the optimal strategy of the government since it could be more efficient to give priority to MFIs in some markets, as their presence could make the location more attractive for mainstream institutions. The optimal policy in terms of which type of loan provider should receive an incentive, as well as the magnitude of the subsidy or tax relief will depend on the characteristics of each market.

In this section, I use the structural model to predict the expected profit and volume of loans of MFIs and mainstream institutions in markets where there are no competitors and the size of the subsidy that the government would have to provide in order to achieve entry in those locations. In order to obtain these predictions, I calculate the expected values of the unobservables entering the profit and the volume of loan equations using their conditional joint distribution. Using these values, I predict the expected profit that a potential loan provider would obtain if it decides to enter a particular market. Figure 2.4 presents the distribution of the subsidies across markets with no competitors (the values are presented as a percentage of the fixed cost). As seen in Figure 2.4, the value of the minimum subsidy required to achieve entry of one loan provider is distributed similarly for mainstream and microfinance institutions. In both cases, the government would need to provide a subsidy of around 10.1% of the fixed cost of operation in order to create enough incentives for entry. As expected, the size of the subsidy needed to achieve entry of a mainstream institutions reduces if the government provides also provides incentives for at least one MFI to enter the same market. In contrast, the size of the subsidy required to achieve MFIs' entry remains almost unchanged if the government subsidizes the entry of a mainstream institution in the same location.

Figure 2.4: Minimum subsidy to satisfy entry condition in markets with no competitors



Notes: The subsidies are calculated as a percentage of the expected fixed cost of operation. The top row presents the distribution of the subsidy that should be provided in order to achieve entry of one financial institution in markets with no competitors. The bottom row presents the distribution of the subsidy required to achieve entry of mainstream institutions (MFIs) if the government also provides entry incentives to lenders of the opposite type.

2.8 Final Remarks

The model presented here allows us to measure the impact of entry of MFIs on the profit of incumbent formal financial institutions in geographically isolated markets. The results indicate that the first type of institutions generate market expansion that benefits all competitors in the market. If these expected gains materialize in the entry of mainstream lending establishments in isolated markets, then MFIs would contribute to consumer welfare by facilitating access to financial products that are beyond the scope of their own portfolio. This new insight about the competitive interaction among MFIs and other formal loan providers could help in the design of policies oriented towards financial inclusion.

The results of the structural model indicate that the positive spillovers generated by the presence of MFIs on the overall profit of mainstream institutions are only partially due to market expansion in the loans market. Other components of the local profit, such as those obtained from the investment of resources captured in the form of the deposits from the public, or the revenue obtained through the supply of other financial services play an important role. In order to obtain more insights on the mechanisms behind this profit increase, more detailed information about local interest rates for both loans and deposits, default rates, and other costs is required. Although the results could be associated with the creation of information about payment behavior that becomes available for other institutions, there are alternative explanations, such as the additional demand for services offered by mainstream institutions in the deposits market. In the long run, the interaction with MFIs could help clients to increase their levels of financial literacy and awareness or trust in formal institutions, which may lead them to demand more products offered by mainstream financial institutions. Finally, the timely access to funding is likely to have a substantial impact on the rate of success of productive projects, translating into sustained improvements in the economic conditions of clients, which would allow them to demand other types of financial services in the future. Exploring these alternative mechanisms requires more detailed information about the portfolio choices of the consumers in those markets over time, and therefore it is left for future research.

One crucial factor that affects the competitive interaction in the retail banking industry and the supply of microcredit is technological change, in the form of virtual and mobile channels that facilitate the access to financial products without traditional 'brick and mortar' branches. These innovations are likely to have a meaningful impact on the way competitors interact in these markets and represent a challenge for econometricians and policy makers since accurate measures of competition need to take into account the potential interaction of lenders across geographic markets and platforms. In Colombia, most of these innovations were not available in small remote towns during the period analyzed here, and even today, the presence of traditional branches or loan officers continues being necessary for the provision of loans, particularly in the case of microcredit, since most of the specialized loan providers perform close monitoring of the clients' ventures.

The use of virtual and mobile transaction channels for capturing deposits and perform transactions have important consequences on the relations between the deposits and the loan market that I have not taken into account in this paper. So far, the banking industry has been faster at developing interaction platforms that facilitate the use of deposits, than at implementing tools that enable remote monitoring of credit risk, particularly in the case of microfinance. As highlighted by Aguirregabiria et al. (2012), these differences have a significant impact in the way that loan providers obtain funding for their operations, exposing financial institutions to different degrees of geographical risk, and may ultimately reduce the possibility of consumers in far locations to get loans, as financial institutions might find it profitable to concentrate their loan operations in the biggest markets.

Table 2.4: Detailed Estimation Results for the Profit Equation

	Substitutes		Complementarity: MFI to banks		Two sided complementarity	
	Mainstream Banks	MFI	Mainstream Banks	MFI	Mainstream Banks	MFI
	Profit equation					
Population	0.7679**	0.8540**	0.7787**	0.8624**	0.7256**	0.7571**
	(0.0071)	(0.0065)	(0.0113)	(0.0173)	(0.0070)	(0.0108)
Number of firms per 1000 inhabitants (log)	0.0325**	-0.0084	0.0217**	-0.0132**	0.0511**	-0.0381**
	(0.0072)	(0.0079)	(0.0052)	(0.0056)	(0.0054)	(0.0052)
GDP per capita (log)	-0.2232**	-0.5943**	-0.1886**	-0.5061**	-0.1402**	-0.7138**
	(0.0043)	(0.0078)	(0.0136)	(0.0112)	(0.0061)	(0.0138)
Population in rural areas (%)	-2.3067**	-1.7735**	-2.4041**	-2.0701**	-2.3774**	-1.3357**
	(0.0305)	(0.0252)	(0.0414)	(0.0557)	(0.0242)	(0.0251)
Distance to closest urban center (log)	-0.4879**	-0.4294**	-0.5414**	-0.4105**	-0.5093**	-0.2474**
	(0.0067)	(0.0085)	(0.0191)	(0.0231)	(0.0072)	(0.0077)
Share of population in poverty (%)	-3.6631**	-2.3475**	-3.8884**	-2.9207**	-3.9923**	-1.5759**
	(0.0608)	(0.0437)	(0.0453)	(0.0585)	(0.0770)	(0.0682)
Robbery to commercial establishments	0.1289**	0.1497**	0.1321**	0.1543**	0.1237**	0.1494**
	(0.0023)	(0.0018)	(0.0019)	(0.0017)	(0.0016)	(0.0023)
Public bank (dummy variable)	-0.3799**	-0.0297**	-0.4079**	-0.0546**	-0.4698**	0.2736**
	(0.0172)	(0.0174)	(0.0274)	(0.0297)	(0.0122)	(0.0157)
Number of attacks by illegal armed groups	-0.0169**	-0.0097**	-0.0233**	-0.0295**	-0.0083**	-0.0478**
	(0.0041)	(0.0047)	(0.0031)	(0.0034)	(0.0035)	(0.0034)
First Mainstream bank	-0.8059**	-0.0056	-0.8838**	-0.6363**	-0.9226**	0.0006
	(0.0054)	(0.0057)	(0.0077)	(0.0076)	(0.0096)	(0.0065)
Additional Mainstream bank	-0.4163**	-0.1825**	-0.4921**	-0.2220**	-0.5384**	0.0430**
	(0.0165)	(0.0157)	(0.0218)	(0.0245)	(0.0223)	(0.0242)
First MFI	-0.0090	-0.5130**	0.0001	-0.7160**	0.5070**	-1.1606**
	(0.0597)	(0.0686)	(0.0511)	(0.0508)	(0.0505)	(0.0636)
Additional MFI	-0.0080	-1.0349**	0.4914**	-0.6366**	0.5366**	-1.2757**
	(0.0083)	(0.0107)	(0.0089)	(0.0093)	(0.0180)	(0.0338)
Log-likelihood	-905.78.37		-927.1418		-890.8555	

Notes: The values of the coefficients for mainstream banks and MFIs are divided by the estimates of σ_{ω_b} and σ_{ω_m}, respectively.

Table 2.5: Detailed Estimation Results for the Revenue Equation

	Substitutes		Complementarity: MFI to banks		Two sided complementarity	
	Mainstream Banks	MFI	Mainstream Banks	MFI	Mainstream Banks	MFI
	Volume of loans per capita					
Number of firms per 1000 inhabitants (log)	-0.0913	-0.0322	-0.0902	-0.0275	-0.0857	-0.0339
	(0.0717)	(0.0802)	(0.1267)	(0.1403)	(0.0705)	(0.0739)
GDP per capita (log)	0.6075**	0.6905**	0.6180**	0.7077**	0.5748**	0.6031**
	(0.0050)	(0.0026)	(0.0049)	(0.0078)	(0.0046)	(0.0081)
Population in rural areas (%)	0.9562**	0.8736**	0.9521**	0.8977**	0.8955**	0.8584**
	(0.0136)	(0.0115)	(0.0343)	(0.0426)	(0.0274)	(0.0201)
Distance to closest urban center (log)	0.9604**	0.6172**	0.9750**	0.6169**	0.9054**	0.5156**
	(0.0089)	(0.0041)	(0.0085)	(0.0081)	(0.0089)	(0.0085)
Share of population in poverty (%)	-2.3549**	-0.3800**	-2.3844**	-0.4186**	-2.1841**	-0.2232**
	(0.0261)	(0.0155)	(0.0356)	(0.0331)	(0.0166)	(0.0126)
Robbery to commercial establishments	-0.0306**	-0.0751**	-0.0304*	-0.0785**	-0.0297**	-0.0692**
	(0.0035)	(0.0037)	(0.0207)	(0.0235)	(0.0096)	(0.0096)
Public bank (dummy variable)	-0.1167**	0.4009**	-0.1232	0.3959**	-0.1117**	0.3478**
	(0.0366)	(0.0394)	(0.1314)	(0.1496)	(0.0520)	(0.0515)
Number of attacks by illegal armed groups	-0.0633**	-0.0482	-0.0628	-0.0472	-0.0601	-0.0434
	(0.0359)	(0.0398)	(0.0493)	(0.0546)	(0.0479)	(0.0499)
First Mainstream bank	0.1019**	-0.1724**	0.0901**	-0.2226**	0.0872**	0.0016
	(0.0471)	(0.0528)	(0.0390)	(0.0410)	(0.0451)	(0.0470)
Additional Mainstream bank	-0.0100	0.0402**	-0.0137	0.0505**	-0.0150	0.0440
	(0.0132)	(0.0145)	(0.0121)	(0.0138)	(0.0335)	(0.0344)
First MFI	0.1295**	-0.2011**	0.1274**	-0.2587**	0.1389**	-0.2493**
	(0.0007)	(0.0007)	(0.0197)	(0.0200)	(0.0702)	(0.0700)
Additional MFI	-0.0409	0.0177	0.0133	0.0006	0.0145	0.0272
	(0.0634)	(0.0705)	(0.0559)	(0.0620)	(0.1182)	(0.1236)
Log-likelihood	-905.78.37		-927.1418		-890.8555	

Notes: The values of the coefficients for mainstream banks and MFIs are divided by the estimates of σ_{ω_b} and σ_{ω_m}, respectively.

Table 2.6: Effects of entry relative to a monopoly situation

Change in market structure vs. monopoly scenario	Mainstream Banks	MFI
	Value of the loan portfolio per capita	
One additional mainstream bank	1.1277**	1.0598
	(0.0492)	(0.0471)
Two additional mainstream banks	1.1047**	1.0620
	(0.0604)	(0.0610)
One additional MFI	1.2110**	1.0366
	(0.0806)	(0.0546)
Two additional MFIs	1.2354*	0.7458**
	(0.1602)	(0.1138)
	Overall profit	
One additional mainstream bank	0.2804**	1.0584
	(0.0180)	(0.0475)
Two additional mainstream banks	0.1335**	1.0592
	(0.0131)	(0.0662)
One additional MFI	2.0113**	0.1855**
	(0.1188)	(0.0219)
Two additional MFIs	4.2139**	0.0400**

Notes: **Significantly different from 1 at 1%. Standard errors are calculated using the delta method.

Table 2.7: Estimates of the unobservables' variance matrix

	(Mainstream Banks)	(MFI)
σ_{ϵ_i}	1.7476**	1.4906**
	(0.0213)	(0.0366)
σ_{η_i}	1.0746**	0.6911**
	((0.0053)	(0.0042)
$cov(\epsilon_i, \eta_i)$	0.4776**	0.8070**
	(0.0137)	(0.1038)
$cov(\eta_i, \eta_j)$	0.3820**	-
	(0.0070)	-
$cov(\epsilon_i, \epsilon_j)$	1.1548**	-
	(0.0188)	-
$cov(\epsilon_i, \eta_j)$	0.3819**	-
	(0.0210)	-

Notes: **Significantly different from 1 at 1%. Standard errors are calculated using the delta method.

Chapter 3

The Effects of Usury Ceilings on Consumers Welfare: Evidence from the Microcredit Market in Colombia

Abstract

Interest rate caps, also called usury ceilings, are a widely used policy tool to protect consumers from excessive charges by loan providers. However, they are often cited as a barrier for the advancement of financial inclusion, since they may reduce the incentives to provide loans to borrowers with lower income or located in remote areas. In this paper, I exploit a change in the usury ceiling applied to micro-loans in Colombia to understand the effects of this policy across geographic markets. To quantify the welfare implications of this policy, I structurally estimate a demand and supply model that incorporates the changes in size and composition of the potential market caused by this policy change, in a context where the distribution of branching networks has a crucial role in the optimal pricing strategies of loan providers. I find that the policy generated an increase in consumer surplus at the national level that is explained by greater credit availability for riskier borrowers and the expansion of branching networks in areas that were previously under-served. A counterfactual exercise reveals that the welfare gains associated to this policy depend greatly on additional investment in branching networks, as the opening of new branches in some locations helps to compensate the consumer welfare loss associated with the increase in interest rates after the relaxation of the ceiling.

3.1 Introduction

Access to affordable credit for the low-income population has become a worldwide spread policy in recent decades. Efforts in this direction are motivated by the premise that access to flexible and affordable funding allows individuals to develop productive projects and support the accumulation of productive assets and human capital, providing protection against unexpected shocks, and leading to an improvement in their socio-economic conditions (Cull et al., 2013).[1] From a macroeconomic perspective, financial inclusion has been associated with higher economic growth. Evidence of this link has been provided by Beck et al. (2007), who use cross-country data in the period from 1960 to 2005 to show that financial development reduces income inequality and contributes to aggregate economic growth, and Donou-Adonsou and Sylwester (2017), who find a significant effect of access to microloans on economic growth using a panel of 85 developing countries in the period 2002 to 2013.

Public and private initiatives have resulted in a broader portfolio of financial services for low-income clients. However, important barriers persist to date for the expansion of this market. Armendariz and Morduch (2007) and Cull et al. (2013) present a detailed overview of the challenges in the provision of financial services for the poor. They identify barriers on the demand side, such as scarce information that low-income clients have about the advantages of formal credit alternatives and low levels of financial literacy. On the supply side, they highlight, among other factors, the presence of higher operational costs that cannot be fully transferred to the borrower via higher interest rates due to regulatory barriers. Microfinance institutions (MFIs) operating in different countries often cite the presence of interest rate caps as a barrier that prevents them from reaching a broader segment of clients (Ledgerwood et al., 2013).

The appropriateness of this type of price regulation has been debated for decades, as it remains a widely used policy tool across countries of all income levels.[2] On the one hand, the imposition of a ceiling may lead to a shortage of formal alterna-

[1]There are numerous empirical studies that have examined the link between economic welfare and credit access, with different conclusions. Banerjee et al. (2015) find that microcredit allows poor households to invest in their small businesses, although they do not find a significant impact on household consumption and other welfare measures. By contrast, Khandker (2005) and Augsburg et al. (2015) find that access to microfinance increased the standard of living of communities that receive microloans in Bangladesh and Ethiopia.

[2]See Maimbo and Gallegos (2014) and Ferrari et al. (2018) for a comparison of interest rate regulations across countries.

tives of funding for poor clients, reducing price transparency, and even facilitating tacit collusion (Knittel and Stango, 2003; Temin and Voth, 2008; Melzer, 2011; Zinman, 2010). On the other hand, usury ceilings can be seen as a mechanism to limit undesirable distortions associated with third-degree price discrimination, protecting vulnerable clients against predatory practices of lenders with excessive market power (Dewatripont and Tirole, 1994; Stango and Zinman, 2015).

Several empirical studies have found that lenders in the consumer loans market may have enough market power and information about potential customers to exert this type of price discrimination.[3] The consumers' inability to evaluate all the alternatives available in the market, as well as the presence of switching costs and imperfect information about credit contracts, contributes to the market power of lenders, particularly in the case of products targeted for low-income borrowers (Agarwal et al., 2014; Stango and Zinman, 2015).

Economic theory suggests that the welfare implications of interest rate caps will depend on how much market expansion can be achieved if they are removed.[4] Theoretical contributions on the topic show that, while the presence of this type of regulation may lead to excess supply in some segments and shortages in those with higher marginal costs, the overall effect in terms of consumer and producer welfare is not necessarily harmful, and the outcome will depend on the curvature of the demand function, the distance between the ceiling and the marginal cost, and the differences in marginal costs across segments.

The type of credit rationing that is associated with the presence of interest rate ceilings is the result of an external distortion and is different from the one described by Stiglitz and Weiss (1981), where rationing arises as a result of adverse selection in a context where the only screening instrument available for lenders is the interest rate. In the situation described by the authors, allowing banks to charge interest rates higher than a certain threshold does not increase the volume of loans because lenders would interpret the willingness to pay such high fees as a signal of a high risk of

[3] Galenianos and Gavazza (2019) and Stango and Zinman (2015) document high levels of dispersion in the interest rates charged for narrowly defined loan products, even after controlling for a rich set of individual characteristics potentially informative of the risk profile of the borrowers.

[4] Schmalensee (1981) uses a formal approach to prove some degree of price discrimination can be welfare improving in cases where there is a significant increase in the volume of sales in segments that could not be served under uniform pricing. His framework has been extended later by Armstrong et al. (1991), Aguirre et al. (2010), among others, to analyze the implications of price ceilings in cases where a monopolist can offer multiple products and marginal costs are allowed to differ across segments. For a detailed exposition of the topic see Stole (2007).

default. These results rely on strong assumptions, such as the role of the interest rate as the only screening tool available, and that all productive projects have identical expected returns and differ on their risk level only. When these assumptions are relaxed, rationing is not optimal anymore in equilibrium (Meza and Webb, 1987)). In the microfinance industry, financial institutions have developed strategies that allow them to gather information about the probability of success of productive projects and the borrowers' payment behavior. These screening and monitoring technologies are relatively expensive, but they allow them to overcome some of the adverse selection problems that could give origin to the equilibrium credit rationing result obtained by Stiglitz and Weiss (1981). Abundant empirical evidence indicates that banks tend to increase their volume of loans after the interest rate restrictions are relaxed, even in the context of microfinance, where the interest rates are typically very high already (Armendariz and Morduch, 2007). In line with these findings, the volume of loans and the overall profit of loan providers in Colombia (particularly microfinance institutions) increased after the interest rates were relaxed.

Whether or not lifting usury ceilings is welfare-improving is, therefore, an empirical question. While there are plenty of studies that describe the evolution of credit markets after the modification of an interest rate cap for different countries and periods (see: Temin and Voth, 2008; Benmelech and Moskowitz, 2010; Maimbo and Gallegos, 2014), only few studies provide a quantification of the welfare effects of this type of policy. Recent developments in this direction, by Cuesta and Sepulveda (2019) and Galenianos and Gavazza (2019), make use of comprehensive data sets that include detailed information on individual loan operations. Unfortunately, this information is often unavailable in low-income regions, where the development of microfinance has been significant and perhaps most relevant. This problem is sometimes exacerbated by the differences in the regulatory framework that applies to loan providers in the microfinance sector, which often translates into different information requirements and confidentiality rules.

In order to measure the welfare implications of this policy in contexts where comprehensive data on individual transactions are not available, I propose a structural model of demand and supply that can be estimated using market-level information. In the model, loan providers operate across multiple market segments and geographic locations. The model incorporates changes in the size and composition of the potential market in each location that may occur as a result of the regulatory change. It allows us to measure to what extent these changes in credit availability are due to an increase in the supply of loans of existing competitors or due to the entry of new competitors in local markets. Consistent with the practice of financial institutions in the microloans market, and motivated by data limitations that are common in this industry, I consider a scenario where price discrimination occurs based on the risk profile of the clients, but it is not perfectly observed by the econometrician.

The link between the evolution of branching networks and changes in the pricing strategies of financial institutions is a critical element of my approach that has not been considered in the literature. The microfinance industry has become increasingly dominated by large specialized institutions that operate across multiple locations by making use of extensive networks of brick-and-mortar branches. These networks are particularly important in the microcredit market, as they facilitate the collection of reliable information about payment behavior of potential borrowers, as well as the monitoring on the performance of productive projects that have received funding. The decisions of loan providers regarding the location of their branches will have, therefore, different welfare implications for consumers across locations, depending on the impact on the local availability of credit.[5] The relaxation of the interest rate cap modifies the incentives of financial institutions to expand their branching networks towards new locations, by making it profitable to offer loans to a wider segment of clients. These effects may be significant even in contexts where financial institutions set a unique interest rate for each type of loan (client) at the national level, because the distribution of branches across geographic markets will determine their exposure to local competitive environments. In this paper, I incorporate the effects of these changes in the size and distribution of branching networks on the optimal pricing strategy of financial institutions.

My identification strategy exploits the variation of market shares and product characteristics across geographic markets, before and after the policy change, to identify the consumers' sensibility to changes in loan characteristics. My approach combines elements from several studies that estimate demand in the context of limited attention (e.g. Abaluck and Adams, 2017; Ho et al., 2017; Hortaçsu et al., 2017; Abrams, 2019), and in the presence of unobserved price heterogeneity (D'Haultfœuille et al., 2018). I combine moment conditions derived from the consumers' utility maximization and the lenders' optimal decision on interest rates, before and after the policy change, to identify changes in the price elasticity and the share of consumers with access to

[5] Bruhn and Love (2014) exploit the opening of a large multi-market bank in Mexico to analyze the effects of financial access on poverty. They find a significant effect of access to finance on labor market activity and income levels, particularly among individuals with low income, located in areas that were under-served before the entry of this agent.

formal loans.

On the supply side, I focus on the optimal pricing strategies of financial institutions for a given market structure. Since I do not model the entry decision of financial institutions across geographic markets, I cannot make conclusions on the effects of changes in usury ceilings on the size and distribution of branching networks. The model, however, allows us to measure how potential borrowers value an extra competitor or branch at a local market, and how their surplus is affected by the increase in the interest rates. This information is used to evaluate to what extent the expected increase in the volume of loans generated by the relaxation of the usury ceiling depends on additional investments on branching networks in new markets, facilitating the comparative analysis of different policy interventions.

I use the model to understand the welfare implications of a modification of the usury ceiling for microloans that took place in Colombia around 2011. This category includes loans that are designed for small entrepreneurs who do not have collateral or cannot provide reliable information about their payment behavior. The Colombian scenario is relevant in the context of microfinance because the institutional framework is comparable to that of other countries in the region, such as Bolivia, Mexico, and Chile, where the main providers of this type of loans are for-profit institutions regulated by the financial supervisory authority.[6] In Colombia, the change in the usury ceiling in 2011 occurred during a period of macroeconomic stability and was followed by a significant increase in the interest rates charged by financial institutions (7 percentage points on average), as well as by an important expansion of the branching networks.

On the supply side, I observe that the expansion in the volume of microloans that occurred after the relaxation in the usury rate was not followed by a significant increase in default risk (see Figure 3.6 in the Appendix). Instead, the regulatory changes were followed by substantial increases in operational costs, salaries and provisions, that suggest a greater effort of financial institutions related with monitoring and screening activities. Overall, the profit of financial institutions increased (the average return over assets (ROA) increased from 2% in 2010 to 2.2% in 2012), particularly for those specialized in microcredit.

I perform a before-and-after comparison of consumer welfare to examine the effects

[6]In many developing countries, institutions specialized in the provision of financial services for the poor have transitioned from non-profit organizations into regulated financial institutions (Ledgerwood et al., 2013).

of the relaxation of the usury rate. I find significant gains associated both with the greater availability of branches in new locations, and the increased funding for borrowers who did not have access to formal loans before the policy change. These gains exceeded the reduction in consumer surplus caused by the increase in the interest rates. When comparing the welfare gains of consumers across markets, the results indicate that those who benefited the most from the policy change were the ones located in markets where the expansion of loan operations towards riskier borrowers was accompanied by entry of new competitors.

In a counterfactual scenario where I examine the effects of relaxing the usury ceiling in the absence of additional investment in branching networks, I find that the policy is still welfare improving. Although there are markets that would experience a reduction in consumer welfare in the absence of additional branches, the overall effect is dominated by the increase in consumer surplus of riskier borrowers who gain access to formal loans after the ceiling is relaxed. Nevertheless, the results suggest that there are other barriers prevent micro-entrepreneurs from considering regulated financial institutions as a source of funding, as there is a significant number of potential borrowers who seem to rely solely on informal lenders even after the policy change.

This paper is organized as follows. Section 3.2 provides a brief review of the related literature. Section 3.3 provides an overview of the characteristics of MFIs and other loan providers that interacted in the retail banking industry in Colombia in the period of analysis. Section 3.4 presents descriptive statistics of the data used in the estimation. Section 3.5 describes the consumer choice model, the supply side optimality conditions on the interest rate, and the estimation strategy. Section 3.6 presents the results of the structural model, introduces measures of the impact of the regulatory change on consumer welfare and discusses a counterfactual exercise where I examine the effects of the policy in the absence of additional investments in branching networks. Finally, I present some concluding remarks and potential extensions of the model.

3.2 Related literature

This paper contributes to different strands of the literature. First, it contributes to a growing number of studies on the effects of interest rates caps on consumer welfare. Most of the studies in this literature focus on consumer loans and payday loans (e.g. Benmelech and Moskowitz, 2010; Temin and Voth, 2008; Melzer and Schroeder, 2017; Rigbi, 2013). For example, Melzer and Schroeder (2017) and Zinman (2010) explore the effects of usury laws applied to automobile loans and payday loans in the U.S., concluding that tightening ceilings is harmful for consumers, as it reduces price transparency in the market and limits access to timely funding for vulnerable borrowers.

Most of this work adopts reduced form approaches and focuses on credit access as the main outcome. Recent papers, however, by Galenianos and Gavazza (2019) and Agarwal et al. (2014) find that usury ceilings can be beneficial for consumers as they limit the ability of banks to exert price discrimination in contexts with product differentiation and consumer inattention, without causing a significant reduction in the volume of credit. Cuesta and Sepulveda (2019) find a contrasting result in the context of the Chilean consumer credit market. They propose a structural model of demand and supply of consumer loans to provide evidence of the effects of interest rate caps on market outcomes and welfare, finding that the adverse implications of tightening the usury ceiling on credit access dominate the consumer protection effects.

This paper is also related to a broader set of studies that explores the competitiveness in the credit market and the sources of market power, particularly in segments of low-income borrowers. Recent work by Meier and Sprenger (2010), Zinman (2010), and Nelson (2019) finds that consumers' present bias and limited search, lender concentration, and adverse selection might be behind the excessive market power exhibited by lenders in some markets. Many of these studies explore these topics in the context of the US credit card market, where recent regulation changes such as the Credit Card Accountability Responsibility and Disclosure (CARD) Act of 2009, have attracted renewed attention. The CARD act limited the ability of financial institutions to raise interest rates and other fees in response respond to new information about the borrowers. The seminal work by Agarwal et al. (2014), who finds significant welfare gains for consumers in this market has been followed by other studies that reveal partial market unraveling among subprime accounts (e.g. Han et al., 2018; Nelson, 2019).

Next, this paper joins a growing literature that uses structural models to examine the role of branching networks as a source of differentiation in the context of retail banking. My paper is related to the work of Dai and Yuan (2013), Berger and Dick (2007), and Dick (2008), who use discrete choice models to estimate consumer demand, price, and entry decisions of bank across geographic markets. Their work focuses on the effects of entry triggered by the Riegle-Neal Banking and Branching Efficiency Act of 1994 in the United States and the interaction of different types of financial institutions in local markets, such as single and multi-market banks. In a recent study, Clark et al. (2017) highlight the contribution of branching networks to the market power of multi-market agents and their role in the geographic flow of credit.

From a methodological perspective, my paper is related to a body of literature concerned with demand estimation in contexts where not all consumers are aware of all the services at their disposal (e.g. Abaluck and Adams, 2017; Hortaçsu et al., 2017; Ho et al., 2017). In these studies, the share of consumers that opt for the outside alternative exhibits some degree of inertia that is often associated with inattention, advertising expenditures or higher switching costs. Recently, Abrams (2019) examined local competition in the banking industry across geographic markets the United States by applying a demand model with consideration sets similar to the one proposed by Goeree (2008), where the probability that a consumer is aware of the services offered by a particular bank is a function of the advertising expenditure of the latter. Their model relies on very detailed information of the distance between borrowers and lending, and advertising expenditure of financial institutions across multiple geographic markets. Here, I use similar methods to identify the share of consumers that gain access to credit from formal loan providers after the usury ceiling is relaxed. In addition, my empirical strategy takes elements from recent literature that estimates demand in the presence of unobserved price heterogeneity (D'Haultfœuille et al., 2018; Huang, 2020, e. g.). I follow the approach by D'Haultfœuille et al. (2018), who propose a method for the structural estimation of a demand and supply model with price discrimination, where information on prices is limited and takes the form of, e.g., observing list prices from catalogs or average prices.

Finally, this paper contributes to the literature that has examined the effects of usury ceilings on credit market outcomes in Colombia. Empirical work on this topic has been developed by Steiner and Agudelo (2012) and Cubillos Rocha et al. (2018). These studies use reduced-form approaches and differences in differences estimation to analyze the effects of the measure on the aggregate value of microloans and the number of clients. This paper complements this work by making use of a structural model that incorporates the changes in the composition of the potential market in the demand estimation. My approach has the advantage of allowing for the implementation of different counterfactual exercises that can provide more insights on the effects of the policy on consumer welfare across geographic markets.

3.3 Usury ceilings and microcredit in Colombia

In this section, I provide a brief overview of the microfinance industry in Colombia and the changes in the regulation related to usury ceilings.

Colombia experienced a favorable macroeconomic environment between 2006 and 2014 that was accompanied by a significant expansion of the demand for loans. After a deep financial crisis at the end of the 90s that triggered the implementation of stricter regulation related to credit risk management and capital requirements for financial institutions, the banking industry experienced a process of consolidation resulting in a relatively concentrated market, where commercial banks with extended branching networks throughout the national territory enjoyed significant market power. The growth in the demand for loans is largely explained by the dynamics of non-collateral loans, including those available for small entrepreneurs. Industry reports indicate that the potential for growth in the niche of micro-loans is high, due to the high levels of informality in the labor market and the scarcity of adequate collateral among entrepreneurs (SFC, 2015). According to Estrada and Rozo (2006), these financial constraints are even more acute in rural areas, where financial services had been almost exclusively provided by a public bank that focuses on funding for productive projects in the agricultural sector.

3.3.1 Microloans supply in Colombia

The oldest private financial institutions specialized in microfinance (MFIs) started operations in Colombia at the end of the 1980s. Before their entry, microloans were provided exclusively by the government through development agencies. According to Barona (2004), during the 1990s, most of these institutions were non-profit organizations that funded their loan operations with donations from private individual donors or international development agencies. Only after the financial crisis at the end of that decade, the number of non-profit organizations that offered loans to poor clients started to increase. Between 2000 and 2011, the number of institutions increased from 4 to 26. During this period, the biggest MFIs transitioned from non-profit organizations into specialized banks, while only a few traditional banks made their incursion in the microfinance sector.

The vast majority of the microloans offered by financial institutions in Colombia are individual, rather than group liability loans, and they comply with the legal definition of microcredit, introduced by the government in 2007. This definition specifies i) a maximum amount that can be borrowed by a single client (around USD 7500), ii) a cap on the total debt that the client can have with the financial system (nearly USD 36000) and iii) the charges that financial institutions can apply for additional services related to the loan (different from the interest rate).[7] These loans are typically used by small entrepreneurs to finance productive projects that involve less than ten direct employees. The average amount of a microloan in 2014 was around USD 2160 and the time of repayment was 1.4 years on average (Fernandez, 2014). Most of these loans have a monthly frequency of payments.

While some of these characteristics are similar to those of non-collateral loans offered to households, the interest rate of microloans has been consistently higher. This gap has been attributed partially to differences in how that financial institutions asses the value of the available collateral and gather information about the payment behavior of their clients. To maintain low levels of default and reduce associated loses, they often exert close monitoring of the productive projects of the clients and include additional services for entrepreneurs, such as guidance on marketing and basic accounting. The implementation of these measures is costly and often requires a higher number of employees. MFIs' branching networks have more nodes in rural areas and intermediate cities compared to those of traditional banks, and sometimes they are complemented with mobile agents with the task of reaching clients in isolated locations. Microloans are the credit product with greater geographical diversification. In 2012, 52% of these loans were given to clients in locations different from the 13 biggest cities in the country, while only 5% of the loans in other categories were given to clients outside these locations.

Although the microloans portfolio typically represents only a small fraction of the total volume of credit provided by financial institutions (3,16% in 2012), it has exhibited significant growth in recent years. The value of the portfolio nearly doubled between 2010 and 2017, while the number of clients has increased from 1.2 million to 3.3 million over the same period (Estrada and Hernandez Rubio, 2019). As of 2017, there were a few financial institutions that concentrate the majority of loan operations in the microcredit market. A public bank concentrated around 70% of the loans operations destined to the rural sector, while a dozen of private regulated financial institutions provided the majority of the loans for micro-entrepreneurs in other sectors.[8] Other entities that were not regulated by the financial supervisory

[7]The values presented here were converted into US dollars by applying the year 2014 Purchasing Power Parity, calculated by the World Bank.

[8]Throughout this paper I refer to regulated financial institutions as those under the supervision Superintendencia Financiera.

authority provided 16% of the total volume of loans.[9] Nevertheless, these institutions were subject to the same regulation in terms of usury ceilings.

3.3.2 Interest rate ceilings

The Colombian government has implemented usury ceilings to protect vulnerable consumers of excessive charges. This regulation has existed in Colombia for decades, and it is applicable for every person or institution that offers a loan.[10] With the introduction of regulation related to the supply of microloan by supervised institutions in 2007, the government started introducing changes to the usury ceilings in order to adjust them to the particularities of this market niche, as illustrated in Figure 3.1. Before 2007, there was a single interest rate cap that applied for all types of loans. This ceiling was calculated as 1.5 times the average interest rate charged by regulated financial institutions for consumer and commercial loans during the previous 12 weeks. This ceiling was heavily influenced by the level and dynamics of the interest rates of commercial loans, which were substantially lower than those of consumer and micro loans. In October 2007, the government defined a new interest rate ceiling that was applied to for the category of microloans exclusively. This cap remained fixed until October 2010 at a level of 33.9%, effective annual.[11] Later, after a transition period that ended in January 2011, the usury rate for microcredit was defined as 1.5 times the average interest rate charged by financial institutions for this type of loan during the previous year.

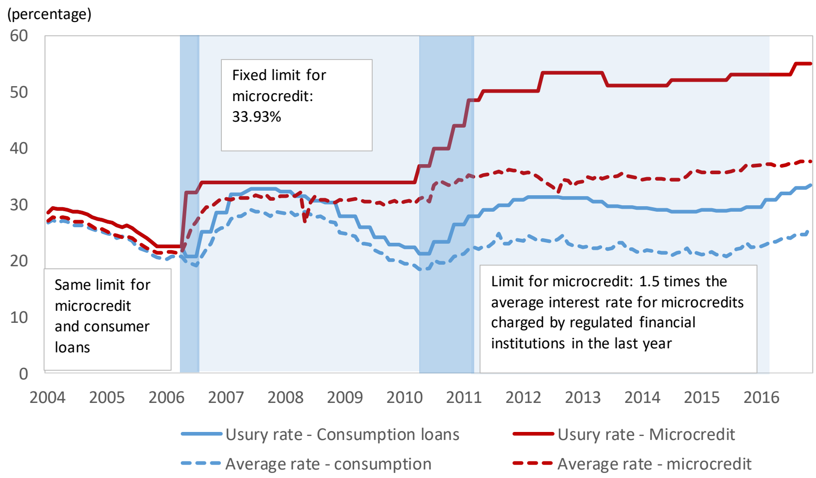
Figure 3.2 presents the distribution of the interest rates (national weighted average) charged by regulated financial institutions. As shown in the figure, the interest rate ceiling applied until September 2010 was binding at least for some of the regulated loan providers. The distribution of the interest rates after the policy change exhibited a shift in the mean and greater dispersion. Banks with the lower interest rates before the policy change maintained them at similar levels or even reduced them after the usury ceiling was modified. These institutions kept a small participation in

[9] Most of these institutions concentrated their operations in a few municipalities and in some cases consumers needed to acquire some type of membership in order to become eligible to obtain a loan. Since these alternatives were not available for all consumers in the market during this period, I consider them as part of the outside option in the demand estimation.

[10] The enforcement of the usury ceiling is more challenging among informal sources of credit, where information about the conditions of the loan contracts is often unavailable.

[11] The inflation rate in Colombia has remained in one digit levels since 2000. Between 2010 and 2012 the average annual inflation rate was 2.95% (based on information of the consumer price index published by Banco de la República (Central Bank of Colombia).

Figure 3.1: Effective annual usury rate 2004-2016

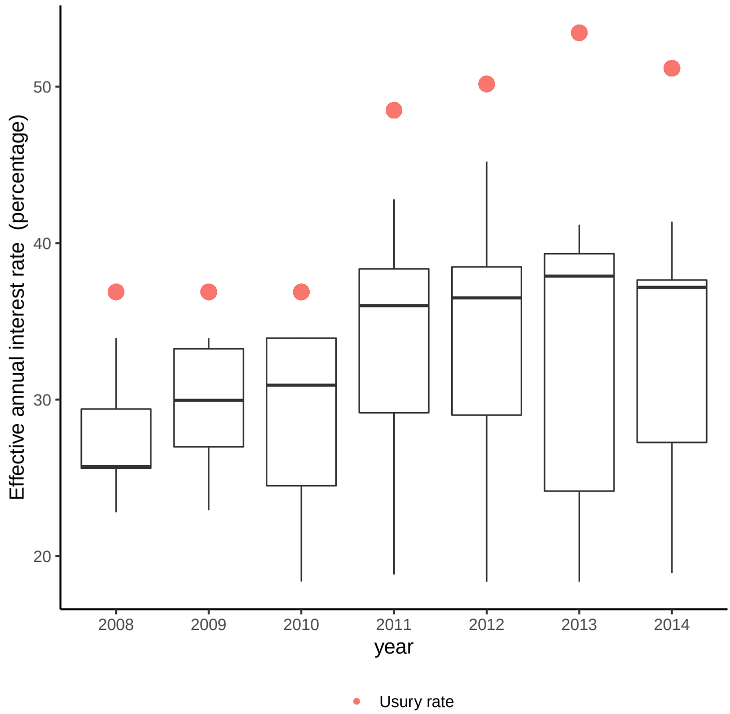


Notes: Figure 3.1 compares the usury ceilings and average interest rates for to micro-loans and consumer loans between 2014 and 2016. Source: Author's calculations based on information published by Superintendencia Financiera de Colombia.

the microcredit market, and their microloans also represented small fraction of their total loans portfolio, even after the policy change. In contrast, entities specialized in this market niche increased their interest rates significantly after the ceiling was relaxed.

The increase in the interest rates was accompanied by a rise in the outstanding value of the microloans portfolio of private regulated loan providers, as shown in Figure 3.3. From 2011 to 2013 the annual growth rate of this portfolio exceeded the one registered in other loan categories. Interestingly, this expansion did not translate into a significant increase in the default risk of loan providers, as seen in Figure 3.6 in the Appendix. The portfolio quality ratio (share of the outstanding portfolio that registers a delay in the payment of more than 30 days) of the cohorts of microloans generated in 2012, after the relaxation of the usury rate, was only slightly higher than the one observed in 2010 and lower than the ratio observed for the cohorts of 2007 and 2008. Financial institutions however, increased their loan provisions substantially between 2010 and 2012, which might be indicative of their willingness to expand their loan operations towards riskier segments of the market after the policy change.

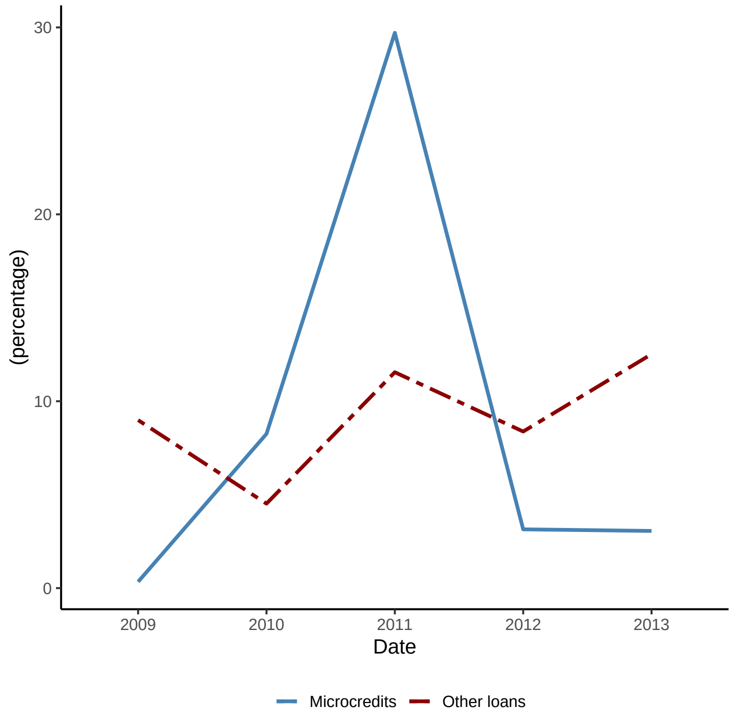
Figure 3.2: Distribution of interest rate of microloans



Notes: Distribution of interest rates of new microloans across private financial institutions (national weighted averages per year). The red dots correspond to the mean usury ceiling for this type of loan in each year . Source: Author's calculations based on information published by Superintendencia Financiera de Colombia.

In addition, the relaxation of the usury ceiling was accompanied by a significant expansion of the branching networks. The entry of new competitors and the branching expansion of incumbents increased the availability of micro-loans in small and intermediate markets. Table 3.1 presents the the number of cities with new competitors between 2008 and 2014. As seen from Table, financial institutions expanded their branching networks substantially in 2011 and 2012, particularly in cities of intermediate size (between 50.000 and 500.000 inhabitants).

Figure 3.3: Annual nominal growth of the microloans portfolio. 2008-2013



Notes: The red solid line corresponds to the average annual growth of the outstanding value of the gross microloans portfolio of private financial institutions regulated by Superintendencia Financiera. Calculations include only those institutions with a microcredit porfolio that represents more than 1% of their total loan portfolio. The blue dotted line represents the annual growth rate of the portfolio comprised by other loan categories. Source: Author's calculations based on information published by Superintendencia Financiera de Colombia.

3.4 Data

Information regarding the bank/loan characteristics, such as the number of branches and the value of the loan portfolio of all financial institutions is published by the Colombian financial supervisory authority (Superintendencia Financiera), while the demographic variables per market were taken from the Municipalities Panel Data Set from Universidad de los Andes, which contains information from several official sources.

I consider information of all the private financial institutions regulated by Super-

Table 3.1: Number of cities with new branches, by population size.

	2008	2009	2010	2011	2012	2013	2014
Less than 50000	0	0	1	0	2	1	1
50.000 to 100.000	0	4	6	5	3	6	3
100.000 - 500.000	0	6	15	7	19	9	8
500.000 - 1'000.000	0	2	4	3	4	0	0
More than 1'000.000	0	2	4	3	3	0	0

Notes: Total number of markets with new competitors compared to previous year, by year and market size. Source: Source: Author's calculations based on information published by Superintendencia Financiera de Colombia.

intendencia Financiera with a microloans outstanding portfolio that represents more than 0.1% of their total loan portfolio. I also include in the analysis the biggest non-profit organizations specialized in microfinance (these institutions transitioned into regulated banks between 2008 and 2011). I focus on private financial institutions only, because the microloans originated by public institutions are often guaranteed by the government and their conditions on interest rate and repayment may differ substantially from those provided by the private sector. The loans originated by public entities are concentrated in the agricultural sector. The data set contains information of 12 out of 26 financial institutions in the period 2019 to 2013. The outstanding value of the microloans portfolio of the institutions included represented 95.67% of the value of microloans provided by private loan providers in 2012.

3.4.1 Financial institutions

Table 3.2 presents summary statistics of the characteristics of these financial institutions at the national level. The average interest rates charged for new microloans in September 2010 ranged from 18,4% to 33.9% (the usury ceiling at the time). While the average deposits rate was relatively similar across financial institutions (between 2.6% to 6.5%), there is significant dispersion across loan providers in terms of their administrative costs and salaries. The differences in the risk management strategies of financial institutions might explain this discrepancy. For example, loan providers that specialize in microfinance exhibit greater administrative costs and typically charge higher interest rates.

Table 3.2: Descriptive statistics of financial institutions at the national level.

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
			September 2010			
Interest rate	0.294	0.049	0.184	0.245	0.339	0.339
Salaries*	0.539	0.453	0.000	0.196	0.744	4.486
Provisions Rate*	0.018	0.024	0.000	0.001	0.050	0.093
Required reserve**	0.095	0.029	0.023	0.084	0.118	0.118
Deposits rate	0.034	0.007	0.026	0.028	0.034	0.051
Microloans portfolio*	0.264	0.394	0.005	0.007	0.528	0.986
Administrative costs*	0.371	1.075	0.046	0.075	0.325	13.364
Previous NGO (dummy var.)	0.228	0.420	0	0	0	1
Bank (dummy var.)	0.874	0.333	0	1	1	1
Number of observations	451					
			September 2012			
Interest rate	0.346	0.070	0.184	0.290	0.385	0.452
Salaries*	0.625	0.612	0.017	0.178	0.886	4.321
Provisions Rate*	0.021	0.026	0.000	0.001	0.054	0.093
Required reserve**	0.084	0.025	0.042	0.059	0.097	0.119
Deposits rate	0.045	0.009	0.034	0.037	0.047	0.065
Microloans portfolio*	0.316	0.415	0.003	0.006	0.917	0.975
Administrative costs*	0.330	0.892	0.042	0.085	0.223	10.053
Previous NGO (dummy var.)	0.280	0.449	0	0	1	1
Bank (dummy var.)	0.866	0.341	0	1	1	1
Number of observations	515					

Summary of descriptive statistics of the characteristics of financial institutions observed at a national level in 2010 and 2012. Source: Author's calculations based on information published by Superintendencia Financiera de Colombia.

*: Values expressed as a percentage of the outstanding value of the loans portfolio.

**: Values expressed as a percentage of the outstanding value of the deposits.

3.4.2 Period of analysis

As shown in Figure 3.1, there is a transition period between the old regulation, that fixated the usury ceiling at 33.93% (effective annual), and the new regulation, that defined the usury rate as 1.5 times the average interest rate charged by regulated financial institutions in the category of microloans in the last 12 months. This period lasted between October 2010 and December 2011. I took September 2010 as the period before the policy change. Anticipation of the policy change does not seem likely on the demand side, as potential borrowers in the segment of microloans are typically not sophisticated in terms of their financial decisions an often exhibit low levels of financial literacy. On the supply side, the number of new loans originated in the months previous to the policy change did not decrease compared to previous periods, suggesting that financial institutions did not strategically restrain the supply of microloans before the relaxation of the usury ceiling. The information available in every geographic location corresponds to the value of the outstanding portfolio, rather than to new loan operations only. In order to make sure that this value fully reflects the new conditions applied by financial institutions after the usury ceiling was modified, I took September 2012 as the period after the policy change.

3.4.3 Geographic markets

The data set contains information of all municipalities in Colombia, where there was at least one branch of a private regulated financial institution at some point between 2019 and 2013 (832 municipalities out of 1122). It includes big urban centers, with a population above 3 million inhabitants, as well as small villages with less than two thousand inhabitants.

My empirical strategy assumes that consumers only consider financial institutions with at least one branch in their vicinity. Using municipality as a proxy for local markets can be problematic, as it is likely that entrepreneurs travel to their closest urban center to request a loan from financial institutions that do not have a branch in their municipality. Since information about the precise location of consumers is not available, I define geographic markets as clusters of municipalities with a maximum distance between them of 40km.[12] This distance is consistent with other studies on the banking industry that measure the average distance that consumers are willing to travel in order to ask for a loan (Berger and Mester (2003)). The resulting number of markets is 134.

Table 3.3 presents the summary statistics of demographic characteristics and market structure. As seen in the table, there is great dispersion in terms of the total population, the share of the population in rural areas and GDP per capita across markets. The number of branches and banking correspondents (BCs) also differs

[12]The distance between municipalities corresponds to the traveling distance obtained using a Google Maps API.

greatly across locations.[13] The microcredit market is highly concentrated, as suggested by the number of competitors in each location. In more than 25% of the markets, there were only two private regulated institutions that offered microloans, with just one branch per entity. Other institutions that offer microloans, such as non-profit organizations and savings associations, were mostly concentrated in urban markets.

Between 2010 and 2012, there was a significant expansion of the branching networks as can be seen in the change in the number of competitors, branches and banking correspondents. 202 new branches were opened during this period in 84 locations, while 55 markets experienced an increase in the number of competitors. During the same period, financial institutions expanded radically their banking correspondents network. The average number of banking correspondents per 100 thousand inhabitants almost quintupled, rising from 1.1 in 2010 to 5.12 in 2012. Table 3.9 in the Appendix presents the summary statistics of the characteristics of financial institutions that change across markets. The most important changes between 2010 and 2012 are the increase in the number of markets with at least one branch and the in the density of banking correspondents.

[13]Banking correspondents are authorized representative individuals of a financial institution. They provide basic financial services to the people like cash transactions (both deposit and withdrawal) and facilitate wire transfers.

Table 3.3: Descriptive statistics of geographic markets.

Variable	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Adults	337,886.10	695,332.60	8,237	64,757.8	285,373	4,237,450
GDP per capita (USD-PPP2014)	32,801.96	70,624.58	267	2,940.5	26,489	397,114
Entrepreneurs	12,110.44	8,036.77	961	5,955	16,198	39,800
Rural productive units	59.45	39.68	1.00	29.10	78.17	197.90
Distance to closest urban center (km)	0.45	0.17	0.05	0.33	0.60	0.80
Market structure 2010						
Public bank	0.98	0.13	0	1	1	1
Banks offering microcredit	3.70	2.47	1	2	6	12
Microfinance NGOs	3.32	4.49	0	1	4	28
Total number of branches	17.76	64.25	1	2	12	635
Banking correspondents	20.65	40.60	0.00	0.33	20.08	218.50
Market structure 2012						
Public bank	0.99	0.12	0	1	1	1
Banks offering microcredit	3.84	2.65	1	2	6	12
Microfinance NGOs	3.04	4.30	0	1	3	33
Total number of branches	17.68	64.39	1	2	12	665
Banking correspondents	95.94	115.00	0.00	0.81	136.31	517.00

Notes: Descriptive statistics of demographic characteristics of local markets in 2010 and 2012. Source: Author's calculations based on information published by Superintendencia Financiera de Colombia.

3.4.4 Market shares

In order to obtain a measure of the market share of each financial institution, it is necessary to define first the size of the potential market. That is, the potential outstanding value of the microloans portfolio in each market. For this purpose, I use information from several surveys by Departamento Administrativo Nacional de Estadistica (DANE) and Superintendencia Financiera.

I started by building a measure of the number of potential borrowers in the market (N_{mt}). I define the set of potential borrowers as all individuals who may need loan to start a productive project or carry on economic activities, either from formal or informal sources. To estimate the number of potential small entrepreneurs in each market, I used information from the GEIH Survey and the Micro-establishments Directory developed by Departamento Administrativo Nacional de Estadistica (DANE). I included in my definition of potential borrowers all small entrepreneurs that already have a formally registered micro-establishment (up to nine employees) and all adults who are either unemployed or have an informal occupation (this definition excludes self-employed professionals, and patrons and employees of micro-establishments with more than 5 employees). This measure of market size allows to account for potential entrepreneurs who need funding in order to start their own business and it also recognizes the existence of many small business that do not have a formal registry. Also, it takes into account that financial institutions often require proof of an employment contract in order to become eligible of other credit alternatives, such as credit card and consumer loans.

I used a survey performed by Superintendencia Financiera in 2014 that asked individuals and micro-entrepreneurs in different geographic locations about the use of financial services (SFC, 2015), to estimate the share of potential entrepreneurs that need a loan. This survey consists of two different questionnaires, one for individuals (households) and one for micro or small entrepreneurs, and it is representative for three types of municipalities: big cities and urban centers, intermediate urban municipalities, and rural towns. The survey asked whether individuals or micro-entrepreneurs have requested a loan in the previous 12 months. Among the response alternatives the survey includes different funding sources, from friends and family, informal sources like loan sharks and thrift stores, to formal loan lenders like financial institutions or traditional banks. The survey also asked to those who claimed not to have asked for a loan in the previous year, the reason behind this decision. Among the response alternatives, the survey includes the option "I am not interested, I did not need one, I have not asked for it". Other options include "I have asked for a loan but it has been denied", "I believe that my request will be denied", "I do not comply with the requirements", and other alternatives indicative of mistrust of available sources of funding and financial constraints. Based on the response alternatives included in the survey, This question permits to identify clearly the proportion of borrowers who did not need a loan, from those who were not able to obtain funding for other reasons.

As seen in the second column of Table 3.4, there is a meaningful share of the population that relies on sources different from the formal financial sector to obtain funding. These sources include family members and friends, as well as informal lenders. The third column presents the proportion of individuals who, according the their responses in the survey, did not asked for a loan in the previous year because they did not need it. I will assume later in the estimation procedure that the shares shown in the Table are identical among markets belonging to the same category (big cities, intermediate urban, and small markets).[14]

Table 3.4: Sources of funding of entrepreneurs and individuals - 2014

Type of municipality	Financial inst.	Other	No need of a loan
Individuals			
Big urban markets	0.181	0.255	0.564
Intermediate markets	0.158	0.183	0.659
Rural/remote markets	0.154	0.1500	0.699
Entrepreneurs			
Big urban markets	0.187	0.241	0.572
Intermediate markets	0.356	0.155	0.489
Rural/remote markets	0.296	0.160	0.545

Notes: Share of individuals and entrepreneurs who obtained their funding from financial institutions or other sources, by market size. Source: Author's calculations based on the Demand for Financial Services Survey by Superintendencia Financiera de Colombia (SFC, 2015).

I calculate the potential size of market m in year t, S_{mt}, using the number of potential small entrepreneurs defined above (N_{mt}), the proportion of them who need a loan (s_m^{loan}) according to the survey by Superintendencia Financiera, and the average

[14]This survey was taken in 2014 (after the ceiling was on the interest rates was removed). The structural model that I propose in Section 3.5 allows to measure in retrospective the share of borrowers who could have been constrained by the existence of the interest rate ceiling, that is, the proportion of borrowers who needed a loan, but were not able to obtain it because financial institutions were not willing to provide credit at the maximum interest rates allowed by the regulation.

value of the microloans portfolio per capita observed in different types of markets (big cities, intermediate urban locations, and small markets), $\bar{l}_{mt}$.[15] The calculation is as follows:

$$S_{mt} = N_{mt}\bar{l}_{mt}(s_m^{\text{loan}}).$$

Let L_{jmt} denote the value of the microcredit portfolio of the loan provider j in market m in year t. The market share of this lender will be given by

$$s_{jmt} = \frac{L_{jmt}}{S_{mt}}.$$

The potential market is comprised of 2.9 million small entrepreneurs and corresponds to a credit volume of 10.4 billion dollars. For comparison, Estrada and Hernandez Rubio (2019), estimate a potential market of 4.7 million entrepreneurs. The main difference with their estimates is explained by my decision to exclude agricultural productive projects and consider only the fraction of entrepreneurs who do not need a loan according to the survey mentioned above.

3.5 Model

As discussed in the previous section, the relaxation of a usury ceiling was followed by a rise in the interest rates and the volume of loans provided by financial institutions. The later effect might have occurred as financial institutions started providing loans to new segments of clients in existing geographic markets, or via additional investments in their branching networks, which allowed them to expand their operations in new geographic markets. These investments have important implications in terms of consumer welfare because the availability of microloans often requires proximity between the client and a brick-and-mortar branch. In practice, clients typically need to approach a traditional branch to complete the procedures related to the loan request. Similarly, financial institutions that provide microloans often exert close monitoring of the productive projects that receive funding, including on-site assessment of

[15] I assume the share of entrepreneurs that require a loan does not change as a result of the policy change. Instead, I assume that this change only affects the decision of entrepreneurs to request the loan from formal or informal sources.

the conditions of the productive projects by bank agents. These activities become prohibitively expensive if the client is too far from the branching network.

In estimating the demand for microloans, it is important, therefore, to account for changes in the interest rate, but also those in other service characteristics such as the size of branching networks and the availability of other transaction channels in the vicinity of the borrowers. To capture these effects in the demand estimation, I use a discrete choice model, where the decision of the consumers is simplified to one in which they select the preferred financial institutions among those who have at least one branch in their local market. Although this approach does not take into account the effects of the interest rate on the size of the loans demanded by potential borrowers, it seems reasonable in the market of microloans, given the small dispersion in the size of the loans observed in this market.[16]

Furthermore, I assume that banks do not price discriminate across geographic markets. Instead, they set a unique interest rate that applies to all their consumers of the same type in all locations. This pricing strategy is consistent with the usual practice of financial institutions in Colombia as well as in other countries, where banks use a reference interest rate in multiple markets and make adjustments based on the client risk profile rather than the local market structure (Berger and Dick (2007)).

3.5.1 Demand side

The microloans market is one in which financial institutions have the possibility to charge different interest rates depending on the characteristics of the clients. Due to data limitations, I am not able to fully capture the heterogeneity in interest rates charged by loan providers. However, the approach that I propose here allows us to capture some of the changes in the composition of the loan portfolio generated by the relaxation of the usury ceiling. I divide the potential borrowers in the microloans market into three segments: the first one (Segment 1) is constituted by all entrepreneurs that are aware of all the credit alternatives available in the market and could obtain a loan from a private regulated institution at an interest rate lower than $\bar{r}_b$; these entrepreneurs are more likely to have a safer profile and may represent lower marginal costs for the loan supplier. The second segment (Segment 2) corresponds to those

[16]The legal definition of microcredit includes a maximum size of the loan (around US3500 as of 2012) and a maximum amount of debt that a client can have with the financial system at a given period . Banks often specify a minimum loan size. Furthermore, I do not observe a significant increase in the average size of a micro-loans after the policy change.

attentive borrowers that can only obtain loans at rates higher than $\bar{r}_b$, but lower than $\bar{r}_a$, the usury ceiling after the policy intervention. The third segment of borrowers corresponds to those individuals who are either not attentive or are not able to obtain loans even under the new usury ceiling.

Before the policy change, the aggregate demand for microloans is composed of borrowers that belong in Segment 1, whereas after the policy change, borrowers from Segment 1 and Segment 2 can demand loans. I assume that there is no price discrimination within these two segments. This is a simplifying assumption motivated by the limitations in the availability of data. If more detailed information about individual transactions is available, it is possible to extend this framework to account for additional market segments.

The utility that an individual i, located in market m and belonging to segment d, derives from choosing a financial institution j can be written as

$$u^d_{ijmt} = \delta^d_{jmt} + \epsilon_{ijmt},$$

where δ^d_{jmt} is the mean utility of consumers in segment d and ϵ_{ijmt} is a term that captures individual preferences and follows a type I extreme value distribution. The mean utility satisfies

$$\delta^d_{jmt} = \beta_0 + \vec{\beta}^d \vec{X}^d_{jmt} + \alpha^d r^d_{jmt} + \xi_{jm}, \tag{3.1}$$

where $\vec{X}^d_{jmt}$ is a vector of characteristics of the bank and ξ_{jm} is a term that captures other aspects unchanged across segments and over time that are not observed by the econometrician. Suppose that there are only two periods: before and after the policy change ($t = \{b, a\}$). According to this specification, preferences of consumers can vary across segments but are constant over time.

Abaluck and Adams (2017), Ho et al. (2017) and Hortaçsu et al. (2017) study situations where the alternatives under study are not available for all consumers, and instead, there is a fraction of consumers whose only alternative is the outside option. In these studies, the probability that consumers choose a particular alternative is calculated, therefore, as the product of the probability that consumers belong in the segment with access to the complete choice set, and the probability that they select that alternative, given that they participate in the choice problem. The first probability is often determined by observed characteristics of the consumers and their environment, while the choice conditional on participation is often modeled using a logit model.

Let ω^1_{bm} be the portion of entrepreneurs in market m that belong to Segment 1 before the policy change. This value is assumed to be dependent on observable characteristics of the market, such as demographics and the availability of alternative (informal) sources of funding. Given the assumptions on ϵ_{ijmt}, the share of bank j in market m before the policy change can be expressed as

$$\begin{aligned} s_{jmb} &= \omega^1_{mb} s^1_{jmb} \\ &= \omega^1_{mb} \left(\frac{e^{\beta_0 + \alpha^1 r^1_{jmb} + \vec{\beta}^1 \vec{X}^1_{jmb} + \xi_{jm}}}{1 + \sum_{k=1}^{K^1_{mb}} e^{\beta_0 + \alpha^1 r^1_{kmb} + \vec{\beta}^1 \vec{X}^1_{kmb} + \xi_{km}}} \right), \end{aligned}$$

where K^1_{mb} is the number of banks in that offer loans in the segment of safer borrowers in market m before the policy change. In consequence, the share of the outside option is given by

$$s_{0mb} = \omega^1_{mb} s^1_{0mb} + (1 - \omega^1_{mb}),$$

where $s^1_{0mb} = \frac{1}{1 + \sum_{k=1}^{K^1_{mb}} e^{\beta_0 + \alpha^1 r^1_{kmb} + \vec{\beta}^1 \vec{X}^1_{kmb} + \xi_{km}}}$.

I assume that the fraction of safer borrowers ω^1_{mb} will depend on a vector of characteristics of the market, $\vec{Z}_{mb}$, such as distance to closest urban center, percentage of population in rural areas, public safety conditions, the presence of a public bank and number of non-regulated institutions that offer loans to entrepreneurs. I modeled ω^1_{mb} using a standard binary logit,

$$\omega^1_{mb} = \frac{e^{\vec{\rho}^1 \vec{Z}_{mb}}}{1 + e^{\vec{\rho}^1 \vec{Z}_{mb}}}. \tag{3.2}$$

This specification is similar to the one used by Hortaçsu et al. (2017), and it can be interpreted as a reduced-form representation of the determinants of inattention. There are plenty of reasons, both on the demand and the supply side, that explain why formal financial institutions might not constitute a relevant source of funding for a portion of potential borrowers, including low levels of financial literacy, distrust for financial institutions, inexperience with formal financial services or long distances between branches and potential clients. Therefore, I do not interpret the initial magnitude of ω^1_{mb}, before the policy change, as the degree of financial exclusion generated solely by the usury ceiling. Instead, I argue that the change in the portion of potential borrowers that participate in the choice problem after usury ceiling is relaxed can be informative of the degree of market expansion that can be associated with the policy change.

Abaluck and Adams (2017) shows that this model is equivalent to a standard logit model with an additional inertia term through which the utility of each alternative depends on the characteristics of rival products. Provided that enough determinants of probability of participating in the choice problem are observed, it is possible to separately identify ξ_{jm} and ω^1_{mb} based on the asymmetry in the response of the market shares of available banks to changes in the characteristics of the outside option, relative to the response of the share of the outside option to changes in the characteristics of banks.

After the policy change, financial institutions can profitably provide loans to a new segment of potential borrowers who were previously excluded due to the initial usury ceiling. Therefore, the market share of bank j in market m will be given by

$$s_{jma} = \omega^1_{ma} s^1_{jma} + \omega^2_{ma} s^2_{jma}, \tag{3.3}$$

where $\omega^2_{ma} = \frac{e^{\vec{\rho}^2 \vec{Z}_{ma}}}{1+e^{\vec{\rho}^2 \vec{Z}_{ma}}}$, and $\omega^1_{ma} + \omega^2_{ma} \leq 1$.

The market shares in each segment, s^1_{jma} and s^2_{jma}, are obtained using the logit formula:

$$s^d_{jma} = \frac{e^{\beta_0 + \alpha^d r^d_{kma} \vec{\beta}^d \vec{X}^d_{jma} + \xi_{jm}}}{1 + \sum_k^{K^d_{ma}} e^{\beta_0 + \vec{\beta}^d \vec{X}^d_{kma} + \xi_{km}}},$$

where K^d_{ma} is the number of banks who offer loans in segment d and market m after the policy change.

3.5.2 Supply side

In modeling the optimal pricing of financial institutions, I abstract from the information problems typically encountered in the context of retail banking, such as adverse selection and moral hazard, that can have important implications in the optimal pricing strategies of loan providers. This is a strong assumption, which could be relaxed in future research if more detailed data on default rates becomes available.[17] Preliminary exploration of the data at the national level reveals that the relaxation of the usury ceiling did not lead to a sustained increase in the default rates of the microloans portfolio (See Figure 3.6). Instead, loan providers seem to have adjusted their expenditure in provisioning, operative costs and salaries, indicating that they might have

[17] Recent work in this direction has been done by Cuesta and Sepulveda (2019) and Nelson (2019). These studies make use of administrative data sets that contain detailed information on individual loan transactions and borrowers' credit history.

resorted to additional monitoring to manage the potential increase in credit risk after the usury ceiling was relaxed. This evidence suggests that financial institutions in the microcredit market have mechanisms in place that allow them to solve the adverse selection problem to some extent.

I focus here on the effect of branching networks on the optimal pricing strategies of loan providers that operate across multiple geographic locations. I consider a situation where they set interest rates based mostly on the risk profile of their borrowers, with no spatial discrimination pricing. This assumption is not incompatible with the presence of substantial differences in the average interest rates across geographic markets, which have been broadly documented in different contexts (e.g. Hannan and Prager, 2006; Brevoort and Hannan, 2006; Petersen and Rajan, 2002; Bellucci et al., 2013), nor does it ignore the ways in which the distance between lenders and borrowers can impact prices and credit availability. Agarwal and Hauswald (2010) finds that once the analysis accounts for proprietary information related to the borrowers' payment behavior, the distance between borrowers and lenders becomes irrelevant as a predictor of the interest rate. These findings, along with those provided by Petersen and Rajan (2002), are in line with information-based theories but are not supportive of discriminatory spatial pricing.

There is some agreement in the literature regarding the effect of competition on pricing in the banking industry. However, the relevant definition of geographic markets differs depending on the context. Degryse and Ongena (2005) find that interest rates are sensitive to the number of competitors in the vicinity of the borrowers. In contrast, Hannan and Prager (2006) find evidence in favor of homogeneous pricing in the deposit market by multi-market banks throughout states and even across broader geographic areas in the US, with interest rates being closely correlated statewide competitive conditions. Similarly, Heitfield and Prager (2004) find that small banks set their interest rates based on the local market competitive conditions, while large multi-market banks set homogeneous prices across broader geographic areas. The authors attribute the presence of uniform pricing to the growth in Internet advertising, which allows borrowers to get more information about rates charged across geographic markets. By quoting uniform rates, rather than local market-specific ones, multi-market banks avoid adverse reactions from consumers that would be offered a relatively unattractive rate due to their location.

By surveying the internet websites of financial institutions in Colombia and interviewing some industry representatives informally, I could confirm that pricing practices in the microloans segment are similar to those found in large multi-market banks in the US, in the sense that interest rates for this particular type of loans are usually set at the national level (this practice is also documented by Armendariz and Morduch (2007) in the context of microfinance in different countries). This pricing strategy might be related to the multi-market nature of all financial institutions included in the sample and the costs associated with allowing differentiated rates across regions. As a result, pricing strategies seem to be more affected by competitive conditions at the national level. Furthermore, regulation on price transparency by Superintendencia Financiera introduced in 2008 created additional incentives for banks to provide very detailed information on interest rates applicable to standardized products on their websites. As a result, financial institutions advertise different types of microloans that differ in their interest rates, repayment periods, and borrowers conditions such as collateral availability or previous experience with formal financial institutions, but do not depend explicitly on the location of the borrower. As mentioned in the previous subsection, heterogeneity in the borrowers' risk profile is captured here by the presence of two segments of potential borrowers in the period after the policy change.

According to this, a bank j that operates across M markets in year t will obtain an aggregate profit that can be written as

$$\Pi_{jt}(r_{jt}) = \sum_{m=1}^{M} S_{mt} \sum_{d=1}^{1,2} \omega_{mt}^{d} s_{jmt}^{d} (r_{jt}^{d} - c_{jmt}^{d}),$$

where S_{mt} is the size of each geographic market. Lenders choose the interest rate that maximizes their profit, subject to the constraint on the interest rate imposed by the usury ceiling. The interest rate that lenders will charge in Segment 1, r_{jt}^{1*}, will be given by

$$r_{jt}^{1*} = \min \left\{ \frac{\sum_{m=1}^{M} S_{mt}\omega_{mt}^{1} s_{jmt}^{1} (\alpha^{1} c_{jmt}^{1}(1 - s_{jmt}^{1}) - 1)}{\alpha^{1} \sum_{m=1}^{M} S_{mt}\omega_{mt}^{1} s_{jmt}^{1}(1 - s_{jmt}^{1})}, \bar{r}_{t} \right\}, \tag{3.4}$$

where $\bar{r}_t$ is the usury ceiling in year t. The optimal interest rate for the second segment is calculated for the period after the policy change only, and it can be written in a similar way, as

$$r_{ja}^{2*} = \min \left\{ \frac{\sum_{m=1}^{M} S_{ma}\omega_{am}^{2} s_{jma}^{2} (\alpha^{2} c_{jma}^{2}(1 - s_{jma}^{2}) - 1)}{\alpha^{2} \sum_{m=1}^{M} S_{ma}\omega_{ma}^{2} s_{jma}^{2}(1 - s_{jma}^{2})}, \bar{r}_{a} \right\}. \tag{3.5}$$

I assume that the marginal cost in the segment of safer clients, c_{jmt}^{1}, depends on a set of bank characteristics $\vec{W}_{jmt}^{1}$ which may vary across banks, markets and periods, and it is given by:

$$c_{jmt}^{1} = e^{\vec{\gamma}\vec{W}_{jmt}^{1} + \eta_{jmt}}, \tag{3.6}$$

where η_{jmt} is an independent unobserved term that follows a normal distribution with variance σ_η^2. I assume that the difference in marginal costs across segments is a constant. Therefore, the marginal cost in segment 2 (after the policy change) can be written as

$$c_{jma}^2 = e^{c_{jma}^1 + \lambda}. \tag{3.7}$$

Since the difference in marginal cost among segments is assumed to be constant, it is not possible to identify the intercept of the utility function for both segments. According to D'Haultfœuille et al. (2018), it is possible to rationalize any price gap between groups of consumers, constant across j, by differences in marginal costs or the intercept of the utility function. In consequence, I assume that this intercept is the same across market segments.

3.5.3 Observed interest rates and market shares

I do not observe the portion of consumers that belongs to each market segment. Instead, the only information available corresponds to the aggregate market share of each loan provider in every location. Furthermore, information about specific characteristics of the loan products offered to each segment, most critically, the interest rate, is not available. Regarding this critical variable, I only observe a weighted average of the interest rate at the national level.

I assume that there is no unobserved price heterogeneity in the period before the policy change, consistent with the premise that only consumers from Segment 1 have access to the loans from regulated loan providers at this time. In turn, after the policy change, the observed price becomes a weighted average that includes the prices in both segments. The observed interest rate r_{ja} can be written as follows:

$$r_{ja} = s_{ja}^1 r_{ja}^{1*} + s_{ja}^2 r_{ja}^{2*}, \tag{3.8}$$

where s_{ja}^1 and s_{ja}^2 are the market shares of bank j in each segment at the national level after the regulatory change.

3.5.4 Estimation procedure

D'Haultfœuille et al. (2018) developed an algorithm for demand estimation that can be used in situations where the researcher can not observe perfectly the price and the market share of competitors across different segments of consumers. In some cases, only a known function of these quantities, such as a weighted average, is available. This model is particularly useful for contexts where firms can exert third price discrimination. They show that identification can be achieved by relying on supply-side moment conditions, in cases where there is only one vector of prices that is consistent with the observed market shares in each segment and the marginal cost structure. They can recover the optimal prices charged in each segment in cases where either the market shares in each segment are observed, or in cases where the characteristics of the consumers used by sellers to price discriminate are known. The convergence of the algorithm holds when there is not too much heterogeneity between groups of customers in terms of their price sensitivity.

In the context studied here, the portion of consumers that belong to each segment is not observed. Instead, I use the information of the periods before and after the policy change to estimate these proportions. Then, I combine the demand and supply moments obtained before the policy change with those obtained with information after the usury ceiling is relaxed to estimate both the optimal interest rates and the market shares of loan providers in each of the two segments defined previously. The algorithm used to recover the parameters that describe the consumer preferences the determinants of the marginal costs of financial institutions is explained below.

Algorithm to retrieve interest rates and market shares in each segment

The algorithm can be divided into two stages that correspond to the periods before and after the policy change. According to the model, before the usury ceiling was modified, there was only one segment of borrowers with access to loans from formal lenders. Since it is assumed that there is no unobserved price heterogeneity in this period, I use a method similar to the one proposed by Berry et al. (1995), to recover an estimate of the unobservable term that affects the borrowers' utility. In the second stage, I use these estimates, along with the algorithm proposed by D'Haultfœuille et al. (2018), to recover the unobserved market shares and optimal prices that financial institutions charge in each segment after the policy change.

To simplify notation, I will denote the vectors of observed interest rates and market shares for all m markets in year t as $\vec{r}_t$ and $\vec{s}_t$. Similarly, $\vec{\xi}$ will denote the vector of unobserved characteristics of loan providers that impact the utility of the consumers, which are assumed to be constant over time. Furthermore, $\vec{X}_t$, $\vec{Z}_t$ and $\vec{W}_t$ will denote matrices that contain the observed information in year t of product characteristics per loan provider and market, demographic characteristics of the markets, and instruments that will be used in the estimation. Lastly, the unobserved interest rates and market shares in each segment, before and after the policy change, are functions of the vector of parameters Θ and the vector of unobservable characteristics that are valued for consumers $\vec{\xi}$, that will be denoted by $\vec{r}_t^d(\Theta, \vec{\xi})$ and $\vec{s}_t^d(\Theta, \vec{\xi})$, with $d \in \{1, 2\}$ and $t \in \{a, b\}$.

1. *Initial setting*

   (a) In order to estimate the optimal interest rate in each period, I will use a set of G vectors of random draws taken from a standard normal distribution. Let $\vec{\eta}_t^g$ denote a specific vector of random draws used to estimate the optimal interest rate in year t. A typical element of this vector, η_{jmt}^g, multiplied by σ_0^η (initial value of the parameter that captures the standard deviation of the unobservables), represents a random shock that affects the marginal cost of lender j in market m (see equations ((3.6)) and ((3.7))). The number of random draws used in each stage is 100. These sets of random draws are set once at the beginning of the algorithm, and they are not renewed after each evaluation of the objective function at a new parameter's values.

   (b) Consider a vector Θ_0 with initial values for the parameters of interest,

   $$\Theta_0 \equiv \{\alpha_0^1, \alpha_0^2, \beta_0^0, \vec{\beta}_0^1, \vec{\beta}_0^2, \vec{\rho}_0^1, \vec{\rho}_0^2, \vec{\gamma}_0, \lambda_0, \sigma_0^\eta\}.$$

   (c) As it will become clear below, I need to define initial values for the interest rates applied to each market segment after the policy change, $\hat{\vec{r}}_a^1(0)$ and $\hat{\vec{r}}_a^2(0)$. I used the vector of observed the interest rates after the policy change $\vec{r}_t$ as starting values for the two segments.

2. *Stage 1: Before the policy change:*

   (a) The first step consists of calculating the share of consumers that belong to Segment 1 according to equation (3.2), using the initial values of the parameters and the matrix $\vec{Z}_b$.

   (b) Consistent with the assumption of no unobserved price heterogeneity before the policy change, I use the observed values of the interest rate, $\vec{r}_b$ and other product characteristics $\vec{X}_b$ to estimate the vector of market shares that correspond to Segment 1, $\hat{\vec{s}}_b^1(\Theta_0)$, using the simple logit formula.

(c) The usual logit inversion ($\ln \vec{s}_t - \ln \vec{s}_0$) can not be used to retrieve an estimate of the vector of unobservables, $\vec{\xi}$, in this case.[18] Instead, I solve numerically for the mean utility of the borrowers of this segment, $\bar{\vec{\delta}}^1_b(\Theta_0)$ by evaluating the following equation recursively:

$$\vec{\delta}^1_b(\Theta_0, n+1) = \vec{\delta}^1_b(\Theta_0, n) + \ln \vec{s}_b - \omega_b(\Theta_0) \ln \hat{\vec{s}}^1_b(\Theta_0, n),$$

where n denotes a step in the iterative process. Berry et al. (1995) shows that for the duple $(\hat{\vec{s}}_b, \Theta)$, the operator defined by the equation above is a contraction mapping with modulus less than one. Therefore, given an initial value for $\vec{\delta}^1_b(\Theta_0, 0)$, I can obtain $\vec{\delta}^1_b(\Theta_0, 1)$ and substitute back until convergence. Let $\bar{\vec{\delta}}^1_b(\Theta_0)$ be the level of borrowers' utility that satisfies the convergence criterion. Using this vector, I obtain estimates of $\vec{\xi}$ and of the vector of market shares in segment 1, $\tilde{\vec{s}}^1_b(\Theta_0)$, by solving equation (3.1), as follows:

$$\tilde{\vec{\xi}}(\Theta_0) = \bar{\vec{\delta}}_b(\Theta_0) - \beta^0_0 - \alpha^1_0 \vec{r}_b - \vec{\beta}^1_0 \vec{X}_b,$$

$$\tilde{\vec{s}}^1_b(\Theta_0) = \frac{e^{\bar{\vec{\delta}}_b(\Theta_0)}}{1 + \sum e^{\bar{\vec{\delta}}_b(\Theta_0)}}.$$

(d) The next step consists of calculating the marginal cost for each vector of random draws, $\vec{u}^g_b$ and the parameter σ^η_0 that captures the standard deviation of the random shocks, according to equation (3.6). Then, the optimal interest rate for each vector or random draws, $\hat{\vec{r}}^1_b(\Theta_0, \vec{u}^g_b)$, is calculated using the estimated market shares from the previous step (equation ((3.4))).

(e) The estimated aggregate interest rate across simulations for the period before the policy change is

$$\hat{\vec{r}}^1_b(\Theta_0) = \frac{1}{G} \sum_g^G \hat{\vec{r}}^1_b(\Theta_0, \vec{u}^g_b).$$

3. *Stage 2: After the policy change*

(a) The first step is to calculate the marginal cost in the two segments for each vector of random draws $\vec{u}^g_a$. Let us denote these vectors by $\vec{c}^1_a(\Theta_0, \vec{u}^g_a)$ and $\vec{c}^2_a(\Theta_0, \vec{u}^g_a)$.

[18] This is because the utility that consumers obtain from the outside option in this model ultimately depends on the characteristics of all the products available in the market. See Abaluck and Adams (2017) for details.

(b) The market shares in each segment, $\hat{\vec{s}}^1_a(\Theta_0, 0)$ and $\hat{\vec{s}}^2_a(\Theta_0, 0)$, are calculated using the initial guess of the interest rates in each segment after the policy change, $\hat{\vec{r}}^1_a(0)$ and $\hat{\vec{r}}^2_a(0)$, and the vector $\hat{\vec{\xi}}(\Theta_0, 0)$, obtained in the previous stage.

(c) I proceed to find the estimates for the optimal interest rates in each segment, $\hat{\vec{r}}^1_a(\Theta_0, \vec{u}^g_a, 1)$ and $\hat{\vec{r}}^2_a(\Theta_0, \vec{u}^g_a, 1)$, using $\hat{\vec{s}}^1_a(\Theta_0, 0)$, $\hat{\vec{s}}^2_a(\Theta_0, 0)$, and the estimates of the marginal costs for each segment obtained in the previous step. Let $f(\hat{\vec{s}}^d_a(\hat{\vec{r}}^d_a(\Theta_0, \vec{u}^g_a, n))$ denote the function that returns the vector of optimal interest rates for each segment, according to equations (3.4) and (3.5). These vectors of interest rates are subsequently used to obtain a new estimate of the market shares in each segment, $\hat{\vec{s}}^1_a(\Theta_0, \vec{u}^g_a, 1)$ and $\hat{\vec{s}}^2_a(\Theta_0, \vec{u}^g_a, 1)$. This process can be summarized by the following expressions:

$$\hat{\vec{r}}^1_a(\Theta_0, \vec{u}^g_a, n+1) = f(\hat{\vec{s}}^1_a(\hat{\vec{r}}^1_a(\Theta_0, \vec{u}^g_a, n))$$
$$\hat{\vec{r}}^2_a(\Theta_0, \vec{u}^g_a, n+1) = f(\hat{\vec{s}}^2_a(\hat{\vec{r}}^2_a(\Theta_0, \vec{u}^g_a, n)),$$

D'Haultfœuille et al. (2018) show that the sequence of interest rates $\hat{\vec{r}}^1_a(\Theta_0, \vec{u}^g_a, n)_{n\in\mathbb{N}}$ and $\hat{\vec{r}}^2_a(\Theta_0, \vec{u}^g_a, n)_{n\in\mathbb{N}}$, defined by the equations above, converge to $\hat{\vec{r}}^1_a(\Theta_0, \vec{u}^g_a)$ and $\hat{\vec{r}}^2_a(\Theta_0, \vec{u}^g_a)$, at least for a set of values of Θ_0 close to the vector of true parameters Θ.[19]

(d) I obtain estimates of the optimal interest rates, $\hat{\vec{r}}^1_a(\Theta_0)$, $\hat{\vec{r}}^2_a(\Theta_0)$, and market shares in each market segment, $\hat{\vec{s}}^1_a(\Theta_0)$, $\hat{\vec{s}}^2_a(\Theta_0)$, by taking the average of the values obtained in the previous step across vectors of random draws.

(e) Finally I calculate the aggregate market share $\hat{\vec{s}}_a(\Theta_0)$ and the aggregate price of each bank $\hat{\vec{r}}_a(\Theta_0)$ using equations (3.3) and (3.8).

Demand and Supply Moments

Once I have recovered estimates of the vector of unobservable characteristics $\vec{\xi}$ and of the interest rates and market shares before and after the policy change, I use moments based on the exogeneity of a set of instruments $\vec{W}_t$. In the period before the policy

[19] A situation of persistent non -convergence may indicate that there are very substantial differences in consumers' preferences across groups.

change, the demand side moments are based on the estimates $\hat{\vec{\xi}}(\Theta)$, whereas in the period after the policy change the moments are based on the differences between the observed market shares the ones estimated with the model:

$$E(\hat{\vec{\xi}}(\Theta)\vec{W}_b) = 0$$
$$E((\vec{s}_a - \hat{\vec{s}}_a(\Theta))\vec{W}_a) = 0$$

Following Abaluck and Adams (2017) approach I also use the asymmetries in the response of the market shares of financial institutions and the market share of the outside option, before and after the policy change in order to identify the share of borrowers that belong to each segments. Therefore, I include moments that are based on the change in the market shares observed one period before the policy was introduced (between 2009 and 2010), and the changes in market shares one period after the policy change took place (between 2012 and 2013), as follows:

$$E((\vec{s}_b - \vec{s}_{b-1}) - (\hat{\vec{s}}_b(\Theta) - \hat{\vec{s}}_{b-1}(\Theta))\vec{W}_{b-1}) = 0$$
$$E((\vec{s}_{a+1} - \vec{s}_a) - (\hat{\vec{s}}_{a+1}(\Theta) - \hat{\vec{s}}_a(\Theta))\vec{W}_a) = 0$$

The assumption that $\vec{\xi}$ is invariant over time is crucial for identifying all the estimates pertaining to the period after the regulatory change, including the share of potential customers constrained due to the presence of the interest rate ceiling. This is an strong assumption, given that financial institutions are likely to offer new services that may result more attractive for clients after the relaxation of the usury ceiling.

Nevertheless, in the context studied here any additional service provided by lenders in each market is likely to imply changes in the variables included in the estimation, such as the number of employees, branches, and BC, particularly in a context where the development of internet and mobile platforms was still incipient. I do observe an increase in these variables before and after the policy change. On the supply side, I control for variables that change across time and financial institutions and have an impact on the marginal costs, such as the deposits rate and expenses on salaries, operative costs, and provisions. These variables capture a substantial portion of the additional spending that financial institutions may have had to incur to provide loans to riskier borrowers immediately after the usury rate relaxation. Consequently, the estimated optimal interest rates charged in the period after the policy change incorporate potential increases in the marginal costs and markup related to additional services.

On the supply side, the sample moments are based on the differences between the observed and the estimated interest rates:

$$E((\vec{r}_b - \hat{\vec{r}}_b(\Theta))\vec{W}_b) = 0$$
$$E((\vec{r}_a - \hat{\vec{r}}_a(\Theta))\vec{W}_a) = 0$$

3.5.5 Instruments

Instruments frequently used in the literature are variables that shift either the marginal costs or the markup, with little direct impact on the observed characteristics of the product that consumers appreciate. In the case studied here, a variable that can be interpreted as a cost shifter is the legal reserve percentage required by the central bank.[20] I build other instruments based on characteristics of competitors that operate in markets of similar characteristics but belonging to other provinces, such as the number of competitors, branches, employees per branch, and their degree of specialization in microfinance. I measure this last variable by computing the average share of microloans within their aggregate portfolio at the national level. These instruments are variables that have an impact on the markup that lenders obtain in local market, but are not likely to have a direct impact on the utility that consumers get from a particular alternative.

The model specification includes characteristics of the product, such as the number of branches and banking correspondents per thousand inhabitants, as well as the number of employees per branch. These characteristics are endogenous since financial institutions have incentives to open extra branches or to hire additional employees in markets where there is a strong demand for their loans. To solve for the potential endogeneity, I use the number of branches, employees and BCs of the bank in similar markets in other provinces as instruments for these product characteristics. Table 3.10 presents the summary statistics of the instrumental variables used in the estimation.

[20] The legal reserve requirement set by the central bank each period is a percentage of certain types of deposits that banks must hold at the central bank without remuneration. Although this percentage is the same across banks, the resulting amount of reserves that a bank must hold at the central bank depends on the composition of the deposits of each financial institution.

Supply side

Among the bank characteristics that determine the optimal interest rate, I included administrative costs, such as salaries and other costs related with the operation of the branching network (number of branches per market and number employees per branch), as well as the deposits interest rate, calculated as the value that was paid for concept of interests to the bank debtors in a year as a percentage of the loan portfolio. Since some of the variables included in the estimation are likely to be endogenous, I use instruments based on the characteristics of competitors.

3.6 Results

Table 3.5 presents the parameters that determine the preferences of consumers and the share of potential borrowers in each segment. Consumers who had access to formal loans before the policy change exhibit a similar sensitivity to the interest rate than those in the second segment. The availability of branches in the market is appreciated by consumers in the two segments, particularly by those who did not have access to loans before the policy was introduced. By contrast, the number of banking correspondents has a negative impact on the utility of consumers that belong to the second segment and is not significant for those in the safer one. This difference might be explained by the fact that the largest banking correspondents' networks have been developed by banks and other financial institutions that are not specialized in microfinance. This transaction channel is perhaps more important in the deposit market, where MFIs are not strong competitors, as it facilitates payments and transfers from existing saving accounts.

The lower segment of the table contains the parameters that determine the share of consumers in each segment. The results indicate that markets with lower GDP per capita and higher share of population in rural areas have a greater share of borrowers with access to loans from private regulated institutions. One explanation for this result is that entrepreneurs from the rural sector tend to have greater experience with credit operations in general, as they routinely use loans and other financial services from the government in their business activity. Agricultural productive projects receive partial default insurance provided by the government, which make them relatively more attractive for private banks. The results for the second segment indicate that microfinance institutions have a greater potential of expansion in areas with higher income, that are relatively close to big urban centers, where public funding

Table 3.5: Demand Side

Variable	Segment 1	Segment 2
Consumer preferences		
Intercept	-3.2278**	
	(0.2378)	
Interest rate	-7.2247**	-7.0505**
	(0.3317)	(1.0891)
Branches per capita	4.187**	11.0455**
	(0.9293)	(2.4139)
Banking correspondents per capita	-0.0268	-0.9608**
	(0.0181)	(0.2334)
Employees per branch	-0.0159	-0.4512**
	(0.013)	(0.0722)
Share of borrowers in each segment		
Intercept	3.614**	-0.8109
	(1.5822)	(0.5217)
Adult population (log)	-0.5759**	0.0131
	(0.1124)	(0.0279)
GDP per capita (log)	0.4261*	-0.1813**
	(0.2341)	(0.0524)
Distance to closest urban center	-0.6823**	-0.0408
	(0.063)	(0.0411)
Population in rural areas	-0.0725	1.4643**
	(0.7543)	(0.2316)
Brand dummies	Yes	Yes
Sample size	966	966

Notes: Standard-errors are robust to heteroscedasticity and computed using the standard formula for GMM. Significance levels: , **: 5%, *: 10%.

might be insufficient to cover the demand for loans by small entrepreneurs. This result is consistent with the pattern of entry observed between 2009 and 2014, when microfinance institutions located their new branches in intermediate cities.

The estimated parameters that describe the marginal cost of financial institutions are presented in Table 3.6. As expected, the effect the deposits rate and the administrative costs are positive and significant. By contrast, the salaries variable has a negative and significant impact on the marginal cost. Institutions that have specialized in microcredit, that is, those with a higher share of their loan portfolio composed by microcredit, tend to have lower costs associated with microloans. The parame-

Table 3.6: Supply side: Marginal cost

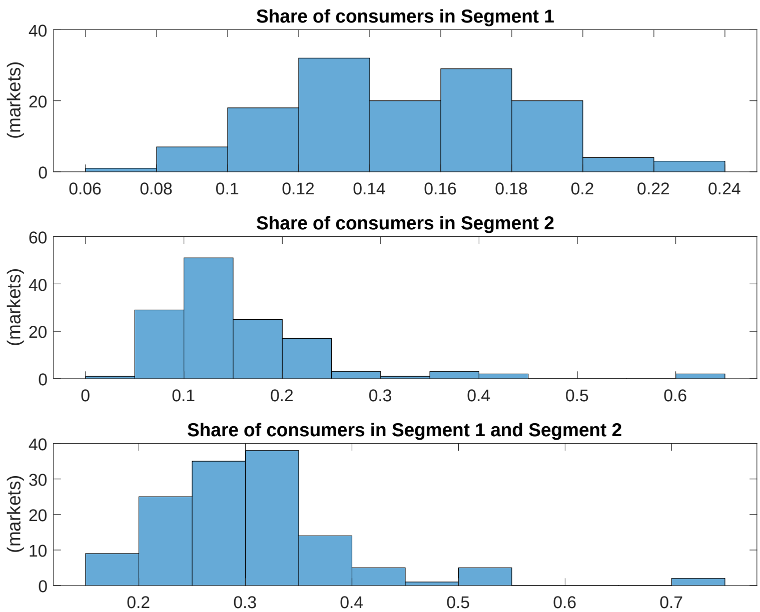
Variable	Estimate
Intercept	-1.8645**
	(0.122)
Salaries	-0.9364**
	(0.3668)
Loans provisions rate	1.0879
	(2.4683)
Required reserve	1.7742
	(2.7725)
Deposits rate	9.7955**
	(2.7529)
Microcredits share (own portfolio)	-3.8189**
	(1.5567)
Administrative costs	0.0951**
	(0.028)
λ	0.5262
	(0.4531)
σ_u	0.0968
	(0.9022)
Brand dummies	Yes
Sample size	966

Notes: Standard-errors are robust to heteroscedasticity and computed using the standard formula for GMM. Significance levels: **: 5%, *: 10%.

ter λ captures the average difference in marginal cost between segments has a large standard error and cannot be considered significant.

Figure 3.4 presents the distribution of the estimated share of consumers that belongs to each segment across geographic markets. As seen in the figure at the top, the share of low-cost consumers differs greatly across markets. In the median, 15.15% of the potential borrowers could choose to request a loan from formal financial institutions at an interest rate lower than the initial usury ceiling. The figure in the bottom panel presents the distribution of the share of consumers that gained access to formal loans from these lenders after the interest rate ceiling was modified. The median share of potential borrowers in this segment was 13.31%. The figure shows that, while the relaxation of the usury ceiling increased access to funding provided by private financial institutions, there is a significant portion of the potential consumers

Figure 3.4: Distribution of the share of consumers in each segment across markets



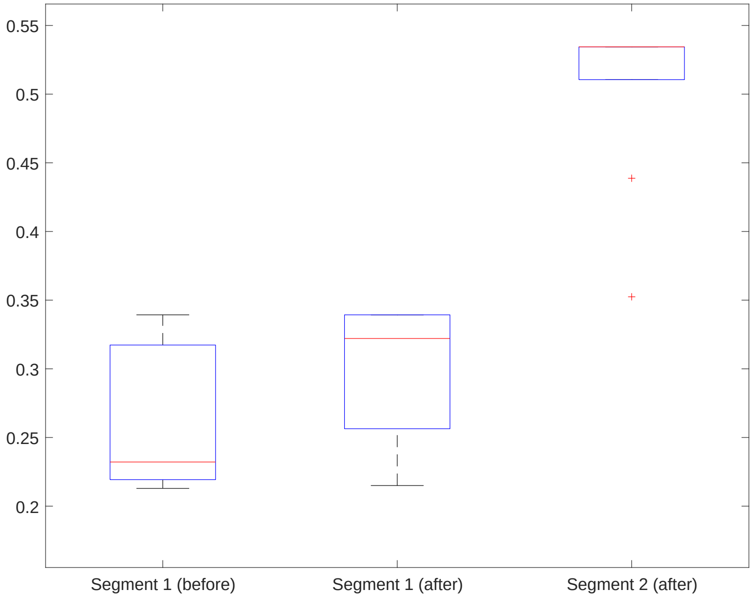
Notes: The top figure presents the distribution of the share of borrowers with access to loans before the policy change. The figure at the bottom presents the distribution of the share of consumers who obtain access after the usury ceiling is relaxed.

that do not include formal funding alternatives in their choice set even after the policy change.

The structural model allows us to estimate the optimal interest rate for both segments. As seen in Figure 3.5, the optimal interest rates are higher in the segment of low-cost borrowers, compared to the period before the policy change. However, not all financial institutions would choose to set their interest rates in Segment 1 above the initial usury ceiling. The increase on the interest rates in those cases could be explained by an increases in the marginal costs (the deposit rates increased between 2010 and 2012, and increasing competition from other lenders in the market could have required additional expending on advertising), as well as by changes in branching networks that could have resulted in greater market power.

The fact that the average interest rate registered by some financial institutions at the national level remained low after the usury ceiling was relaxed could signal

Figure 3.5: Estimated interest rates before and after the policy change in each segment



Notes: Distribution of the optimal interest rates that financial institutions would charge in each segment.

the presence of very high costs of providing loans to Segment 2, which could not be covered even with rates as high as the new interest rate ceiling. I observe that the institutions with the lowest interest rates did not increase their market share in the microloans markets, nor microloans became more important in the composition of their own loan portfolio. This suggest that they continue focusing exclusively on clients belonging to Segment 1.

Figure 3.8 in the Appendix presents the estimated share of consumers in each segment who would choose to borrow a loan from a financial institution instead of choosing the outside option before and after the policy change. In the first segment, there is a significant increase in the share of consumers choosing one financial institution rather than the outside option. This share is lower in the second segment, where only 4,97% of the potential borrowers chose to borrow from a bank rather than from an informal source.

3.6.1 Consumer Surplus

To explore the effects of the relaxation of the usury ceiling on consumers' welfare, I carry out a calculation of the welfare changes between 2010 and 2012. Following the approach of Small and Rosen (1981) in the context of the discrete choice problem modeled here, welfare effects are measured as the expected equivalent variation of the changes in product characteristics. This term is defined as the amount of money that would make consumers in market m indifferent, in expectation, between facing the two choice sets (before and after the policy change). Let $\vec{EV}$ denote the vector that contains the expected variation of the changes for all markets.

$$\vec{EV} = \vec{\Gamma}_a(\vec{r}_a, \vec{X}_a, \Theta) - \vec{\Gamma}_b(\vec{r}_b, \vec{X}_b, \Theta),$$

where $\vec{\Gamma}_t(\vec{r}_{mt}, \vec{X}_{mt}, \Theta)$ denotes the level of consumer surplus in year t. A typical element of this vector, Γ_{mt}, is calculated as,

$$\begin{aligned}\Gamma_{mt}(\vec{r}_{mt}, \vec{X}_{mt}, \Theta) &= \sum_{d}^{1,2} \hat{\omega}_{mt}^{d} S_{mt}^{d} \\ &= \sum_{d}^{1,2} \hat{\omega}_{mt}^{d} \ln(\sum_{k}^{K_{mt}^{d}} exp(\delta_{jmt}(\vec{r}_{mt}, \vec{X}_{mt}, \Theta))/\alpha^{d}.\end{aligned}$$

Table 3.7 presents the results of this calculation for markets that experienced entry between 2010 and 2012, and those which did not, by market size. The first panel presents the change in consumer welfare for borrowers that belong to the low-cost segment. The borrowers that were located in markets without new competitors experienced a small welfare loss, particularly those located in bigger markets. The greater gains in this segment are experienced by consumers in smaller markets where new competitors opened branches. The second panel corresponds to consumers that gain access to formal loans after the relaxation of the usury rate. As seen in the table, the consumers with the lowest welfare gains are those located in markets with a population greater than 100.000 inhabitants that did not experienced entry, whereas the greater gains are registered in small markets. The average size of a microloan around the time of the policy was around USD 2.160 according to Fernandez (2014). With a welfare gain of USD 0.022 per each 1 USD borrowed, such as the estimated for Segment 2 in small markets, a borrower carrying a loan of average size would experience an annual benefit of USD 47.52. By contrast, a borrower with a loan of this size, belonging to the first segment and located in a big market that did not experience entry would experience an annual loss of USD 23.3.

Overall, the average change in consumer welfare was small but positive for all market types/entry status combinations, a result that suggests that the market expansion generated both by the entry of financial institutions in new locations, and the expansion in the volume of loans due to the provision of financial services in the segment of high-risk consumers, exceeded the reduction in welfare associated to the increase in the interest rate.

Table 3.7: Average change in consumer surplus by market size

	less than 50.000 inhabs.	50.000-100.000 inhabs.	More than 100.000 inhabs.
Segment 1			
Entry	0.0194	0.0091	-0.0044
No Entry	-0.0064	-0.0104	-0.0108
Segment 2			
Entry	0.0221	0.0125	0.0228
No Entry	0.0359	0.0281	0.0130
All borrowers			
Entry	0.0065	0.0033	0.0018
No Entry	0.0059	0.0012	0.0009
Number of Markets			
Entry	11.0000	18.0000	17.0000
No Entry	36.0000	23.0000	20.0000

Notes: The values in the table correspond to the average consumer welfare change from 2010 to 2012 across geographic markets, expressed in monetary units per each US dollar borrowed, based on the equivalent variation calculation by Small and Rosen (1981).

Counterfactual exercise: the importance of branching networks investment

Previous calculations on consumer welfare are based on the assumption that the growth observed in the number of branching networks and employees is a consequence of the changes in the usury ceilings. However, other factors that might have affected the investment in branching networks at the local level, such as economic growth or improvements in public infrastructure and safety.

Since I do not model the entry decisions of financial institutions at the local level, my estimates can only provide an upper bound on the policy effects on consumer welfare. Nevertheless, I propose a simple counterfactual exercise that can help us to understand how much of the consumer welfare can be attributed solely to the change of the interest rate after the ceiling was relaxed. In the counterfactual scenario, I assume that the branching networks remain as they were before the policy change. The optimal interest rates are adjusted accordingly.

Table 3.8 compares the changes in consumer welfare in the observed and counterfactual scenarios. Each entry corresponds to the average change in consumer surplus across markets within each category. As seen from the Table, the welfare gains are closely linked to the expansion of branching networks of financial institutions. The overall gains from the policy in the absence of new branches is close to zero in all types of markets. Consumers in the Segment 1 experience a greater welfare loss in the counterfactual scenario, particularly those located in bigger markets. In these markets, the increase in market expansion created by the relaxation of the usury rate is smaller than the one estimated for smaller and intermediate markets. Consumers in the second segment, that is, borrowers that gained access to credit after the policy change, would experience a welfare gain, although smaller than the one obtained in the original scenario. In smaller markets the gains are 45,2% of the ones they would experienced in the scenario with new branches, whereas in the biggest markets the welfare gains would be reduced by almost 90%. Furthermore, the number of locations that would experience a consumer welfare loss increases from 49 to 92 in the scenario without branching network expansion. These results indicate that new branches play a crucial role in the expansion of loans towards new clients, even in intermediate and big markets.

Table 3.8: Average change in consumer surplus per type of market.

	Scenario 1: Observed after policy change	Scenario 2: No additional branches
Less than 50.000 inhabitants		
Total	0.0060	0.0008
Segment 1	0.0002	-0.0039
Segment 2	0.0318	0.0144
50.000-100.000 inhabitants		
Total	0.0025	-0.0000
Segment 1	-0.0004	-0.0082
Segment 2	0.0223	0.0076
More than 50.000-100.000 inhabitants		
Total	0.0017	-0.0011
Segment 1	-0.0065	-0.0131
Segment 2	0.0197	0.0018

Notes: This table compares the changes in consumer surplus at the national level in two scenarios, expressed in monetary units per each US dollar borrowed, based on the equivalent variation calculation by Small and Rosen (1981). The first one uses the observed characteristics before and after the policy change. The second one compares the consumer surplus before the policy change with a scenario where the usury ceiling is relaxed and there is no change in the number of branches, banking correspondents or employees.

3.7 Concluding remarks

In this paper, I have developed a structural model of demand and supply to explore the implications of a modification of the usury ceiling applied to microloans in Colombia. The model explores a scenario where large multi-market institutions offer loans to borrowers with different loan profiles. By considering firms that compete across multiple geographic markets, I focus on the role of branching networks in the optimal pricing strategies of loan providers, in an industry where credit access is still closely linked to the presence of a traditional branch in the vicinity of the borrower. This is a crucial element of the analysis of interest rate regulation that has not been considered in the literature, and it is vital to understand the consumer welfare implications of the policy in the context of microfinance. In Colombia, the relaxation of the usury ceiling was accompanied by a significant expansion of the branching networks of loan providers, thereby exposing consumers to significant changes in terms of local credit availability and a potential increase in interest rates, that could have also obeyed to additional investments in branching networks from loan providers.

One advantage of my approach is that it can be carried out in the absence of detailed individual information on loan transactions. Data availability is often scarce in the context of microfinance, because loan providers often operate under different regulatory frameworks and supervisory authorities face limitations to gather detailed information of clients from remote or poor geographic areas, where microfinance institutions concentrate their operations. Notwithstanding, estimating the effects of this policy using market-level information comes with additional challenges, as it is necessary to account for potential changes in the size and composition of the potential market that might be unobserved. The relaxation of an interest rate cap opens the possibility for financial institutions to offer their services to a segment of borrowers that could not have access to loans due to their risk profile or their geographic location. Ultimately, the degree of market expansion will determine whether the policy is welfare enhancing despite the predictable increase in the interest rates.

I estimate a structural model that takes into account that there is a fraction of borrowers that is excluded from the choice problem, due in part to the presence of a usury ceiling in the period before the policy change. Market expansion and changes in the pool of borrowers, generated as a result of the relaxation of the rate ceiling, is incorporated by allowing for unobserved price heterogeneity in the period after the policy change. This approach makes it possible to recover the changes in demand sensitivity to product characteristics such as the interest rate and the number of branches and banking correspondents in local markets.

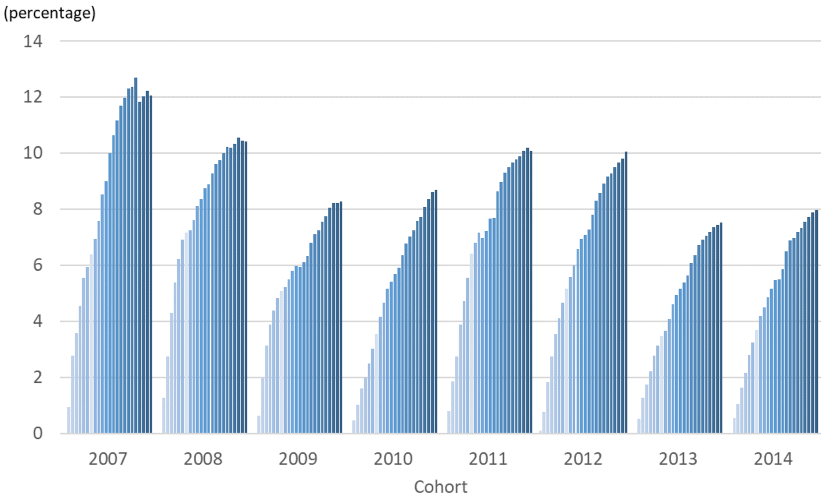
I use the model to understand the changes in consumer welfare that occur as a result of the policy change. The results indicate that welfare gains associated with this policy depend greatly on additional investments on branching networks. The entry of new competitors is important in small markets, where opening a branch can represent a dramatic change in the availability of financial services. At the same time, additional branches and banking correspondents in intermediate and big markets provide a valuable service to consumers, helping to compensate the welfare losses associated with the increase in interest rates, particularly for safer borrowers who already had access to formal loan before the usury ceiling was removed. Branching networks expansion after the usury ceiling modification accounts for nearly 90% of the consumer welfare gains in the biggest markets.

These consumer welfare gains that followed the relaxation of the usury ceiling do not seem to have occurred in economic detriment of financial institutions, who experienced an increase in their profit, particularly in the case of microfinance institutions.

These findings open new avenues for future research, as it becomes clear that the welfare gains are closely linked to the distribution of branching networks across geographic markets. From the borrowers' perspective, the presence of a branch has important implications in terms of credit access, while for financial institutions, branching networks have an essential role in their optimal pricing strategies by determining their exposure to different local competitive environments. By modeling the decision to enter in different locations, it would be possible to build other counterfactuals that allow us to compare the local welfare implications of alternative policies. These analyses can provide better guidance for the public and private initiatives that aim to diminish inequality in the access to financial services and promote economic development in the poorest regions.

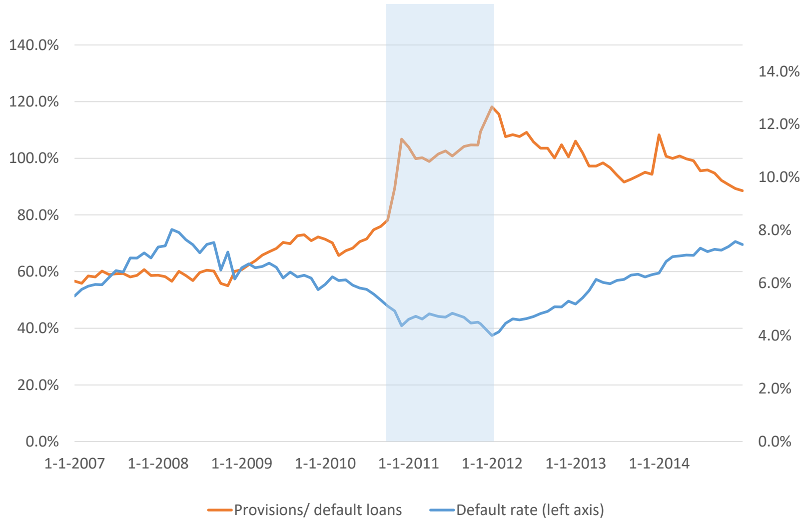
3.8 Appendix

Figure 3.6: Portfolio at risk ratio, by cohort. 2008-2014



Notes: The portfolio at risk ratio is calculating by dividing the outstanding balance of all microloans with arrears over 30 days, by the outstanding gross loan porfolio. Source: Superfinanciera Financiera de Colombia.

Figure 3.7: Average loan provisions rate and default rate of microloans. 2008-2014



Notes: Author's calculations based on information published by Superfinanciera Financiera de Colombia.

Table 3.9: Information of bank characteristics per market

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
			September 2010			
Interest rate	0.29	0.05	0.18	0.24	0.34	0.34
Branches per capita	0.11	0.09	0.001	0.05	0.15	0.67
Banking correspondents per capita	0.30	2.27	0.00	0.00	0.02	45.30
Number of employees per branch	11.03	8.12	0.00	7.00	13.00	98.00
Previous NGO (dummy variable)	0.23	0.42	0	0	0	1
Bank (dummy variable)	0.87	0.33	0	1	1	1
			September 2012			
Interest rate	0.35	0.07	0.18	0.29	0.38	0.45
Branches per capita	0.11	0.10	0.001	0.05	0.15	0.67
Banking correspondents per capita	1.33	3.85	0.00	0.00	1.19	65.27
Number of employees per branch	11.18	8.74	1.00	6.00	13.25	118.00
Previous NGO (dummy variable)	0.28	0.45	0	0	1	1
Bank (dummy variable)	0.87	0.34	0	1	1	1

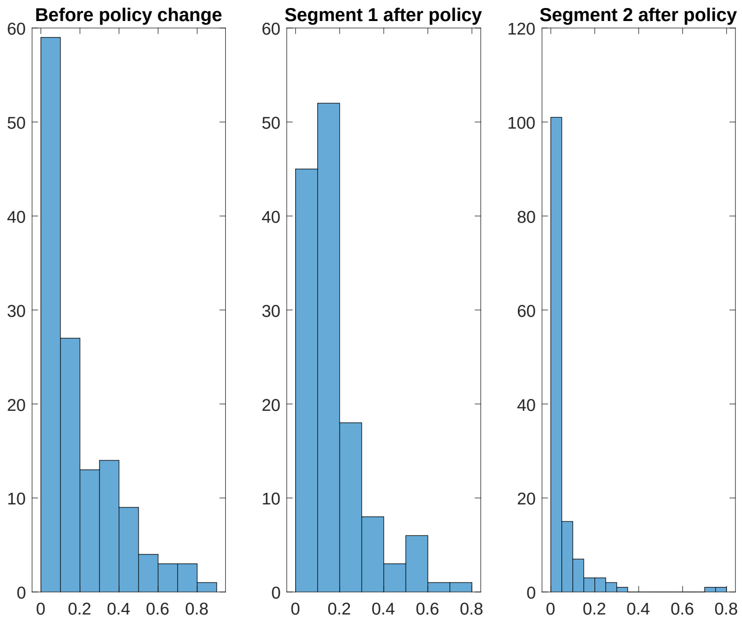
Notes: Summary of descriptive statistics of the characteristics of financial institutions that change across local markets in 2010 and 2012. Branches and banking correspondents density is measured as the number of branches/banking correspondents per 100.000 inhabitants. Source: Author's calculations based on information published by Superfinanciera Financiera de Colombia.

Table 3.10: Instruments used in the supply equation

Variable	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
December 2010						
Branches of same bank in similar markets	0.06	0.05	0.00	0.02	0.08	0.28
Branches of competitors in similar markets	2.84	2.01	0.09	1.06	4.19	8.80
BCs of same bank in similar markets	0.14	0.25	0.00	0.00	0.18	0.97
BCs of competitors in similar markets	6.98	12.12	0.00	0.0005	9.36	76.68
Competitors microloans share (own portfolio)	0.24	0.34	0.01	0.03	0.67	0.83
Interest rate of similar banks	0.29	0.01	0.25	0.29	0.30	0.32
December 2012						
Branches of same bank in similar markets	0.06	0.05	0.00	0.02	0.09	0.28
Branches of competitors in similar markets	3.08	2.35	0.12	1.02	4.71	10.46
BCs of same bank in similar markets	0.69	0.80	0.00	0.00	1.36	3.07
BCs of competitors in similar markets	38.97	44.38	0.00	0.02	68.25	190.51
Competitors microloans share (own portfolio)	0.29	0.37	0.02	0.02	0.80	0.84
Interest rate of similar banks	0.33	0.02	0.22	0.32	0.34	0.36

Notes: Summary of descriptive statistics of instruments used in the estimation. Source: Author's calculations based on information published by Superfinanciera Financiera de Colombia.

Figure 3.8: Distribution of the share of consumers who choose to borrow a loan from a financial institution across markets



Notes: Segment 1: consumers with access to loan before the policy change. Segment 2: consumer that gained access to loans after the policy change (at an interest rate higher than the usury ceiling).

Chapter 4

FinTech in the US Mortgage Industry

Abstract

The US mortgage industry has experienced a rapid transformation, with an increasing number of lenders adopting technological innovations that allow potential borrowers to complete their mortgage application process online, reducing the need for face-to-face interaction with loan officers. The market share of financial institutions offering this type of service has increased significantly in recent years, reaching 9.5% of the originations in 2017. This paper examines the response of incumbent mortgage lenders to the advent of this technology. I find that the increased availability of lenders providing online mortgages has had a differentiated impact on the volume of applications and loan originations for incumbent providers depending on their size. The results suggest that local lenders are better able to differentiate from FinTech institutions by offering services that are appealing to some segments of borrowers. By contrast, mortgages provided by FinTech seem to be a closer substitute for the services provided by large financial institutions, who have seen a reduction in their market share after FinTech entry.

4.1 Introduction

After the Great Recession in 2008, financial intermediation in the US mortgage market has experienced a process of transformation, with lenders incorporating new business models and services to compete in an environment with lower interest rates, weak credit growth, and increased regulatory requirements. In order to attract new clients and reduce operating costs, financial institutions have increased their use of information technology (IT) and automation technologies in financial services provision. The increased use of these developments has transformed how financial institutions perform core business functions, such as those related to maturity transformation and provision of transaction services, resulting in a lower reliance on physical branches.[1] This process has been driven by supply-side factors such as the development of application programming interfaces (APIs), blockchain technologies and broader access to high-speed internet and smartphones, as well as demand-side factors, such as changes in consumers' preferences and increased integration of digital services in daily life activities.

Mortgage lenders have developed to a different extent, platforms that allow their customers to complete transactions, initiate loan applications and receive detailed and up to date information about their products and services.[2] In recent years, however, the speed of adoption of new digital technologies has accelerated markedly, with IT developments moving from facilitating transactions and payments towards supporting completely online loan origination. The arrival of this type of service is disruptive in this industry for several reasons. In the first place, because it allows loan providers to offer financial services in different locations without the need for a physical branch or the presence of loan officers in the vicinity of the borrower, reducing the costs of entry and operation across geographic markets. In the second place, because the development of an online application platform is often accompanied by the implementation of centralized underwriting algorithms that can modify the response of lending supply to local conditions, and reduce the role of soft information, typically obtained through face-to-face interaction between borrowers and loan officers.

The arrival of online mortgage lending comes at a time when both the number of traditional lenders and the size of branching networks have decreased significantly. The decline that occurred immediately after the financial crisis in 2008 has been at-

[1]Vives (2019) presents a detailed overview of the effects of digital disruption in the banking industry.

[2]LaCour-Little (2000) provides a detailed discussion of the technological developments applied to mortgage lending in the 1990s.

tributed to the need to reduce costs through the closure of inefficient office locations, along with a wave of mergers and acquisitions of failed financial institutions. With the simultaneous decrease in the number of branching networks and the increased availability of platform-based lenders with centralized underwriting procedures, potential borrowers are experiencing a transformation of the credit alternatives available at the local level. The substantial change in composition in the credit alternatives available in local markets may have contrasting effects for different groups of borrowers, as some might experience an increase in the variety and convenience of financial services, while others might face a reduction in credit alternatives.

Recent studies have focused on the characteristics of the institutions that offer a loan application process that can be completed online, also known as FinTech lenders, examining their role at reducing frictions in the mortgage markets such as lengthy processing times, capacity constraints and limited access to credit, (e.g. Fuster et al., 2019; Jagtiani et al., 2019). Among the studies that examine the response of traditional lenders to the arrival of these new competitors, the focus has been placed on the regulatory and business-model differences between conventional banks and shadow banks (e.g. Buchak et al., 2018, 2020). In this paper, I contribute to this literature by exploring the reaction of incumbent lenders of different sizes across geographic markets with varying levels of income, with the purpose of determining whether the arrival of this technology contribute to alleviate some of the inefficiencies in the allocation of credit across regions, or on the contrary, can exacerbate existing inequalities in the availability of credit in under-served areas.

Industry reports indicate that small lenders, such as community banks, have comparative advantages in the provision of loans for certain groups of borrowers, since they have greater knowledge of the local market and their customers' preferences, which allows them to maximize the advantages of relationship lending (Lux and Greene, 2015; Jagtiani and Lemieux, 2016). Furthermore, these institutions are more likely to keep the loans in their balance sheet rather than selling immediately in the secondary market, which allow them to guarantee some continuity in the customer service standard during the time it takes to the borrower to complete the payment of the mortgage. At the same time, small lenders might find it more difficult to migrate towards a business model similar to the one developed by FinTech lenders due to regulatory requirements, high compliance costs and greater reliance on obsolete legacy technologies.[3] McCord

[3]These topics have been discussed by policymakers in several public discussions. See for example the speech by the Chicago FED Governor Elizabeth Duke at the Community Bankers Symposym avaliable here: https://www.federalreserve.gov/newsevents/speech/duke20121109a.htm

et al. (2015) find that the decline in branches has been accompanied by a substantial decrease in the number of community banks, which have shown a competitive advantage on lending to small business and lower-income households, particularly in rural communities.

Large financial institutions have shown greater capacity to adopt IT technologies, which has allowed them to develop services that compete with those provided by FinTech institutions. Nevertheless, it may be more difficult for them to build a differentiation strategy that allows them to retain market participation in an environment with greater competition by FinTech lenders. A growing number of studies has concluded that the increased regulatory burden that depository institutions have experienced in recent years has raised costs and limited the scope of financial services that they can offer, limiting their ability to adapt to a more competitive environment (Buchak et al., 2018, 2020; Vives, 2019).

Differences in the loan portfolio composition suggest that small lenders seem to have an advantage in the provision of unconventional mortgages, but there are differences in what drives this non-conformity of mortgages in lower and higher income counties. In the first group, a higher proportion of mortgages is classified as unconventional because the borrowers' particular conditions, such as inadequate credit scores, result in ineligibility for the government-sponsored insurance programs (GSE). In the latter case, small lenders focus on non-conventional mortgages such as *jumbo* mortgages, which are not eligible for GSE insurance because their size exceeds the maximum limit defined by the government. These differences in the loan portfolio composition indicate that the type of clients that small lenders target in poorer and richer counties is likely to be different, not only in terms of income but also in terms of their familiarity with digital platforms and their knowledge of the local real market conditions. As a result, it is possible that the sustitutability pattern observed among services provided by FinTech and incumbent lenders differ in markets with lower and higher income.

I find that the arrival of FinTech has led to a reduction in the volume of applications and originations of big financial institutions and multi-state banks. This result suggests that consumers may have found a close substitute of their services in online mortgage platforms provided by FinTech lenders, particularly in the case of refinancing loans. These result is consistent with the evidence provided by Fuster et al. (2019) on the substantial gains that FinTech have achieved in reducing the processing time of this type of loan applications. By contrast, local and small lenders have been more resilient to the entry of this new type of competitors, particularly in higher-income counties, where the number of applications has increased significantly. While some industry reports have highlighted the competitive advantages of small lenders in the midst of the disruption generated by the accelerated development of the FinTech sector, this paper provides quantitative evidence on this direction and contrast the

A second question that I address in this paper is whether the response of incumbent lenders regarding credit availability towards minority borrowers has changed after the entry of FinTech lenders. Online mortgage lending may have a role at increasing the availability of loans for borrowers belonging to racial or ethnic minorities across geographic markets, as they offer services with reduced face-to-face interaction with loan officers, which may result inconvenient or intimidating for some potential minority borrowers. For example, Hanson et al. (2016) show that loan officers are less likely to respond and provide more information to potential borrowers with names typically associated with minorities, whereas Begley and Purnanandam (2020) find a higher incidence of consumer complaints in areas with higher share of minorities.

Furthermore, FinTech lenders have developed an approval process supported by centralized underwriting operations, which allows them to reduce processing times and labor costs as they rely on algorithms that examine and analyze enormous amounts of information in a more consistent and repeatable way. Algorithmic decision-making can alleviate frictions in the mortgage market by increasing the efficiency of the borrowers' screening process and reducing processing times. The broader implementation of centralized underwriting algorithms has the potential of increasing financial inclusion by groups of borrowers currently under-served by traditional financial institutions. There is also a concern that it may also lead to inadvertent systematic discrimination, as these sophisticated methods are often trained on past historical datasets. Fuster et al. (2020) find that machine learning methods can incorporate the association between race and default more efficiently using the remaining borrower characteristics, even though datasets cannot explicitly include information on race or ethnicity law.

As the biggest traditional banks move towards the incorporation of these elements in their loan origination process, small lenders may keep relying on traditional methods if this allows them to differentiate and target minority borrowers effectively. I find that the incumbents' response to the increased availability of FinTech services in terms of the volume of applications and loan originations of minorities follows a similar pattern to the one observed for all borrowers. Medium size and large lenders register the greatest reductions in applications and originations after entry, whereas in the case of local and small lenders this variables exhibit an increase, particularly in high-income counties.

The rest of the paper is organized as follows: Section 4.2 describes the contribution to existing literature on FinTech in the mortgage industry. Sections 4.3 and 4.4, describe the data sources, present a precise definition of FinTech and examines the characteristics of FinTech lenders in contrast with traditional lenders across markets. Section 4.5 describes the estimation strategy, Section 4.6 discusses the results of the estimations for each group of lenders and section 4.7 presents some final remarks.

4.2 Literature Review

This paper connects to the growing literature on financial technology that has explored the ways in which IT development has transformed the provision of financial services (see Philippon, 2016; Claessens et al., 2018; Vives, 2019, for surveys). In particular, it relates to two strands of the literature that explore the role of financial technology in the mortgage industry:

The effects of FinTech on incumbent lenders

A growing number of studies describe the impact of technological innovation and the development of a secondary market for mortgages on the local market structure and the overall availability of credit supply (e.g. Basten and Ongena, 2019; Foote et al., 2019; Philippon, 2016; Korgaonkar, 2019). Foote et al. (2019) argue that increasing automatization of mortgage underwriting exhibited by FinTech institutions is not a new phenomenon. Advances in information technology during the nineties contributed significantly to credit growth during this period. Philippon (2016) finds, however, that the benefits of the improvements in information technologies have not been completely passed through to the end users of financial services. The authors highlight the role of FinTech startups in solving some of these inefficiencies and discuss the challenges of financial regulation.

Recently, increasing attention has been paid to the role of online lending platforms. Basten and Ongena (2019) analyze the effects of the development of an online platform in Switzerland, where consumers can apply and different banks can respond to their applications. Their findings suggest potential improvements for borrowers as well as for financial stability derived from the presence of online platforms, since they create incentives for banks to provide more attractive loan conditions to customers, regardless of the local level of concentration. In line with these findings Jagtiani et al. (2019) conclude that the arrival of online platform-based lenders in the US mortgage industry have contributed to the expansion of credit in areas under-served by traditional loan providers.

Recent work by Buchak et al. (2018) and Fuster et al. (2019) on the US mortgage industry provide a clear contrast of the characteristics of FinTech lenders' business model with that of traditional banks; (Fuster et al., 2019) show that FinTech lenders can process mortgage applications faster and display greater flexibility in response to mortgage demand shocks, compared to conventional depository institutions and non-FinTech shadow banks, whereas Buchak et al. (2018) finds that differences in regulatory requirements have contributed to the development of shadow banking and the dramatic growth of online FinTech lenders.

The analysis presented in this paper is based on the definition of FinTech proposed by Fuster et al. (2019) and Buchak et al. (2018). While Buchak et al. (2018) focuses on the differences between depository institutions and shadow banks, I analyze the impact of FinTech entry on the volume of applications and loan origination of lenders of different sizes across markets with varying levels of income. By exploring the response of small lenders, a group largely composed by depository institutions, this paper contributes to an extensive literature that has studied the advantages and challenges of the community banking sector in the US (e.g Deyoung et al., 2004; Rosen, 2011; Critchfield et al., 2018; McCord et al., 2015).

Discrimination in the mortgage market

By exploring the response of minority borrowers to the increasing availability of FinTech mortgage lenders, my work also connects with a broad literature that has studied discrimination in the US mortgage market (e.g. Munnell et al., 1996; Ross and Yinger, 2002; Bartlett et al., 2019). Many recent studies on discrimination in the mortgage market in the US focus on the pre-crisis period (e.g. Ladd, 1998; Ghent et al., 2014; Bayer et al., 2017), finding that African-American and Hispanic borrowers face higher rejection rates and tend to be charged higher interest rates after controlling on credit characteristics. Among the studies that consider the role of IT developments in the access of minorities to mortgages after the crisis, particular attention has been given to the role of centralized underwriting algorithms in alleviating discrimination in the loan approval decisions (Fuster et al., 2020). Recent work by Bartlett et al. (2019) concludes that online mortgage platforms tend to alleviate discrimination arising from personal interaction with loan officers, making mortgage lending more accessible to minority borrowers. This paper complements these results by examining the recent evolution of non-FinTech lenders with respect to this group of borrowers.

4.3 FinTech Institutions

Fuster et al. (2019) identify two defining features of the FinTech business model, that differentiate them from other lenders: an end-to-end online mortgage application platform and a centralized mortgage underwriting. While these features are not fully observable, the authors base their classification on whether the lenders offer the possibility of obtaining a preapproval online[4]. This classification distinguishes FinTech lenders from other mortgage originators that use online platforms, but still require personal interaction to complete the loan approval.[5]

According to Fuster et al. (2019), FinTech institutions have reached a much larger degree of automation relative to other lenders. Their approval process is done in a centralized manner, rather than through brick-and-mortar branches or local brokers. They are mostly non-depository institutions (shadow banks) that originate loans and later sell them trough channels supported by government guarantee schemes such as Fannie Mae and Freddie Mac. It is worth noting that the differences between FinTech institutions and other shadow banks will become more tenuous over time, as more traditional lenders can incorporate new technologies in their origination process.

The presence of an online platform reduces the need for face-to-face interaction with the borrowers, allowing them to upload all supporting documents electronically, instead of having sent them by mail or fax. These platforms are supported by algorithms that analyze and compare the borrower information with reference databases,

[4] A similar classification is developed by Buchak et al. (2018). In both studies, the authors emphasize that while many lenders in recent years allow their clients to start their application process online, only those institutions that completely automate the mortgage origination process are classified by FinTech lenders.

[5] According to Fuster et al. (2019), obtaining a purchase mortgage involves three main steps: (1) Completing an initial application and obtaining a preapproval letter. This document is indicative of a borrower's credit capacity and is often required to make an offer on a home, although it is not binding. (2) once a property has been identified and sale price agreed upon, the underwriting process takes place. This step involves verification of all supporting documentation, often requiring many interactions between the processor, loan officer, and borrower and can take from 1 to 2 days to several weeks or more. (3) The final step is known as 'Closing', and it implies the transfer of the funds and property deed. FinTech lenders partially automate the first two steps and allow them to be completed online.

making the mortgage underwriting process more standardized and consistent (Fuster et al., 2019). Compared to the traditional mortgage underwriting method, the FinTech automated approach can reduce processing times, labor costs associated with the underwriting process, and allow lenders to react faster to demand shocks. However, there are potential disadvantages, such as the possibility of consistent errors created by poorly designed algorithms and the loss of soft information that could be gathered through personal interaction.

Table 4.1 presents the largest institutions that are considered as FinTech by Fuster et al. (2019) and Buchak et al. (2018).[6] Among them, the biggest FinTech lenders are *Quicken Loans*, *LoanDepot* and *Guaranteed Rate*. Some of these institutions have operated in the market for more than thirty years, but only recently they have introduced online mortgage platforms. The third column in the Table registers the date, after which they are considered as FinTech institutions according to the definition by Fuster et al. (2019). Table 4.1 presents the date when a completely online mortgage application process was launched, according to the FinTech websites and online industry reports. Most of these changes took place in 2016. As seen in Figure 4.5 in the Appendix, all FinTech institutions experienced an important growth in the number of originations between 2010 and 2017, particularly in 2011 and 2016, which coincides with the development of online applications platforms.[7] The percentage of applications and loans originated by FinTech institutions has increased steadily over time, reaching 8.1% and 9.6% of the total in 2017. Nevertheless, many of these lenders still rely on broad branches networks and sponsored mortgage loan operators (MLO), which allow them to reach clients who still prefer the conventional mortgage application process.

FinTech lenders have become an increasingly important source of mortgage credit to U.S. households. Their lending has grown from \$34bn of total originations in 2010 to \$161bn in 2016. Figure 4.1 presents the average number of applications and loan originations of FinTech lenders between 2008 and 2017. While there is an upward trend for FinTech lenders, the number of applications and originations of traditional lenders does not exhibit a clear trend over the period. Instead, there have been significant fluctuations in the number of applications and loan originations, decreasing in 2014, but increasing again in 2016 (Figure 4.2).

[6] A similar classification is used by Jagtiani et al. (2019).

[7] For example, *Quicken Loans* experienced a spike in the number of applications after introducing the platform *Rocket Mortgage* in late 2015, which allows customers to obtain a pre-approval minutes after the documentation has been uploaded (Fuster et al., 2019)

Table 4.1: FinTech institutions in the U.S. loan market

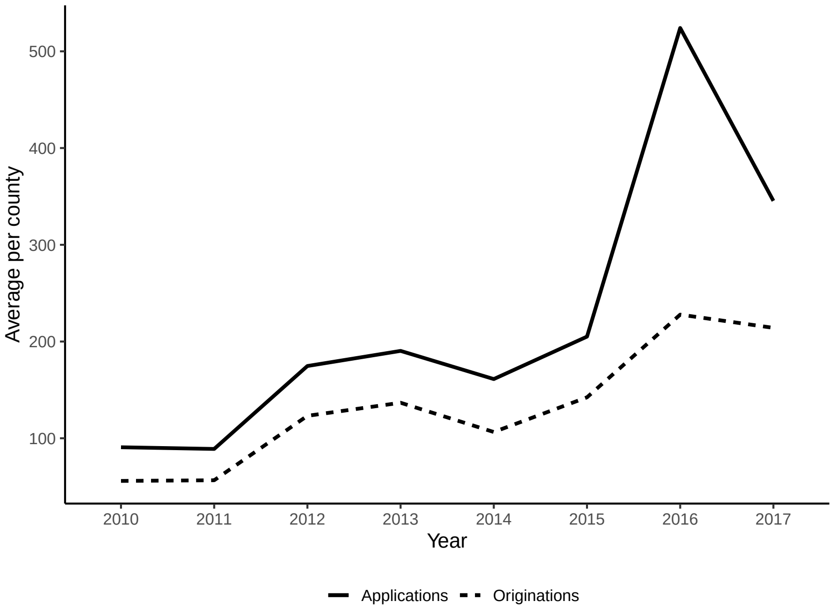
Name	Founded	Online lender	Branches	Sponsored MLO	States (2017)
Quicken Loans	1985	2010	615	6425	52
LoanDepot.com	2009	2016	463	2702	52
Guaranteed Rate Inc.	1999	2010	388	1773	52
Movement Mortgage	2007	2014	520	1820	48
Everett Financial Inc.	1997	2016	271	961	51
Better.com	2003	2016	7	221	15
Amerisave	2002	–	22	555	50
SoFi	2012	2016	6	35	47
CashCall*	2000	–	1	0	0

Notes: Based on the classifications proposed by Fuster et al. (2019) and Buchak et al. (2018). The second column, refers to the date that (Fuster et al., 2019) uses to classify these lenders as FinTech institutions. The column named "Fully online" refers to the date when these financial institutions launched completely online application platforms that do not require interaction with loan officers (verified on the websites of these lenders and industry reports). The last column presents the number of states with at least one application registry in the HMDA data set as of 2017. Finally, CashCall has suspended its operations in many states after a series of adverse court decisions.

4.4 Descriptive Statistics: Markets and Borrowers

In order to explore the characteristics of borrowers across geographic markets, I use the mortgage application records collected under the Home Mortgage Disclosure Act (HMDA) Act. This legislation required mortgage lending institutions with offices in metropolitan areas to disclose to the public information about the geographic location and other characteristics of the home loans they originate or purchase during a calendar year. This data set contains the vast majority of home mortgage applications and approved loans in the United States, and it has been widely used by policymakers and academics that study the characteristics and evolution of the mortgage industry in the US. It provides the originator's identity, the application outcome, the loan type and purpose, the borrower's race, ethnicity, income, loan amount, year, census tract. It is estimated that the lenders covered by the law account for approximately 86% of all home lending nationwide, providing a representative picture of the US mortgage industry (Avery et al., 2007). I complement this information with county demographics from the Census, Census tract consumer credit characteristics, house price indexes, and bank CRA assessment area data from the Federal Financial Institutions Examination Council (FFIEC).

Figure 4.1: Applications and loan originations of FinTech institutions 2008-2017



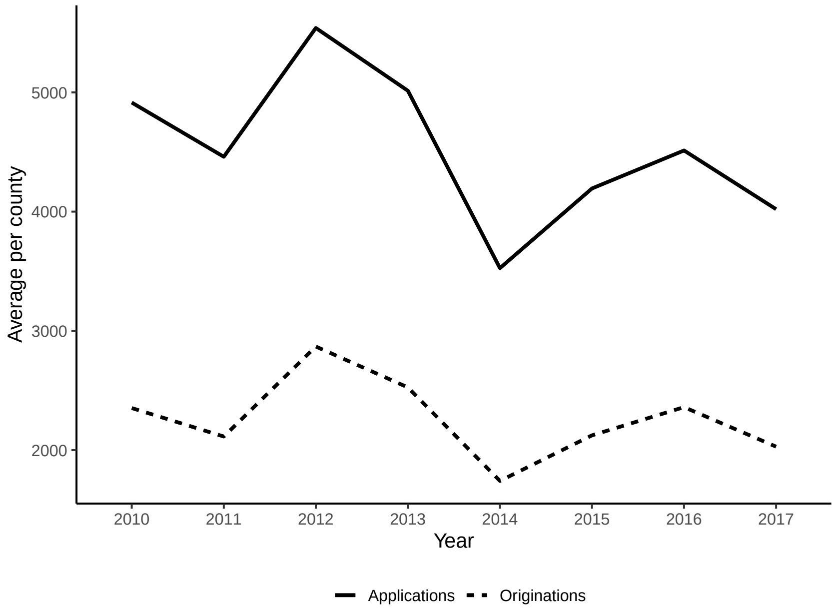
Notes: This Figure shows the evolution of the average number of applications and loan originations per county of those institutions classified as FinTech according to the definition presented in Section 4.3. Calculations are based on HMDA data.

Table 4.2 presents summary statistics of mortgage originations and applications provided by FinTech institutions and traditional lenders based on the HDMA data set for 2010, 2016, and 2017.[8] Panel A shows that both the number of traditional lenders and their market share has decreased between 2010 and 2017, whereas FinTech lenders have increased their market participation both in terms of applications and loan originations. Nevertheless, while the number of applications that FinTech lenders received increased in 2016. the number of originations did not change in the same proportion. During that year, the approval rate decreased significantly for this type of lender, reaching 43% of the applications. In 2017, the approval rate exhibited levels similar to those observed in 2010, around 62%. This fluctuation was not experienced by traditional lenders, whose approval rate varied less during those years, situating in 50,8% in 2017.

Panels B, C, and D of Table 4.2 present information about the composition of

[8]Tables 4.13 in the Appendix present additional statistics of the information included in the HDMA data set.

Figure 4.2: Applications and loan originations of non-FinTech institutions 2008-2017



Notes: This Figure shows the evolution of the average number of applications and loan originations per county of lenders that do not satisfy the definition of FinTech presented in Section4.3. Calculations are based on HMDA data.

applications in terms of the type of guarantees of the loans, the purpose of the loan, and the socio-demographic characteristics of the borrowers included in the HDMA data set. In 2010, most of the borrowers that choose a FinTech lender had the purpose of refinancing, rather than buying a new home. Between 2010 and 2017, the percentage of refinancing applications has reduced, while the share of borrowers who are choosing FinTech institutions with the purpose of home purchasing has increased from 10,1% to 41.8% (Panel B).

A large proportion of FinTech applications are conventional, that is, eligible to be sold to a government-sponsored enterprise (GSE) like Freddie Mac of Fannie Mae (68% in 2017). In contrast, loan applications that can be insured by the Federal Housing Administration (FHA) amounted to 20.2% of the total in 2017 (Panel C). Between 2010 and 2017, the number of loan applications eligible for guarantees from the US Department of Veterans Affairs (VA) has increased from 3% to 11.2%. By contrast, traditional lenders have seen a reduction in the percentage of conventional and FHA-insured loan applications.

Panel D presents information on the socio-demographic characteristics of borrowers. I do not observe significant differences in the composition of borrowers of FinTech lenders and traditional loan providers in terms of gender, race, and ethnicity except for the higher proportion of borrowers who do not disclose this information in the case of FinTech lenders. For the latter group of loan providers, I find an increase in the proportion of African American and Hispanic borrowers. Regarding the income of the borrowers, I observe a decrease in the average income for FinTech institutions in 2016, while in the case of traditional lenders, this variable increased compared to the value found in 2010. This change suggests that the introduction of online lending motivated borrowers with lower income to apply for mortgages.

4.4.1 Non FinTech Lenders

Tables 4.3 and 4.4 present descriptive statistics of non FinTech lenders by size, for the years 2015 and 2017, before and after the substantial increase in the number of online mortgage platforms available across states observed in 2016. I classify non-FinTech loan providers in four categories depending on the average number of counties with at least one branch between 2008 and 2010.[9] Local lenders are those available in less than ten counties in a single state. Small lenders have loan operations in 10 to 30 counties, and medium-sized lenders provide loans in up to 100 counties. Large lenders are those active in more than 90 counties.

As seen in Panel A of Table 4.3, the total number of non-FinTech lenders included in the HDMA database decreased between 2015 and 2017, particularly in the category of local lenders. The total number of loan providers in this group dropped from 4069 in 2015 to 3077 in 2017. Nevertheless, the number of local lenders in each county has increased, likely as a result of a surge in the number of branches and sponsored loan officers. At the same time, large financial institutions have increased the number of counties where they carry on loan operations; thus, the average number of large mortgage providers has increased from 193 to 204 during this period.

Despite the increase in the number of large lenders per county, the number of applications and loan originations provided by institutions in this group has decreased,

[9]This information was obtained from the Call Reports published by the FDIC in the case of depository institutions. In the case of non-depository institutions, I classified institutions according to the number of counties with applications recorded in the HDMA data set between 2008 and 2010.[10] In the case of new lenders I used the number of counties where they were active during their first two years of operation in the market.

Table 4.2: Borrowers Descriptive Statistics of loan providers per type.

	FinTech institutions			Traditional lenders		
Year	2010	2016	2017	2010	2016	2017
Panel A. Number of lenders and market shares						
Number of lenders	5	7	8	7699	6650	5763
Market share (applications)	0.018	0.106	0.080	0.982	0.894	0.920
Market share (loan value)	0.026	0.079	0.083	0.974	0.921	0.917
Approval rate	0.620	0.435	0.619	0.479	0.524	0.508
Panel B. Purpose of the Loan						
Home purchase loans	0.101	0.336	0.418	0.328	0.498	0.595
Refinancing operations	0.899	0.658	0.576	0.627	0.431	0.322
Home improvements loans	0.00002	0.005	0.006	0.045	0.071	0.083
Panel C. Type of Guarantee						
Conventional loans	0.763	0.669	0.680	0.766	0.737	0.743
FHA-insured loans	0.207	0.208	0.202	0.182	0.153	0.152
VA guaranteed loans	0.030	0.118	0.112	0.040	0.094	0.087
FSA-guaranteed loans	0.0002	0.005	0.006	0.012	0.015	0.018
Panel D. Borrowers' characteristics						
Female	0.236	0.269	0.260	0.246	0.250	0.262
Male	0.601	0.583	0.514	0.616	0.583	0.568
Gender not available	0.163	0.148	0.226	0.062	0.054	0.054
Gender not applicable	0.000	0.000	0.000	0.076	0.113	0.116
White	0.666	0.636	0.571	0.711	0.665	0.655
Black	0.034	0.080	0.070	0.051	0.064	0.070
Race not available	0.218	0.266	0.298	0.092	0.088	0.088
Not Hispanic	0.755	0.726	0.649	0.753	0.706	0.697
Hispanic	0.034	0.080	0.075	0.065	0.091	0.095
Other	0.211	0.194	0.276	0.106	0.090	0.092
Income of applicant (median)	84	75	78	76	81	79
Median HUD family income	68.2	66.9	67.9	66.7	67.2	68.3

Notes: Income categories based on median Census Tract income (2010) for each county. Size of lenders based on the number of counties with at least one client between 2010 and 2014: Local: less than 10 counties (same state), Small: less than 30 counties, Medium: less than 90 counties, Large: More than 90 counties.

on average. By contrast, small loan providers have seen an increase in these variables between 2015 and 2017. Panel B of Table 4.3presents the market shares of each lender category, based on the number of applications and the number of loan originations. Despite the substantial decrease in the number of local lenders, the market share of this group remained unaltered between 2015 and 2017. By contrast, the market share of large non-FinTech institutions decreased from 68.4% of the applications in 2015 to 65.6% in 2017.[11]

Panels A and B of Table 4.4 present the composition of the loan originations according to the type of guarantee and the purpose of the loan. The composition in terms of the type of loan guarantees has not changed significantly in recent years. Local lenders have a larger share of conventional loans than large non-FinTech institutions, whereas the latter group has a higher percentage of FHA loans.[12]. In terms of the purpose of the loan, the share of loans obtained for a home purchase has increased for all types of loan providers, whereas refinancing operations have decreased, particularly in the case of large lenders. These results indicate that the loan portfolio of large non-FinTech institutions is the one that has greater similarity with the loan portfolio of FinTech institutions.

Finally, Panel C of Table 4.4 presents the share of applications and loan originations where the applicant was African-American or Hispanic. Between 2015 and 2017, the percentage of minority borrowers increased for local lenders and remained mostly unchanged for the other categories of loan providers.

[11] This trend is also observed when comparing these values with those from 2010, when these institutions received 75.3% of the applications and originated 64% of the loans.

[12] Conventional mortgages that satisfy some requirements can be guaranteed by GSEs such as Fannie Mae and Freddie Mac.

Table 4.3: Summary statistics of loan providers by size. 2015-2017

	Local		Small		Medium-sized		Large	
Year	2015	2017	2015	2017	2015	2017	2015	2017
Total No. of lenders	4,069	3,077	1,347	1,321	822	822	562	555
Average No. of counties	12	14	31	32	80	80	1,029	1,133
Panel A. Number of lenders, applications and loan originations per county								
Lenders	37	42	24	25	21	21	193	204
Applications	494.5	527.9	252.1	260.0	175.0	175.0	3,496.9	3,303.1
Loan originations	325.1	328.6	179.0	179.5	126.6	126.56	1,648.6	1,557.5
Denial Rate	0.357	0.379	0.299	0.306	0.251	0.251	0.577	0.569
Panel B. Market shares								
Total applications	0.127	0.129	0.086	0.083	0.054	0.054	0.684	0.656
Total loan originations	0.161	0.162	0.116	0.113	0.077	0.077	0.581	0.563

Notes: The values correspond to the average per county, except for the number of lenders, which correspond to the total number at the national level. Income categories based on median Census Tract income (2010) for each county. Conventional loans are all loans that are not FHA/VA/FSA/RHS loans. Size of lenders are classified as: local (active in less than 10 counties in the same state), small (less than 30 counties), medium-sized (less than 90 counties) and large (more than 90 counties).

Table 4.4: Summary statistics of loan applications according to providers' size. 2015-2017

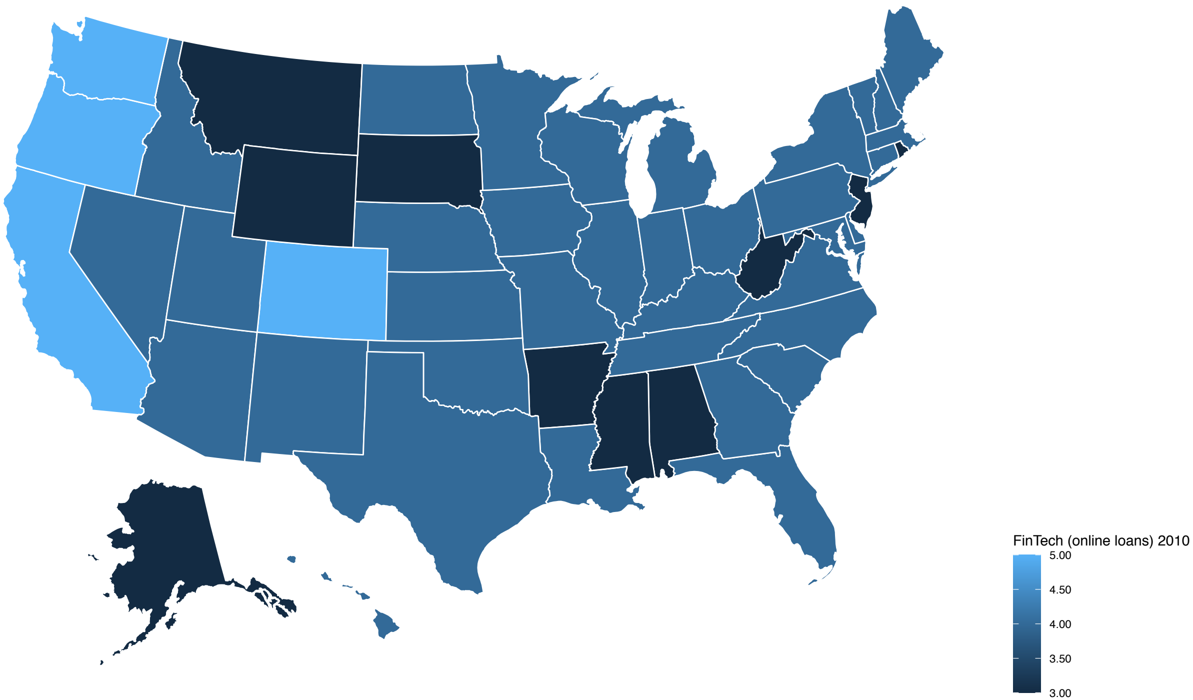
	Local		Small		Medium-sized		Large	
Year	2015	2017	2015	2017	2015	2017	2015	2017
Panel A. Type of guarantee								
Conventional	0.934	0.930	0.862	0.869	0.785	0.785	0.700	0.702
FHA	0.041	0.038	0.092	0.085	0.150	0.150	0.183	0.172
FSA	0.008	0.008	0.015	0.015	0.022	0.022	0.017	0.018
VA	0.017	0.024	0.030	0.031	0.043	0.043	0.101	0.108
Panel B. Purpose of the loan								
Home purchase	0.495	0.536	0.535	0.596	0.560	0.560	0.467	0.542
Refinancing	0.393	0.347	0.375	0.302	0.371	0.371	0.486	0.398
Home improvement	0.112	0.118	0.090	0.102	0.068	0.068	0.047	0.059
Panel C. Minority Borrowers (share of own portfolio)								
Applications	0.133	0.180	0.116	0.115	0.126	0.126	0.142	0.146
Originations	0.087	0.096	0.106	0.115	0.125	0.125	0.080	0.086

Notes: The values correspond to the average per county, except for the number of lenders, which correspond to the total number at the national level. Income categories based on median Census Tract income (2010) for each county. Conventional loans are all loans that are not FHA/VA/FSA/RHS loans. Size of lenders are classified as: local (active in less than 10 counties in the same state), small (less than 30 counties), medium-sized (less than 90 counties) and large (more than 90 counties).

4.4.2 Local markets

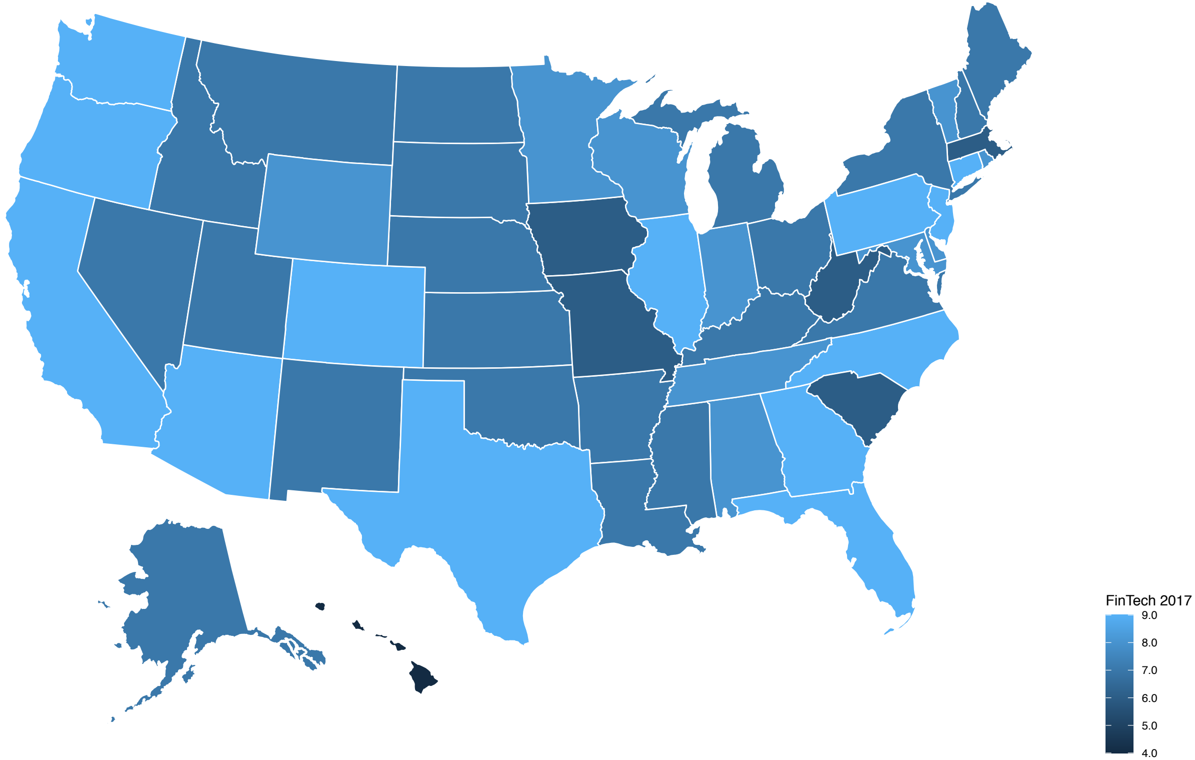
FinTech lenders can offer mortgages in a particular market without the presence of a branch or a loan officer. Nevertheless, in order to provide their services in a particular region, they need to obtain a license issued by the relevant state regulatory agency. Differences in license costs and requirements contribute to explain the heterogeneity in the number of FinTech lenders that are available across states. I use information from the Nationwide Multistate Licensing System & Registry (NMLS) to identify the date of entry of FinTech lenders in each state. Figures 4.3 and 4.4 present the number of Fintech institutions available in each state in 2010 and 2017.

Figure 4.3: Number of FinTech institutions per state. 2010



Notes: The number of Fintech per state is calculated using the date of introduction of mortgage lending platforms and license information published by NMLS.

Figure 4.4: Number of FinTech institutions per state. 2017



Notes: The number of Fintech per state is calculated using the date of introduction of mortgage lending platforms and license information published by NMLS.

Table 4.5 presents information on the mortgage market structure for counties with varying levels of income for the years 2015 and 2017. I classify counties in three categories of income based on the 30th and 70th percentiles of the income distribution per county calculated using 2010 Census information.

Panel A indicates that the number of Fintech has increased in counties of all levels of income, although those with higher income have a greater number of FinTech lenders (5.3 on average in 2017). The number of local and small lenders has remained stable across counties between 2015 and 2017, except for local lenders in middle-income countries, where there was a slight reduction between those years. In contrast, the number of medium-size lenders and large lenders has increased during this period in all categories of counties. This increase is more substantial for the biggest loan providers in lower-income counties, where the average number of lenders of this type increased from 61.9 to almost 70.

Panel B describes the evolution of the market shares, based on loan originations, for these groups of lenders between 2015 and 2017. The market share of FinTech lenders has increased similarly in counties of all income levels. In lower-income counties, this market expansion seems to have occurred at the expense of local lenders, whose market share has reduced from 10% to 7%, whereas in higher-income counties, larger non-FinTech lenders are the group with the more significant reduction in market share during this period.

Finally, Panel C presents the Herfindahl-Hirschman index based on applications and loan originations. The HHI based on applications has decreased for all categories of counties, indicating that the market has become more competitive between 2015 and 2017. However, the HHI based on originations shows that market concentration has increased in lower-income locations.

4.5 Incumbents' response to the arrival of FinTech lenders

In this section I examine the response of different lenders to the increase in availability of online mortgage platforms across geographic markets. Using county-lender category observations from 2010 to 2017 included in the HDMA database, I estimate the following regression:

Table 4.5: Market structure for counties of different levels of income

	Lower income		Middle Income		Higher Income	
Year	2015	2017	2015	2017	2015	2017
Panel A. Number of lenders						
FinTech	1.93	3.59	2.41	4.51	2.85	5.29
No FinTech	83.30	85.32	132.57	144.76	209.12	211.65
No FinTech local	5.77	5.20	10.65	9.59	18.90	16.21
No FinTech small	7.07	7.20	12.15	13.32	20.92	20.48
No FinTech medium	10.15	12.66	17.65	21.11	31.43	34.88
No FinTech large	61.90	69.81	93.39	101.10	139.87	141.75
Panel B. Market shares (originations)						
FinTech	0.06	0.09	0.06	0.09	0.07	0.09
No FinTech local	0.10	0.07	0.08	0.07	0.06	0.06
No FinTech small	0.13	0.12	0.12	0.11	0.10	0.10
No FinTech medium	0.20	0.20	0.18	0.18	0.17	0.18
No FinTech large	0.53	0.54	0.55	0.54	0.60	0.57
Panel C. HHI index						
Applications	829.37	732.82	626.60	559.09	538.95	498.50
Originations	1,156.96	1,232.93	892.00	824.01	722.71	662.70

Notes: Income categories based on median Census Tract income (2010) for each county. Size of lenders are classified as: local (active in less than 10 counties in the same state), small (less than 30 counties), medium-sized (less than 90 counties) and large (more than 90 counties).

$$y_{b,c,t} = \alpha_c + \alpha_t + \alpha_s t + \beta_1 \text{FinTech}_{s,t} + \beta_2 \text{FinTech}_{s,t-1} + \gamma X_{c,t-1} + \epsilon_{b,c,t}, \tag{4.1}$$

where $y_{b,c,t}$ is the logarithm of the average number of applications (originations) provided by lenders of size b in county c in year t.[13] These values are modeled as a function of the number of FinTech institutions available in each state (s) in years t and $t-1$. I included the lagged number of FinTech available at the state level, since it is possible that there is some delay in the response of potential borrowers, as not of all them might be immediately aware of the new alternatives available in the market in every period.

The matrix of control variables, $X_{c,t-1}$, include the logarithm of the median income observed in the county, based on the estimated tract median family income reported in the Census 2017, the percentage of minority population per county, the logarithm of the county population, the number of tracts designated as under stress due to poverty, unemployment or natural disaster in each period.[14] I also included variables intended to capture the dynamics of the real state market in the area, such as the percentage of sub-prime mortgages provided in the market in period $t-1$ and the average house pricing index (HPI) published by the Federal Housing Finance Agency at the state level.[15] $\epsilon_{b,c,t}$ is an unobservable term that is assumed to be not correlated with the variables included in $X_{c,t-1}$ or the variables of interest ($\text{FinTech}_{s,t}$ and $\text{FinTech}_{s,t-1}$). In order to control for unobserved local characteristics, macroeconomic factors and state specific factors that can have an impact in the demand for loans, I include county and time fixed effects and a state-level year trend.[16]

[13]By examining the behavior of groups of institutions per county, rather than using bank-level data, intra-group heterogeneity is not taken into account. The correlation among unobservables of institutions belonging to the same group can create differences in the magnitude of the coefficients obtained with type-of-lender-county data vs. bank-county data. Preliminary results with bank-county data show qualitatively similar to the ones presented here.

[14]These tracts are designated by the Board of Governors of the Federal Reserve System as distressed, based on rates of poverty, unemployment, and population loss, or underseved, according to population size, density, and dispersion. Areas that have been exposed to natural disaster are reported by the Federal Emergency Management Agency (FEMA).

[15]This variable is only available at the county level for metropolitan statistical areas (MSA). The result of the specifications based on the sample of markets with information of the housing pricing index at the county level are not qualitatively different from the ones reported here.

[16]The error term in this context is likely to exhibit autocorrelation. Therefore I consider a dynamic panel specification by including a lag of the dependent variable. The results of the Arellano-Bond estimation regarding the variables that capture the effects of the presence of FinTech lenders do not differ significantly in magnitude or direction from the ones presented here. This indicates that the effect of an additional FinTech competitor in the market largely dissipates after two periods. To

I examine the changes in the number applications and loan originations of incumbent lenders. The changes in the number of applications of incumbent lenders are informative of the attractiveness of the financial services offered by traditional lenders relative to online lending. They constitute a direct measure of the preferences of consumers regarding online lending vs traditional application protocols. In contrast, changes in the number of loan originations reveal the effects of increased online mortgage lending on credit availability and are also the result of a selection process determined by risk considerations on the side of loan providers. By examining both variables, we can gain some insights on the incumbents' strategies after the arrival of mortgage lending, For example, an increase in the number of loan originations of similar magnitude of that observed in the number of applications could indicate market expansion generated via increased advertising, whereas an increase in the number of loans originations alone could signal a relaxation of the credit risk standards that could be the result of greater competition in local markets.

Finally, after the arrival of FinTech, it is possible that some incumbent loan providers implement changes in order to make their services more appealing for borrowers belonging to minority groups. I explore this possibility by estimating Equation [4.1], using the number of applications and loan originations where the borrower is African-American or Hispanic as the dependent variable.

The development of technologies applied to the provision of financial services is the result of investments that are guided by expectations on future market returns. The specification above assume that the number of FinTech loan providers is not correlated with unobserved shocks that can occur at the county level. I consider that this assumption is reasonable given that the variables $\text{FinTech}_{s,t}$ and $\text{FinTech}_{s,t-1}$ are defined at the state level. The number of available FinTech lenders is likely determined by technological developments that allow lenders to enter multiple markets simultaneously. These investments are more likely to be determined by aggregate return considerations rather than shocks at the county level.

4.6 Results

Table 4.6 presents the results of the regression with the logarithm of the number of applications as the dependent variable. In all specifications, I included only those counties that registered more than 50 applications at the beginning of the sample.

facilitate the exposition of the results I included only those of the fixed effects regression.

The columns in Table 4.6 present the results for different groups of counties according to the income categories defined in Section 4.4. Standard errors are clustered at the county level.

Panel A presents the effects of an increase in the number of FinTech lenders at the state level on the average number of applications provided by local and small lenders. The results indicate that the contemporaneous effect of an additional FinTech lender is positive and significant in middle-income counties. In contrast, the coefficient of the lagged number of FinTech is not significant in any of the specifications. The presence of an additional FinTech lender increases the volume of applications of small lenders by 3.8% in those markets. Although the coefficient of the lagged value of the dependent variable is positive and significant, the magnitude is not very high, indicating that the effect is mostly contemporaneous. In the case of small lenders (Panel B), additional FinTech lenders' presence has a positive effect on applications in lower-income counties, where the average contemporaneous increase is 2.8%. The response of incumbent small lenders in higher-income counties is only significant one period after entry, but the magnitude is relatively more substantial, as the number of applications increases by 4,5% after the entry of FinTech lenders.

The increase in the number of applications associated to the greater availability of FinTech at the state level could be the result of more aggressive competition among local lenders or to a renewed interest on real-state investment generated by the increase of expending in advertising by both entrants and incumbent lenders. While the increase in the volume of applications or loan originations does not necessarily imply a higher market share or markup for incumbent lenders, reduction in these volumes is indicative a loss in market participation.

By contrast, medium-size and large lenders experience a decrease in the number of applications after the entry of FinTech. For the first group (Panel C), the reduction is more considerable in low-income counties, where the number of applications reduces by around 4.4% one period after the entry of FinTech loan providers. In high-income counties, the effect is smaller but significant (2.2%). As for large lenders, the impact seems to be larger in middle-income counties, although it is also negative and significant for the other groups of counties. Overall, the results support the idea that the products offered by FinTech lenders are a closer substitute for those provided by large financial institutions rather than by small and local providers.

Table 4.7 presents the estimates for specifications where the dependent variable is the logarithm of the number of loan originations. Here, I do not find a significant effect of entry on the volume of applications provided by local or small lenders, except for the latter group in high-income countries, where the entry of FinTech is associated with an increase of around 3.2% in the volume of originations. By contrast, loan originations by medium-size and large lenders decrease significantly; in the case of middle-sized lenders, the effect is larger in lower-income countries, where the number of originations is reduced by around 4.3% one period after the entry of FinTech lenders. In the case of large loan providers, the greater drop occurs in middle-income counties, where the entry of FinTech is followed by a reduction of 3.7% in the number of originations.

The drop in loan originations experienced by traditional lenders is consistent with the evidence provided by Buchak et al. (2018) of a substantial migration of the financial activity from traditional banks to the *shadow banking* sector (to which FinTech lenders belong). They attribute these changes to the excessive regulatory burden experienced by the first group of lenders, including non-capital requirement-related regulatory constraints, such as the risk of enforcement actions and lawsuits.

For low-income counties and high-income counties the results are consistent with market expansion, since the expected reductions in the number of loan originations by incumbent traditional lenders (-2.7 and -62.5, respectively) are smaller in magnitude than the average number of loan originations provided by an additional FinTech lender (10 and 86, respectively). By contrast, in middle income counties, the reduction in the number of loans provided by incumbent traditional lenders is not fully compensated by the additional supply provided by the new FinTech lender. Nevertheless, these changes are not very substantial. In low-income counties, the arrival of a new FinTech loan provider would be associated to an increase of 1.92% in the number of loan originations, whereas in high-income markets such an increase would represent 0.5% of the loans. In middle income markets, the presence of an additional FinTech lender would be followed by a decrease of 1.5% in the total number of originations.

4.6.1 Home-purchase vs. refinancing

I conducted the analysis separating refinancing operations and home-purchase originations, because the application process is simpler for borrowers and they typically have more experience in selecting financial services. When refinancing, lenders do not have to perform many on-the-ground activities that are required for purchasing a home, such as a title check, *in situ* examination of a property, and negotiations between buyer and seller. This gives and advantage to FinTech institutions, who are able to offer cheaper products via an online platform that can be perceived as efficient and convenient. Fuster et al. (2019) finds that Fintech are able to achieve higher reductions in the processing times of refinance loans, compared to home-purchase loans.

Tables 4.8 and 4.9 present the estimates of specifications where the dependent variables are the logarithm of the number of home-purchase loan originations and the logarithm of the number of refinancing loans, respectively. When disaggregating the volume of loan originations by purpose it becomes clear that the increased availability of FinTech has a stronger impact on refinancing loans compared to home-purchase originations. In the latter case, the estimated effect of the number of FinTech per state is very close to zero and it is not significant for any of the subsamples (Table 4.8). By contrast, the the increased availability of FinTech has a greater impact on medium-sized and large lenders in the case of refinancing operations (Table 4.9)

The relative resilience of traditional incumbent lenders in higher-income areas is consistent with their comparative advantage at extending *jumbo* mortgages, more frequently demanded by wealthier borrowers. This advantage arises from the traditional banks' ability to finance loans with their balance sheets. Conforming loans are much easier to sell than jumbo loans, because they are eligible for securitization with the participation of GSEs, while jumbo loans are not, and must, therefore, be kept in the balance sheet. This argument is explored in depth by Buchak et al. (2020), who argue that the balance sheet capacity of traditional banks is higher than that of FinTech, who almost exclusively originate to distribute, due to higher capitalization.

Minority borrowers

Tables 4.10 and 4.11 presents the results of the regressions with the volume of applications and loan originations for minorities as dependent variables. In line with Bartlett et al. (2019) I define "minority borrowers" as a single group of borrowers who are either African Americans or Hispanic, according to the HDMA records.[17]

I find that small and local lenders experience an increase in the volume of applications of minority borrowers after entry of FinTech lenders, particularly in higher-

[17]Previous studies that have analyzed credit access for minority borrowers using HDMA data indicate that the increasing number of applications that do not report information on race and ethnicity could diminish the validity or alter the interpretation of the results (e.g Avery et al., 2007; Bartlett et al., 2019). I find that in the case of non-FinTech lenders the percentage of applications where information on race or ethnicity is not available has not experienced significant changes in recent years

income counties (Panels A and B of Table 4.10). The effect is more substantial for small lenders, who would see an increase in the number of applications in the period where entry occurs and even one period after. Small lenders would also register an increase in the number of applications lower and middle-income counties of around 2.8% and 4.3%, respectively.

In the case of medium-sized and large lenders, the results are similar to those found in the specifications that include all applicants: after the entry of FinTech lenders, there is a significant decrease in the number of applications. However, different patterns emerge when analyzing the effects of entry across counties with varying levels of income. The reduction in the number of applications of middle size lenders is greater in the case of middle and higher-income counties. In contrast, for large lenders, the largest drops would be seen in lower-income counties.

Table 4.11 presents the estimated effects of entry of FinTech on the number of originations. I do not find significant effects associated to FinTech entry on the volume of originations in low income counties. In middle income counties, I find that an additional FinTech competitor would reduce the number originations of small, medium-sized and large lenders, whereas in higher income counties the effects are mixed, as small lenders would see an increase in the number of loan originations, whereas large lenders would experience a reduction.

Denial Rates

Table 4.12 presents the results for the specifications where the dependent variable is the denial rate. Panel A presents the results, including all applications, and Panel B contains the results for minority borrowers. The magnitude of the effect of entry on the total denial rate is small and not significant, except for medium and large lenders. In the case of minority borrowers, the denial rate increased for small and local lenders and reduced slightly for large lenders. These results are consistent with those presented in Tables 4.10 and 4.11, since these types of loan providers experienced a significant increase in their number of applications and no significant changes in the volume of loan originations.

Table 4.6: Effects of FinTech on the incumbents' number of applications, by size and type of lender

	(1) Total	(2) Low Income	(3) Middle Income	(4) Higher Income
Panel A. Local Lenders				
Number FinTech (t)	0.0199**	0.0131	0.0382**	-0.0136
	(0.00931)	(0.0176)	(0.0157)	(0.0167)
Number FinTech ($t-1$)	-0.00623	-0.0137	-0.0183	-0.00923
	(0.0110)	(0.0242)	(0.0170)	(0.0211)
Panel B. Small Lenders				
Number FinTech (t)	0.00913	0.0285*	0.0125	0.00454
	(0.00826)	(0.0165)	(0.0131)	(0.0154)
Number FinTech ($t-1$)	0.0177*	0.0200	-0.00822	0.0456***
	(0.00931)	(0.0201)	(0.0154)	(0.0174)
Panel C. Medium-sized Lenders				
Number FinTech (t)	0.00229	-0.00913	0.0142	0.0104
	(0.00687)	(0.0149)	(0.0108)	(0.0114)
Number FinTech ($t-1$)	-0.0235***	-0.0444***	-0.0179	-0.0211*
	(0.00710)	(0.0146)	(0.0121)	(0.0120)
Panel D. Large Lenders				
Number FinTech (t)	-0.00374	-0.0146***	0.0104	0.00463
	(0.00245)	(0.00504)	(0.0107)	(0.00389)
Number FinTech ($t-1$)	-0.0109***	-0.00958	-0.0202*	-0.0109**
	(0.00257)	(0.00585)	(0.0121)	(0.00435)
Observations	15,125	4,255	6,265	4,605
Number of counties	3,025	1,072	1,689	1,131
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State time trend	Yes	Yes	Yes	Yes

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

Robust standard errors in parentheses.

Notes: The dependent variable is the natural logarithm of the number of applications received by non-FinTech incumbent lenders, per type of lender and county. Lenders are classified as local (active in less than 10 counties in the same state), small (present in less than 30 counties), medium-sized (active in less than 90 counties) and large (active in more than 90 counties). Columns present the results of the linear regression for different groups of counties based on median Census Tract income (2010). Every specification includes a set of control variables defined in Section 4.5.

Table 4.7: Effects of FinTech on the incumbents' number of loan originations, by size and type of lender

	(1) Total	(2) Low Income	(3) Middle Income	(4) Higher Income
Panel A. Local Lenders				
Number FinTech (t)	0.0145	0.0258	0.0212	-0.0190
	(0.0100)	(0.0193)	(0.0165)	(0.0172)
Number FinTech ($t-1$)	-0.0102	-0.00602	-0.0211	-0.0254
	(0.0116)	(0.0249)	(0.0185)	(0.0214)
Panel B. Small Lenders				
Number FinTech (t)	0.00282	0.0141	0.0137	0.000211
	(0.00927)	(0.0183)	(0.0147)	(0.0176)
Number FinTech ($t-1$)	0.00356	0.0149	-0.0216	0.0321*
	(0.0101)	(0.0215)	(0.0173)	(0.0186)
Panel C. Medium Lenders				
Number FinTech (t)	-0.00431	-0.0104	0.00706	-0.00195
	(0.00756)	(0.0160)	(0.0119)	(0.0133)
Number FinTech ($t-1$)	-0.0317***	-0.0435***	-0.0349**	-0.0175
	(0.00811)	(0.0158)	(0.0138)	(0.0150)
Panel D. Large Lenders				
Number FinTech (t)	0.00389	0.00379	0.00356	0.00923*
	(0.00332)	(0.00694)	(0.0118)	(0.00549)
Number FinTech ($t-1$)	-0.00706**	-0.00125	-0.0369***	-0.0158***
	(0.00338)	(0.00778)	(0.0138)	(0.00593)
Observations	15,125	4,255	6,265	4,605
Number of counties	3,025	1,072	1,689	1,131
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State time trend	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1.

Robust standard errors in parentheses.

Notes: The dependent variable is the natural logarithm of the number of loan originations by non-FinTech incumbent lenders, per type of lender and county. Lenders are classified as local (active in less than 10 counties in the same state), small (present in less than 30 counties), medium-sized (active in less than 90 counties) and large (active in more than 90 counties). Columns present the results of the linear regression for different groups of counties based on median Census Tract income (2010). Every specification includes a set of control variables defined in Section 4.5.

Table 4.8: Effects of FinTech on the incumbents' number of loan home-purchase originations, by size and type of lender

	(1) Total	(2) Low Income	(3) Middle Income	(4) Higher Income
Panel A. Local Lenders				
Number FinTech (t)	0.000379	0.0218	0.00309	-0.0394*
	(0.0117)	(0.0230)	(0.0199)	(0.0207)
Number FinTech ($t-1$)	-0.00242	0.0312	-0.00158	-0.0410
	(0.0139)	(0.0281)	(0.0234)	(0.0261)
Panel B. Small Lenders				
Number FinTech (t)	0.00219	0.0104	-8.75e-05	0.00185
	(0.0136)	(0.0257)	(0.0215)	(0.0186)
Number FinTech ($t-1$)	-0.00170	0.0152	-0.0410	0.0453**
	(0.0152)	(0.0310)	(0.0258)	(0.0203)
Panel C. Medium-sized Lenders				
Number FinTech (t)	-0.0274**	-0.0217	-0.0336*	-0.0125
	(0.0119)	(0.0259)	(0.0178)	(0.0215)
Number FinTech ($t-1$)	-0.0193	-0.0536**	-0.0119	0.00869
	(0.0123)	(0.0269)	(0.0206)	(0.0215)
Panel D. Large Lenders				
Number FinTech (t)	-0.00152	0.00150	0.00160	-0.00497
	(0.00513)	(0.0112)	(0.00754)	(0.00714)
Number FinTech ($t-1$)	-0.00297	-0.00590	0.00208	-0.00141
	(0.00543)	(0.0128)	(0.00691)	(0.00774)
Observations	13,468	3,747	5,582	4,139
Number of counties	3,002	1,040	1,607	1,128
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State time trend	Yes	Yes	Yes	Yes

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

Robust standard errors in parentheses.

Notes: The dependent variable is the natural logarithm of the number of loan originations by non-FinTech incumbent lenders, per type of lender and county. Lenders are classified as local (active in less than 10 counties in the same state), small (present in less than 30 counties), medium-sized (active in less than 90 counties) and large (active in more than 90 counties). Columns present the results of the linear regression for different groups of counties based on median Census Tract income (2010). Every specification includes a set of control variables defined in Section 4.5.

Table 4.9: Effects of FinTech on the incumbents' number of loan refinancing operations, by size and type of lender

	(1) Total	(2) Low Income	(3) Middle Income	(4) Higher Income
Panel A. Local Lenders				
Number FinTech (t)	0.00894	-0.00524	0.0265	0.00912
	(0.0131)	(0.0264)	(0.0200)	(0.0235)
Number FinTech ($t-1$)	-0.00993	0.0252	-0.00338	-0.0430
	(0.0140)	(0.0261)	(0.0233)	(0.0278)
Panel B. Small Lenders				
Number FinTech (t)	0.0173	0.0288	0.0223	0.00185
	(0.0121)	(0.0260)	(0.0198)	(0.0186)
Number FinTech ($t-1$)	-0.000483	0.0145	-0.0118	-0.0453**
	(0.0132)	(0.0303)	(0.0227)	(0.0203)
Panel C. Medium-sized Lenders				
Number FinTech (t)	-0.0232**	0.000317	-0.0480***	0.0162
	(0.00912)	(0.0179)	(0.0153)	(0.0161)
Number FinTech ($t-1$)	-0.0367***	-0.0141	-0.0412**	-0.0555***
	(0.0115)	(0.0252)	(0.0201)	(0.0188)
Panel D. Large Lenders				
Number FinTech (t)	-0.0124***	0.00709	0.00524	-0.0151**
	(0.00458)	(0.00923)	(0.00708)	(0.00745)
Number FinTech ($t-1$)	-0.00617	0.0194	-0.0196**	-0.0165*
	(0.00569)	(0.0118)	(0.00899)	(0.00999)
Observations	13,974	3,932	5,803	4,239
Number of counties	3,025	1,058	1,634	1,140
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State time trend	Yes	Yes	Yes	Yes

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

Robust standard errors in parentheses.

Notes: The dependent variable is the natural logarithm of the number of loan originations by non-FinTech incumbent lenders, per type of lender and county. Lenders are classified as local (active in less than 10 counties in the same state), small (present in less than 30 counties), medium-sized (active in less than 90 counties) and large (active in more than 90 counties). Columns present the results of the linear regression for different groups of counties based on median Census Tract income (2010). Every specification includes a set of control variables defined in Section 4.5.

Table 4.10: Effects of FinTech on the incumbents' number of loan applications (minority borrowers), by size and type of lender

	(1) Total	(2) Low Income	(3) Middle Income	(4) Higher Income
Panel A. Local Lenders				
Number FinTech (t)	-0.0290**	-0.0610**	-0.00421	-0.0265
	(0.0121)	(0.0241)	(0.0211)	(0.0206)
Number FinTech ($t-1$)	0.0256*	0.0233	0.0165	0.0464*
	(0.0132)	(0.0259)	(0.0221)	(0.0249)
Panel B. Small Lenders				
Number FinTech (t)	0.0278**	0.0285*	-0.00950	0.0597***
	(0.0119)	(0.0165)	(0.0191)	(0.0206)
Number FinTech ($t-1$)	0.0455***	0.0200	0.0428**	0.0727***
	(0.0121)	(0.0201)	(0.0207)	(0.0211)
Panel C. Medium-sized Lenders				
Number FinTech (t)	-0.00229	0.00545	-0.00367	0.00183
	(0.0113)	(0.0236)	(0.0186)	(0.0186)
Number FinTech ($t-1$)	-0.0253**	0.00457	-0.0327*	-0.0533***
	(0.0116)	(0.0231)	(0.0192)	(0.0200)
Panel D. Large Lenders				
Number FinTech (t)	-0.0194***	-0.0266**	-0.0192**	-0.0106
	(0.00491)	(0.0104)	(0.00798)	(0.00769)
Number FinTech ($t-1$)	-0.0169***	-0.0214*	-0.0156*	-0.0160*
	(0.00501)	(0.0118)	(0.00795)	(0.00837)
Observations	15,125	4,255	6,265	4,605
Number of panel_id	3,025	1,125	1,757	1,188
Country FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1.

Robust standard errors in parentheses.

Notes: The dependent variable is the logarithm of the average number of applications of African-American and Hispanic borrowers received by non-FinTech incumbent lenders, per type of lender and county. Lenders are classified as local (active in less than 10 counties in the same state), small (present in less than 30 counties), medium-sized (active in less than 90 counties) and large (active in more than 90 counties). Columns present the results of the regression for different groups of counties based on median Census Tract income (2010).Every specification includes a set of control variables defined in Section 4.5.

Table 4.11: Effects of FinTech on the incumbents' number of loan applications (minority borrowers), by size and type of lender

	(1) Total	(2) Low Income	(3) Middle Income	(4) Higher Income
Panel A. Local Lenders				
Number FinTech (t)	-0.0127	-0.0376	0.00478	-0.00437
	(0.0122)	(0.0244)	(0.0212)	(0.0206)
Number FinTech ($t-1$)	0.0142	0.0220	0.00572	0.0159
	(0.0130)	(0.0260)	(0.0223)	(0.0243)
Panel B. Small Lenders				
Number FinTech (t)	0.0115	0.0313	-0.0331*	0.0582***
	(0.0122)	(0.0260)	(0.0187)	(0.0214)
Number FinTech ($t-1$)	0.0101	-0.0282	0.0154	0.0346
	(0.0124)	(0.0252)	(0.0222)	(0.0213)
Panel C. Medium-sized Lenders				
Number FinTech (t)	0.00355	0.00449	0.00352	0.00703
	(0.0110)	(0.0220)	(0.0190)	(0.0179)
Number FinTech ($t-1$)	-0.0205*	0.0279	-0.0445**	-0.0286
	(0.0119)	(0.0262)	(0.0204)	(0.0185)
Panel D. Large Lenders				
Number FinTech (t)	0.00375	-0.0204	0.00111	0.0273**
	(0.00850)	(0.0179)	(0.0190)	(0.0138)
Number FinTech ($t-1$)	-0.00767	0.0185	-0.0457**	-0.0251*
	(0.00843)	(0.0188)	(0.0204)	(0.0139)
Observations	15,125	4,255	6,265	4,605
Number of panel_id	3,025	1,125	1,757	1,188
Country FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1.

Robust standard errors in parentheses.

Notes: The dependent variable is the logarithm of the average number of loan originations of African-American and Hispanic borrowers by non-FinTech incumbent lenders, per type of lender and county. Lenders are classified as local (active in less than 10 counties in the same state), small (present in less than 30 counties), medium-sized (active in less than 90 counties) and large (active in more than 90 counties). Columns present the results of the regression for different groups of counties based on median Census Tract income (2010). Every specification includes a set of control variables defined in Section 4.5.

Table 4.12: Effect of FinTech on the denial rate of incumbent traditional lenders

	(1) Local	(2) Small	(3) Medium	(4) Large
Panel A. Total denial rate - all borrowers				
Number FinTech (t)	-0.00267	-0.00276	0.00320**	-0.00291***
	(0.00302)	(0.00205)	(0.00163)	(0.000679)
Number FinTech ($t-1$)	-0.00233	0.000107	0.00213	-0.000225
	(0.00318)	(0.00212)	(0.00162)	(0.000672)
Panel B. Total denial rate - minorities				
Number FinTech (t)	-0.00287	0.00181	-0.00842	-0.00200**
	(0.00762)	(0.00690)	(0.00549)	(0.000989)
Number FinTech ($t-1$)	0.0165**	0.0170**	0.00334	-0.000187
	(0.00786)	(0.00698)	(0.00561)	(0.000905)
Observations	10,820	10,820	10,820	10,820
R-squared	0.131	0.125	0.263	0.102
Number of counties	2,309	2,309	2,309	2,309
Country FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1.

Robust standard errors in parentheses.

Notes: The dependent variable is the share of applications that were denied by non-FinTech incumbent lenders, per type of lender and county. Lenders are classified as local (active in less than 10 counties in the same state), small (present in less than 30 counties), medium-sized (active in less than 90 counties) and large (active in more than 90 counties). Columns present the results of the linear regression for different groups of counties based on median Census Tract income (2010). Every specification includes a set of control variables defined in Section 4.5.

4.7 Final Remarks

In this paper, I explore the response of incumbent lenders to the increased availability of online mortgage lending in the United States. Several studies have focused on understanding the business model of FinTech institutions and their direct role in improving the mortgage market's efficiency and accessibility. In this paper, I offer a complementary analysis by describing the response of incumbent loan providers to the increased competition created by these lenders and exploring the differences across counties with varying levels of income.

I find that large financial institutions are the ones that exhibit the most considerable reduction in their volume of applications and originations after entry of FinTech competitors. In contrast, local and small lenders tend to experience an increase in their number of loan operations, particularly in higher-income counties after the arrival of FinTech competitors. The reduction in the volume of loans provided by large lenders is largely explained by the behavior of refinancing loan operations, where FinTech lenders seem to have a greater relative advantage. By contrast, large lenders seem to be highly resilient to the advent of the new FinTech competitors in the segment of home-purchase mortgages. This resilience is consistent with the argument that these institutions have a greater capability at financing unconventional mortgages that have more difficulties for securitization in the secondary market.

When examining the behavior of the volume of loan originations of minority borrowers in response to the increased availability of FinTech, I find that small lenders seem to experience an increase in their volume of loan applications and originations after an additional FinTech lender becomes available in the state. This results highlight the importance of small lenders in the provision of credit for minority borrowers across regions with different income levels and contrast previous studies that have indicated that small and local lenders are more vulnerable to the arrival of platform-based competitors. The mechanisms behind the positive effect on credit growth in this segment will be explored in further detail in future extensions of this work.

The results highlight the differences in the financial services offered by incumbent loan providers. Although the analysis presented here does not take into account important differences in incumbent lenders' regulatory requirements, this insight could help us understand the effects of the development of online mortgage lending on credit access across geographic markets.

When examining the overall effect of an increased availability of Fintech on the volume of loans at the county level, I find that their arrival was followed by a decrease in the number of applications and loan originations by incumbent loan providers that might not have been entirely compensated by online mortgage lending. Nevertheless, this result could change if traditional lenders start to exploit the benefits of technological innovation developed by FinTech by transforming their own processes of application and loan underwriting. Recently, policymakers and industry experts have highlighted the benefits of partnerships between FinTech institutions and local lenders to expand the portfolio of services available for consumers, exploiting the competitive advantages of two different business models. While the effects of these alliances were still incipient during the period of analysis that I consider here, their role in shaping the competitive environment in the mortgage market industry should be considered in more detail in future research.

4.8 Appendix

4.8.1 HDMA data set: List of variables

For each application or loan:

- Application date and the date an action was taken on the application
- Action taken on the application
  - Approved and originated
  - Approved but not accepted by the applicant
  - Denied (with the reasons for denial—voluntary for some lenders)
  - Withdrawn by the applicant
  - Closed for incompleteness
- Preapproval program status (for home-purchase loans only)
  - Preapproval request denied by financial institution
  - Preapproval request approved but not accepted by individual
- Loan amount
- Loan type
  - Conventional
  - Insured by the Federal Housing Administration
  - Guaranteed by the Department of Veterans Affairs
  - Backed by the Farm Service Agency or Rural Housing Service
- Lien status
  - First lien
  - Junior lien
  - Unsecured
- Loan purpose
  - Home purchase
  - Refinance

  - Home improvement
- Type of purchaser (if the lender subsequently sold the loan during the year)
  - Fannie Mae
  - Ginnie Mae
  - Freddie Mac
  - Farmer Mac
  - Private securitization
  - Commercial bank, savings bank, or savings association
  - Life insurance company, credit union, mortgage bank, or finance company
  - Affiliate institution
  - Other type of purchase

For each applicant or co-applicant:

- Race
- Ethnicity
- Sex
- Income relied on in credit decision

For each property:

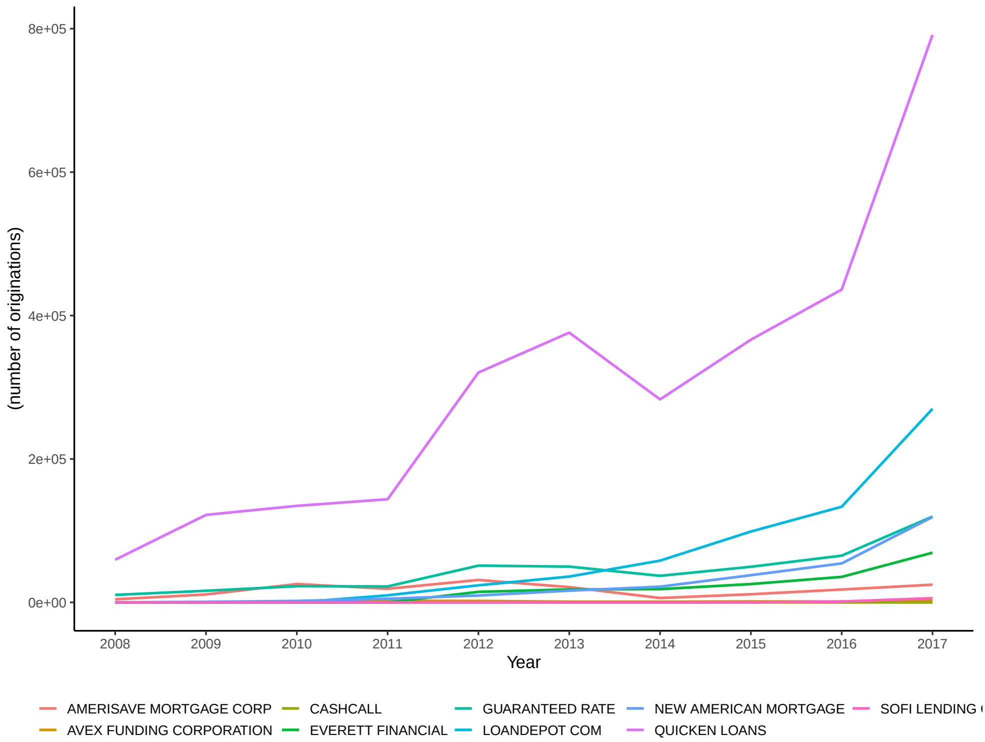
- Location, by state, county, metropolitan statistical area, and census tract
- Type of structure
- Occupancy status (owner occupied, non-owner occupied, or not applicable)

For loans subject to price reporting:

- Spread above comparable Treasury security for applications taken prior to October 1, 2010
- Spread above average prime offer rate for applications taken on or after October 1, 2010
- Indicator of whether loan is subject to the Home Ownership and Equity Protection Act

4.8.2 Additional descriptive statistics

Figure 4.5: Loan originations of FinTech institutions 2008-2017



Notes: This Figure shows the evolution of the total number of loan originations of those institutions classified as FinTech according to the definition presented in Section4.3. Calculations are based on HMDA data.

Table 4.13: Summary Statistics: minority counties and rural areas

	Minority counties			Rural areas		
	2015	2016	2017	2015	2016	2017
Minority population (%)	47.96	47.94	47.96	15.20	15.19	14.87
Population	4,804.78	4,803.09	4,864.62	3,167.91	3,153.73	3,116.27
Number of disaster areas	9.89	7.53	8.10	0.13	0.13	0.19
Number of rural and underserved areas	0.18	0.18	0.18	2.30	2.30	2.32
Median income (2000)	55,608.27	56,189.47	56,564.84	56,765.72	57,959.23	58,360.55
MSA median income	103.26	103.40	102.36	96.51	96.47	97.66
Number of distressed areas	0.34	0.34	0.32	0.54	0.52	0.49
Number of Fintech lenders	2.44	4.38	4.63	1.55	2.86	2.76
Number of non Fintech lenders	166.75	174.30	175.68	51.17	54.08	54.33
Total applications	7,962.15	9,111.28	7,861.34	264.81	292.09	271.21
Total loan originations	4,080.19	4,634.50	3,990.70	134.74	145.92	138.18
FHA insured loans	722.38	768.30	657.41	13.80	15.31	14.93
Denial rate	0.24	0.25	0.23	0.23	0.24	0.21
Denial rate no Fintech	0.47	0.47	0.46	0.50	0.51	0.50
Denial rate Fintech	0.64	0.36	0.56	0.62	0.37	0.53
Market share FinTech (applications)	0.07	0.11	0.08	0.09	0.12	0.10
Market share FinTech (originations)	0.08	0.08	0.09	0.08	0.09	0.11
HHI applications	726.05	662.91	631.89	939.63	866.26	858.23
HHI originations	935.05	868.69	817.62	1,412.16	1,294.51	1,315.64

References

Abaluck, J. and A. Adams (2017). What Do Consumers Consider Before They Choose? *NBER Working Paper 23566*, 1–72.

Abrams, E. (2019). Assessing bank deposit market power given limited consumer consideration. Working Paper 3431374, SSRN.

Adams, R. M., K. P. Brevoors, and E. K. Kiser (2007). Who competes with whom? the case of depository institutions. *The Journal of Industrial Economics 55*(1), 141–167.

Agarwal, S., S. Chomsisengphet, N. Mahoney, and J. Stroebel (2014, 11). Regulating Consumer Financial Products: Evidence from Credit Cards *. *The Quarterly Journal of Economics 130*(1), 111–164.

Agarwal, S. and R. Hauswald (2010, 04). Distance and Private Information in Lending. *The Review of Financial Studies 23*(7), 2757–2788.

Aguirre, I., S. Cowan, and J. Vickers (2010). Monopoly price discrimination and demand curvature. *American Economic Review 100*(4), 1601–1615.

Aguirregabiria, V., R. Clark, and H. Wang (2012). Diversification of geographic risk in retail bank networks: Evidence from bank expansion after the riegle-neal act. Working papers, University of Toronto, Department of Economics.

Armendariz, B. and J. Morduch (2007). *The Economics of Microfinance*, Volume 1 of *MIT Press Books*. The MIT Press.

Armstrong, M., J. Vickers, and M. Armstrong (1991). Welfare effects of price discrimination by a regulated monopolist. *The RAND Journal of Economics 22*(4), 571–580.

Augsburg, B., R. De Haas, H. Harmgart, and C. Meghir (2015). The impacts of microcredit: Evidence from Bosnia and Herzegovina. *American Economic Journal: Applied Economics 7*(1), 183–203.

Avery, R. B., K. P. Brevoort, and G. B. Canner (2007). Opportunities and Issues in Using HMDA Data. *Journal of Real Estate Research 29*(4), 351–380.

Banca de las Oportunidades (2014). Reporte de inclusion financiera. Technical report, Banca de las Oportunidades.

Banerjee, A., E. Duflo, R. Glennerster, and C. Kinnan (2015, January). The miracle of microfinance? evidence from a randomized evaluation. *American Economic Journal: Applied Economics 7*(1), 22–53.

Banerjee, A. V. (2013). Microcredit under the microscope: What have we learned in the past two decades, and what do we need to know? *Annual Review of Economics 5*(1), 487–519.

Barona, B. (2004). Microcrédito en colombia. *Estudios Gerenciales 90*(20), 79–102.

Bartlett, R., A. Morse, R. Stanton, and N. Wallace (2019). NBER Working Paper: Consumer-Lending Discrimination in the FinTech Era. Technical Report 25943.

Basten, C. and S. R. G. Ongena (2019). The Geography of Mortgage Lending in Times of FinTech. *SSRN Electronic Journal* (December).

Bayer, P., F. Ferreira, and S. L. Ross (2017, 04). What Drives Racial and Ethnic Differences in High-Cost Mortgages? The Role of High-Risk Lenders. *The Review of Financial Studies 31*(1), 175–205.

Beck, T., A. Demirgüç-Kunt, and R. Levine (2007, Mar). Finance, inequality and the poor. *Journal of Economic Growth 12*(1), 27–49.

Begley, T. A. and A. Purnanandam (2020). Color and credit: Race, regulation, and the quality of financial services. *SSRN Electronic Journal*.

Bellucci, A., A. Borisov, and A. Zazzaro (2013). Do banks price discriminate spatially? Evidence from small business lending in local credit markets. *Journal of Banking & Finance 37*(11), 4183–4197.

Benmelech, E. and T. J. Moskowitz (2010). The political economy of financial regulation: Evidence from u.s. state usury laws in the 19th century. *The Journal of Finance 65*(3), 1029–1073.

Berger, A. N. and A. A. Dick (2007, 06). Entry into Banking Markets and the Early-Mover Advantage. *Journal of Money, Credit and Banking 39*(4), 775–807.

Berger, A. N. and L. J. Mester (2003). Explaining the dramatic changes in performance of us banks: technological change, deregulation, and dynamic changes in competition. *Journal of Financial Intermediation 12*(1), 57 – 95.

Berry, S. (1994). Estimating discrete-choice models of product differentiation. *RAND Journal of Economics 25*(2), 242–262.

Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile prices in market equilibrium. *Econometrica 63*(4), 841–90.

Bresnahan, T. F. and P. C. Reiss (1990). Entry in monopoly markets. *The Review of Economic Studies 57*(4), 531–553.

Brevoort, K. and T. Hannan (2006, 12). Commercial lending and distance: Evidence from community reinvestment act data. *Journal of money credit and banking 38*, 1991–2012.

Brevoort, K. P. and J. D. Wolken (2008). Does distance matter in banking? Finance and Economics Discussion Series 2008-34, Board of Governors of the Federal Reserve System (U.S.).

Bruhn, M. and I. Love (2014). The real impact of improved access to finance: Evidence from mexico. *The Journal of Finance 69*(3), 1347–1376.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics 130*(3), 453–483.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru (2020, January). Beyond the balance sheet model of banking: Implications for bank regulation and monetary policy. Working Paper 25149, National Bureau of Economic Research.

Claessens, S., F. Zhu, J. Frost, and G. Turner (2018). Fintech Credit Markets around the World: Size, Drivers and Policy Issues. *BIS Quarteley Review* (September), 29–49.

Clark, R., H. Wang, and V. Aguirregabiria (2017, November). The Geographic Flow Of Bank Funding And Access To Credit: Branch Networks And Local-market Competition. Working Paper 1402, Economics Department, Queen's University.

Cleeren, K., F. Verboven, M. G. Dekimpe, and K. Gielens (2010). Intra-and interformat competition among discounters and supermarkets. *Marketing science 29*(3), 456–473.

Cohen, A. (2004). Market structure and market definition: the case of small market banks and thrifts. Finance and Economics Discussion Series 2004-02, Board of Governors of the Federal Reserve System (U.S.).

Cohen, A. and M. J. Mazzeo (2010). Investment Strategies and Market Structure: An Empirical Analysis of Bank Branching Decisions. *Journal of Financial Services Research 38*, 1–21.

Cohen, A. M. and M. J. Mazzeo (2007, February). Market Structure and Competition among Retail Depository Institutions. *The Review of Economics and Statistics 89*(1), 60–74.

Comité Nacional de Inclusión Financiera de México (2018). 9 reporte nacional de inclusión financiera. Technical report.

Critchfield, T. S., J. Dey, N. Mota, and S. Patrabansh (2018). Mortgage experiences of rural borrowers in the united states: Insights from the national survey of mortgage originations (march 14, 2018). *SSRN Electronic Journal*.

Cubillos Rocha, J. S., J. Gamboa Arbelaez, L. F. Melo Velandia, S. Restrepo Tamayo, M. J. Roa Garcia, and M. Villamizar Villegas (2018). Effects of Interest Rate Caps on Financial Inclusion. *Borradores de Economía, Banco de la República de Colombia. 1060*(10).

Cuesta, J. I. and A. Sepulveda (2019). Price regulation in credit markets: A trade-off between consumer protection and credit access. Job market paper.

Cull, R., R. J. Cull, A. Demirgüç-Kunt, and J. Morduch (2013). *Banking the world: empirical foundations of financial inclusion.* MIT Press.

Cull, R., A. Demirgüç-Kunt, and J. Morduch (2014, Aug). Banks and microbanks. *Journal of Financial Services Research 46*(1), 1–53.

Cull, R., A. Demirgüç-Kunt, and J. Morduch (2009, Winter). Microfinance Meets the Market. *Journal of Economic Perspectives 23*(1), 167–192.

Dai, M. and Y. Yuan (2013). Product differentiation and efficiencies in the retail banking industry. *Journal of Banking & Finance 37*(12), 4907 – 4919.

de Elejalde, R. (2009). Local entry decisions in the us banking industry. Working paper.

de Juan, R. (2003). The independent submarkets model: an application to the spanish retail banking market. *International Journal of Industrial Organization 21*(10), 1461–1487.

Degryse, H. and S. Ongena (2005). Distance, lending relationships, and competition. *The Journal of Finance 60*(1), 231–266.

Demont, T. (2016). Microfinance spillovers: A model of competition in informal credit markets with an application to Indian villages. *European Economic Review 89*, 21–41.

Dewatripont, M. and J. Tirole (1994). The prudential regulation of banks. Ulb institutional repository, ULB – Universite Libre de Bruxelles.

Deyoung, R., W. Hunter, and G. Udell (2004). The past, present and probable future for community banks. *Journal of Financial Services Research 25*(2), 85–133.

Dick, A. (2008). Demand Estimation and Consumer Welfare in the Banking Industry. *Journal of Banking anf Finance 32*, 1661–1676.

Donou-Adonsou, F. and K. Sylwester (2017). Growth effect of banks and microfinance: Evidence from developing countries. *Quarterly Review of Economics and Finance 64*, 44–56.

D'Espallier, B., J. Goedecke, M. Hudon, and R. Mersland (2017). From ngos to banks: Does institutional transformation alter the business model of microfinance institutions? *World Development 89*(Supplement C), 19 – 33.

D'Haultfœuille, X., I. Durrmeyer, and P. Février (2018, 10). Automobile Prices in Market Equilibrium with Unobserved Price Discrimination. *The Review of Economic Studies*.

Estrada, D. and A. Hernandez Rubio (2019). *Situacion Actual e Impacto del Microcredito en Colombia.* Banco de la Republica.

Estrada, D. and S. Rozo (2006). Multimarket spatial competition in the Colombian deposit market. *Borradores de Economía. Banco de la República 413.*

Fernandez, D. (2014). Impacto del microcrédito sobre las utilidades de las microempresas en colombia. Working paper, Banco de la República.

Fernandez, R. (2016, November). Spillovers Effects and City Development. *Job Market Paper - Tilburg University 1*(1).

Ferrari, A., O. Masetti, and J. Ren (2018). Interest Rate Caps: The Theory and The Practice. *Policy Reasearch Working Paper 8398*(April), 42.

Foote, C. L., L. Loewenstein, and P. S. Willen (2019, 04). Technological innovation in mortgage underwriting and the growth in credit, 1985-2015. *FRB of Boston Working Paper* (11).

Fuster, A., P. Goldsmith-Pinkham, T. Ramadorai, and A. Walther (2020). Predictably unequal? the effects of machine learning on credit markets. *SSRN Electronic Journal*.

Fuster, A., M. Plosser, P. Schnabl, and J. Vickery (2019). The Role of Technology in Mortgage Lending. *Review of Financial Studies 32*(5), 1854–1899.

Galenianos, M. and A. Gavazza (2019, June). Regulatory Interventions in Consumer Financial Markets: The Case of Credit Cards. CEPR Discussion Papers 13807, C.E.P.R. Discussion Papers.

Ghent, A. C., R. Hernandez-Murillo, and M. T. Owyang (2014). Differences in subprime loan pricing across races and neighborhoods. *Regional Science and Urban Economics 48*, 199 – 215.

Goeree, M. S. (2008). Limited information and advertising in the u.s. personal computer industry. *Econometrica 76*(5), 1017–1074.

Han, S., B. J. Keys, and G. Li (2018). Unsecured Credit Supply, Credit Cycles, and Regulation. *Review of Financial Studies 31*(3), 1184–1217.

Hannan, T. H. and R. A. Prager (2006). Multimarket bank pricing: An empirical investigation of deposit interest rates. *Journal of Economics and Business 58*(3), 256 – 272.

Hanson, A., Z. Hawley, H. Martin, and B. Liu (2016). Discrimination in mortgage lending: Evidence from a correspondence experiment. *Journal of Urban Economics 92*, 48 – 65.

Heitfield, E. and R. A. Prager (2004). The geographic scope of retail deposit markets. *Journal of Financial Services Research 25*(1), 37–55.

Hermes, N. and R. Lensink (2007). The empirics of microfinance: What do we know? *The Economic Journal 117*(517), F1–F10.

Ho, K., J. Hogan, and F. Scott Morton (2017). The impact of consumer inattention on insurer pricing in the Medicare Part D program. *RAND Journal of Economics 48*(4), 877–905.

Ho, K. and J. Ishii (2011). Location and competition in retail banking. *International Journal of Industrial Organization 29*(5), 537 – 546.

Holmes, T. J. (2011). The diffusion of wal-mart and economies of density. *Econometrica 79*(1), 253–302.

Hortaçsu, A., S. A. Madanizadeh, and S. L. Puller (2017). Power to choose? An analysis of consumer inertia in the residential electricity market. *American Economic Journal: Economic Policy 9*(4), 192–226.

Huang, G. (2020). When to haggle, when to hold firm? lessons from the used-car retail market. *Journal of Economics & Management Strategy 29*(3), 579–604.

Huysentruyt, M., E. Lefevere, and C. Menon (2013). Dynamics of retail-bank branching in antwerp (belgium) 1991-2006: Evidence from micro-geographic data. *Journal of Banking & Finance 37*(2), 291 – 304.

Jagtiani, J., L. Lambie-Hanson, and L.-H. T. (2019). Fintech lending and mortgage credit access. Technical Report 19-47, Consumer Finance Institute - Federal Reserve Bank of Philadelphia.

Jagtiani, J. and C. Lemieux (2016). Economic perspectives - small business lending after the financial crisis: A new competitive landscape for community banks. Technical Report 3, Federal Reserve Bank of Chicago.

Kaboski, J. P. and R. M. Townsend (2012, April). The impact of credit on village economies. *American Economic Journal: Applied Economics 4*(2), 98–133.

Khandker, S. R. (2005). Microfinance and poverty: Evidence using panel data from Bangladesh. *World Bank Economic Review 19*(2), 263–286.

Knittel, C. R. and V. Stango (2003). Price ceilings as focal points for tacit collusion: Evidence from credit cards. *The American Economic Review 93*(5), 1703–1729.

Korgaonkar, S. (2019). Funding Shocks and Competition in the Mortgage Market. *SSRN Electronic Journal* (October), 1–45.

LaCour-Little, M. (2000). The evolving role of technology in mortgage finance. *Journal of Housing Research 11*(2), 173–205.

Ladd, H. F. (1998, June). Evidence on discrimination in mortgage lending. *Journal of Economic Perspectives 12*(2), 41–62.

Ledgerwood, J., J. Earne, and C. Nelson (2013). *The New Microfinance Handbook: A Financial Market System Perspective.* The World Bank.

Lux, M. and R. Greene (2015). Working paper: The state and fate of community banking. Technical Report 37, Harvard Kennedy School. Mossavar-Rahmani Center for Business and Government.

Ly, P. and G. Mason (2012). Competition Between Microfinance NGOs: Evidence from Kiva. *World Development 40*(3), 643–655.

Maimbo, S. M. and C. A. H. Gallegos (2014). Interest rate caps around the world: Still popular, but a blunt instrument. Policy Research Working Papers 7070, World Bank.

Mazzeo, M. J. (2002). Competitive outcomes in product-differentiated oligopoly. *The Review of Economics and Statistics 84*(4), 716–728.

McCord, R., E. S. Prescott, and T. Sablik (2015). Economic brief: Explaining the decline in the number of banks since the great recession. Technical report, Federal Reserve Bank of Richmond.

McIntosh, C., A. de Janvry, and E. Sadoulet (2005). How rising competition among microfinance institutions affects incumbent lenders*. *The Economic Journal 115*(506), 987–1004.

Meier, S. and C. Sprenger (2010, January). Present-biased preferences and credit card borrowing. *American Economic Journal: Applied Economics 2*(1), 193–210.

Melzer, B. and A. Schroeder (2017). Loan contracting in the presence of usury limits: Evidence from automobile lending. Working paper, CFPB Office of Research Working Paper Series.

Melzer, B. T. (2011). The real costs of credit access: Evidence from the payday lending market. *The Quarterly Journal of Economics 126*(1), 517–555.

Meza, D. D. and D. C. Webb (1987). Too much investment: A problem of asymmetric information. *The Quarterly Journal of Economics 102*(2), 281–292.

Mookherjee, D. and A. Motta (2016). A theory of interactions between MFIs and informal lenders. *Journal of Development Economics 121*, 191–200.

Munnell, A. H., G. M. B. Tootell, L. E. Browne, and J. McEneaney (1996). Mortgage lending in boston: Interpreting hmda data. *The American Economic Review 86*(1), 25–53.

Nelson, S. (2019). Private information and price regulation in the us credit card market. Working paper, MIT.

Petersen, M. A. and R. G. Rajan (2002). Does distance still matter? the information revolution in small business lending. *The Journal of Finance 57*(6), 2533–2570.

Philippon, T. (2016). The FinTech Opportunity. *SSRN Electronic Journal* (655).

Rigbi, O. (2013, October). The Effects of Usury Laws: Evidence from the Online Loan Market. *The Review of Economics and Statistics 95*(4), 1238–1248.

Rosen, R. J. (2011). Competition in Mortgage Markets: The Effect of Lender Type on Loan Characteristics. *Federal Reserve Bank of Chicago Economic Perspectives 35*(1), 2–21.

Ross, S. and J. Yinger (2002). *The Color of Credit: Mortgage Discrimination, Research Methodology, and Fair-Lending Enforcement* (1 ed.), Volume 1. The MIT Press.

Rozo, S., D. Vásquez, and D. Estrada (2008). An industrial organization analysis for the colombian banking system. *Borradores de Economía - Banco de la República 413*.

Salamanca, D. (2005). Competencia en los Mercados de Crédito y Depósitos en Colombia: aplicación de un Modelo Oligopolio Fijador de Precios. *Tesis (Magíster en Economía) Universidad de los Andes*.

Schaumans, C. and F. Verboven (2015, March). Entry and Competition in Differentiated Products Markets. *The Review of Economics and Statistics 97*(1), 195–209.

Schmalensee, B. R. (1981). Output and welfare implications of monopolistic third-degree price discrimination. *The American Economic Review 71*(1), 242–247.

SFC (2015). Inclusion financiera en colombia: Estudio de demanda para analizar la inclusion financiera en colombia. informe de resultados. Technical report, Superintendencia Financiera de Colombia.

Small, K. A. and H. S. Rosen (1981). Applied welfare economics with discrete choice models. *Econometrica 49*(1), 105–130.

Stango, V. and J. Zinman (2015, 11). Borrowing High versus Borrowing Higher: Price Dispersion and Shopping Behavior in the U.S. Credit Card Market. *The Review of Financial Studies 29*(4), 979–1006.

Stanton, R., J. Walden, and N. Wallace (2014). The Industrial Organization of the US Residential Mortgage Market. *Annual Review of Financial Economics 6*(1), 259–288.

Steiner, R. and M. I. Agudelo (2012). Efectos y consecuencias del sistema de calculo aplicado a las tasas de referencia y la determinación de la tasa de usura. *Programa de políticas públicas de USAID*.

Stiglitz, J. E. and A. Weiss (1981). Credit rationing in markets with imperfect information. *The American Economic Review 71*(3), 393–410.

Stole, L. A. (2007). Chapter 34 Price Discrimination and Competition. *Handbook of Industrial Organization 3*(06), 2221–2299.

Temin, P. and H. Voth (2008, 03). Interest Rate Restrictions in a Natural Experiment: Loan Allocation and the Change in the Usury Laws in 1714. *The Economic Journal 118*(528), 743–758.

Vives, X. (2019). Digital disruption in banking. *Annual Review of Financial Economics 11*(1), 243–272.

Zinman, J. (2010, March). Restricting consumer credit access: Household survey evidence on effects around the Oregon rate cap. *Journal of Banking & Finance 34*(3), 546–556.