Essays in Peer-to-Peer Lending

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To my Mother

Abstract

Online lending marketplaces are increasingly growing as an alternative source of finance. This thesis examines online lending marketplaces in the United States. It specifically focuses on peer-to-peer lending, one of the products offered by online marketplaces. First, this thesis examines the extent to which the absence of banks in the local market impacts the growth of online lending marketplaces. We provide evidence that online lending marketplaces increase access to finance in areas that are underserved by the traditional banking system. Furthermore, online lending marketplaces do not increase market frictions that could exist as a result of bank's absence in the local market. In addition, peer-to-peer lending help borrowers improve their financial position. Second, this thesis studies the benefits of social capital for individuals in peer-to-peer lending. We find that social capital benefits borrowers in peer-to-peer lending through having a lower interest rate. Furthermore, we find that the effect of social capital is stronger for borrowers who are more susceptible to moral hazard. This implies that social capital is effective at mitigating market frictions. Our results also show that social capital constrains opportunistic behavior. An increase in region's social capital is associated with a lower likelihood of default. Last, we examine the extent to which the presence of income rounding behavior in peer-to-peer lending affects loan performance and borrower's credit position. We find that the occurrence of rounding behavior is associated with a higher risk of default and negative changes in borrower's credit score. Furthermore, we find that investors are not compensated for the increased risk associated with rounding. Borrowers who round their income receive a significantly lower interest rate than those who do not round.

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Table of Contents

List of Tables

Chapter 1

Introduction

1.1. Background

Consumer lending represents a significant share of the United States credit market, reaching around $3.6 trillion at the end of 2016. Traditionally, banks are considered the main providers of credit to individuals and businesses (Diamond and Dybvig 1983; Allen and Santomero 1998; Kashyap et al. 2002; Berger and Bouwman 2009). However, market imperfections such as credit rationing and information asymmetry have created a gap in the financial market (Stiglitz and Weiss 1981). This facilitated the emergence of new players that use innovative technology to provide financial products. Online marketplaces are transforming the structure of the conventional financial landscape by creating a more diverse market (Boot 2016; Boot 2017). These marketplaces were created from scratch, and now they are making most of the financial services from comparing deposits rates among traditional banks to getting a loan just a click away. Most of the bank's services are unbundled by these start-ups. Wealth management, money transfer, and most types of loans are just an example of services that online marketplaces provide with increased convenience and lower cost.

Personal loans are one of the key financial products that are extensively provided by online marketplaces, where investors shop freely for investment opportunities according to their risk preferences. Moreover, obtaining and funding a loan is not an intricate process anymore. These online marketplaces are making the most out of technology, employing it in a way that eases the credit process. Online marketplaces are revolutionizing the current lending process rather than offering new financial products. Peer-to-peer lending is one of the services offered by these marketplaces. Peer-to-peer lending is an online process in which borrowers and lenders are matched directly without the existence of an intermediary. Peer-to-peer lending provides consumers with a quick and convenient way of borrowing. These online marketplaces mainly specialize in small personal loans. However, the concept of peer-to-peer lending is not restricted only to personal loans and is expanding to other types of finance: student loans, small business loans, real estate finance and many more.

Online lending marketplaces are increasingly growing as an alternative source of finance, which raises the importance of a study that addresses how these marketplaces fit in the local financial market. Consequently, this thesis aims to provide a better understanding of the credit dynamics of online lending marketplaces and its implications for the financial environment in terms of mitigating market frictions. It mainly focuses on the industry of online lending marketplaces in the United States. This thesis study how online lending industry is affected by the characteristics of the local markets. First, this thesis examines how the financial structure of the local market affects the growth of online lending marketplaces. Second, we try to determine how the social structure of the local market benefits borrowers in peer-to-peer lending. Last, in order to gain a better understanding of the behavior of online borrowers, this thesis studies how the rounding patterns of borrowers in different local markets affect credit performance in online lending marketplaces.

1.1.1. Peer-to-Peer Lending Overview

The industry of peer-to-peer lending started in 2005 with the launch of Zopa, the first online lending marketplace, in the U.K. A year later, the U.S. joined the industry with the launch of Prosper followed by Lending Club. The emergence of online lending marketplaces coincided with the financial crisis, a period during which banks reduced the supply of credit substantially (Ivashina and Scharfstein 2010). In 2016, peer-to-peer lending generated around $21 billion worth of consumer loans in the U.S., increasing from $18 billion in 2015 and $7.6 billion in 2014 (Ziegler et al. 2017). Online marketplaces are growing at an increased pace and are estimated to reach $150 billion or more by 2025 (PwC 2015).

Online lending marketplaces distinguish themselves from conventional banks in a number of ways. The innovative technology employed in online marketplaces results in a momentous cost saving. Online marketplaces have low overhead costs, as they do not need to have local offices or local agents. Furthermore, the online nature of these marketplaces reduces costs related to applications screening and search costs. Unlike banks, online marketplaces do not face capital requirements or rigorous regulations. Thus, they exhibit a cost advantage over traditional banks. These cost savings are then passed on to borrowers and investors through lower interest rates and higher returns. In addition, online marketplaces provide investors with an opportunity to diversify their risk across different types of loans and various platforms. Similarly, borrowers usually do not rely on a single investor and thus have greater chances of being funded. The decision-making process in online marketplaces is expeditious, owing to the implemented data and technology-driven assessment. Thus, the convenience of the credit process makes online marketplaces appealing to most users. These features might allow online marketplaces to reach underserved segments of the population that are usually difficult for banks to finance. The U.S. Department of Treasury (2016) states that one of the foremost gains from peer-to-peer lending is that it can arguably expand access to credit to underserved segments.

The ease of the credit process through online marketplaces is accompanied by inherent risk. Since most marketplaces do not put their own capital at risk, investors are the ones who bear the whole loss in case of default.[1] Furthermore, loans facilitated through most online marketplaces are not secured by any type of collateral. Online platforms might have the incentive to understate the risk associated with online lending, which could mislead marketplace users (Verstein 2011). In addition, investors in online marketplaces are exposed to liquidity risk as only some platforms provide access to the secondary market.[2] Therefore, users face higher default risk as notes can only be transferred to investors on the same platform and if investors could not reach an appropriate price, they are required to hold those notes until maturity (Verstein 2011; Moenninghoff and Wieandt 2013).

[1] However, online lending marketplaces report all default and late payment cases to the credit bureaus.
[2] Investors in Lending Club and Prosper have only access to *FOLIOfn*, an online secondary market.

1.2. Motivations, Research Questions, and Chapter Summary

1.2.1. Chapter 2: Online Financial Inclusion and Its Implications for Borrowers: Evidence from Peer-to-Peer Lending

Chapter 2 investigates the extent to which the structure of the local credit market, in terms of the presence and lending capacity of traditional banks, shapes the growth and local outreach of peer-to-peer lending. More specifically, it examines whether online marketplaces can satisfy the needs of those who could be underserved by the traditional banking system.

Traditional banks have a local informational advantage that is reduced by increasing distance (Agarwal and Hauswald 2010). This local informational advantage provides banks with the market power needed to capture borrowers (Dell'Ariccia and Marquez 2004). Consequently, the loss of informational advantage could lead banks to reduce their loan funding (Cortés and Strahan 2017). Moreover, the loss of banks' informational advantage gives competitors an opportunity to enter the market and to start competing for borrowers as they face lower adverse selection problems (Hauswald and Marquez 2006; Agarwal and Hauswald 2010). Businesses that depend mainly on technology usually face low barriers to enter the market (Einav et al. 2016). Therefore, online lending marketplaces can tap into underserved markets and increase access to finance in areas where banks could have a lower informational advantage.

In the main analysis of the second chapter, we examine how the absence of banks in the local market shapes the local growth of peer-to-peer lending. Moreover, we differentiate between the impact of small and large banks on the local growth of online lending marketplaces, as small and large banks have different roles in the local credit market. Small banks play a greater role in the local credit market than large banks as they tend to serve local and small borrowers (Berger et al. 2004). Due to their decentralized structure, small banks have more local knowledge and are considered repositories of soft information (Berger and Udell 2002; Stein 2002; Berger et al. 2005; Liberti and Mian 2009; Canales and Nanda 2012; Kysucky and Norden 2016). These characteristics of small banks make them more effective in alleviating credit constraints than large banks (Stein 2002; Hakenes et al. 2015). The absence of banks in the local market could lead to banks' loss of local information and monitoring advantage and thus increase market frictions (Gilje et al. 2016). The local growth of online lending marketplaces might mitigate or exacerbate these market frictions. On the one hand, they could mitigate market frictions by using big-data models and reaching credit rationed individuals. On the other hand, online lending marketplaces might exacerbate market frictions if higher risk borrowers self-select into peer-to-peer lending. We identify this issue by examining whether the local growth of peer-to-peer lending is associated with lower borrower quality. Furthermore, we examine whether peer-to-peer lending deteriorates or enhances borrower's financial position by looking at future changes in borrower's credit score.

The results of this chapter show that areas that are financially underserved by the traditional banking system experience higher growth of peer-to-peer lending. Moreover, we find that the growth of peer-to-peer lending is more pronounced in areas with a lower presence of small banks. Furthermore, it shows that the local growth of peer-to-peer lending is associated with a lower risk of borrower default. This implies that online lending marketplaces do not exacerbate market frictions. In addition, the findings of this chapter suggest that online marketplaces benefit borrowers through improving their credit scores. Overall, the results provided in this chapter imply that online lending marketplaces fill the market gap created by the absence of banks in the local market as well as that these marketplaces meet the demands of underserved segments.

This chapter contributes to the current literature as follows. First, it contributes to the growing literature on peer-to-peer lending by providing evidence on how the local growth of online lending marketplaces fits into the financial market. Second, it adds to the studies that focus on the relationship between the traditional banking system and online lending marketplaces by providing evidence that online marketplaces meet the needs of individuals that are underserved by the traditional banking system (Butler et al. 2016; Wolfe and Yoo 2018). Last, this chapter provides evidence on the implications of online lending marketplaces growth for the local credit market and borrowers welfare.

1.2.2. Chapter 3: Does Social Capital Matter? Evidence from Peer-to-Peer Lending

The focus of Chapter 3 is to examine how social capital affects the lending conditions in peer-to-peer lending. We investigate whether borrowers in peer-to-peer lending benefit from social capital. In addition, we examine the extent to which social capital is effective in mitigating market frictions.

In broad terms, social capital can be defined as the community's norms and networks that arise from social interactions, which enables cooperative actions (Woolcock and Narayan 2000; Woolcock 2001). Social capital can ease the attainment of certain ends that is harder to achieve without it (Coleman 1990). Furthermore, social capital is considered a public good since it resides within the social network structure and all members of the network can access and benefit from it (Coleman 1988). There is growing evidence on the positive impact of social capital on economic outcomes (Knack and Keefer 1997; La Porta et al. 1997; Zak and Knack 2001; Francois and

Zabojnik 2005; Algan and Cahuc 2010; Bjørnskov 2012). Communities with high levels of social capital tend to perform better than low social capital communities. Furthermore, the benefits of having high levels of social capital are documented at corporate, individual, and household levels. At the corporate level, firms benefit from social capital by having lower interest rates, lower cost of equity, and lower audit fees (Ferris et al. 2017; Hasan et al. 2017b; Gupta et al. 2018). Individuals in high social capital communities show higher participation rates in the stock market (Guiso et al. 2004; Hong et al. 2004; Brown et al. 2008; Changwony et al. 2014). Furthermore, households in high social capital communities show higher levels of financial awareness (Guiso and Japelli 2005).

In the main analysis, we examine the impact of social capital on borrowers' interest rates in peer-to-peer lending. Furthermore, we differentiate between borrowers based on their risk, as the impact of social capital on interest rate can be different across borrowers. The benefits of social capital should increase as market frictions increase (Guiso et al. 2004; Ferris et al. 2017; Lin and Pursiainen 2018). In addition, social capital could be effective at mitigating market frictions as it constrains opportunistic behavior through shared trust, norms, and values (Coleman 1988; Knack and Keefer 1997; Durlauf and Fafchamps 2004). We examine this by observing the impact of social capital on borrower's likelihood of default. The norms in high social capital should encourage borrowers to repay their debt promptly (Costa and Kahn 2003; Guiso et al. 2004).

The findings of this chapter show that social capital has a significant impact on borrowers' interest rates in peer-to-peer lending. An increase in the region's social capital significantly reduces the interest rate charged in peer-to-peer lending. We find that this effect is stronger for borrowers with higher levels of moral hazard. This suggests that social capital is associated with a reduction in market frictions. Furthermore, we find that a higher level of social capital is associated with a lower likelihood of default. This implies that social capital constrains individuals' opportunistic behavior and promotes altruistic inclinations. Overall, the findings of this chapter confirm that social capital benefits individuals in peer-to-peer lending by having better lending conditions. Furthermore, it implies that social capital is effective at mitigating moral hazard and information asymmetry problems.

This chapter directly contributes to peer-to-peer lending literature. Most studies focus on the role of online social networks and friendship in online lending marketplaces (Lin et al. 2013; Freedman and Jin 2017). Nonetheless, this chapter provides evidence of the importance of social capital. Furthermore, it adds to the literature that documents the impact of social capital on economic outcomes (e.g., Knack and Keefer 1997; Guiso et al. 2004; Jha and Cox 2015; Javakhadze et al. 2016; Gupta et al. 2018). This chapter provides robust evidence on the benefits of social capital in online lending marketplaces. Lastly, it contributes to the literature that examines the effect of social environment on debt contracting by focusing on individuals' economic outcomes. Most studies focus on the economic outcomes of corporations (Cheng et al. 2017; Hasan et al. 2017b).

1.2.3. Chapter 4: The Prevalence of Income Rounding Behavior and Credit Performance in Peer-to-Peer Lending

Chapter 4 investigates the extent to which the presence of income rounding behavior in peer-to-peer lending affects loan performance and borrower's credit position. Furthermore, we examine whether investors are compensated for the extra risk associated with rounding behavior.

Despite the increased growth of online lending marketplaces, the industry still suffers from the absence of a unified regulatory framework. Furthermore, the lack of consistent background checks and credit models across different platforms increases the risk of information falsification by borrowers either intentionally or by mistake. This chapter identifies behavior patterns in misreporting income in peer-to-peer lending and its impact on subsequent loan performance. Individuals are naturally drawn to round numbers, as they are more cognitively accessible than other numbers (Tarrant et al. 1993; Schindler and Kirby 1997). Furthermore, round numbers act as a cognitive reference point (Rosch 1975; Bhattacharya et al. 2012). Consequently, individuals tend to provide round numbers when reporting a value especially in case of large numbers (Kaufman et al. 1949; Pudney 2008; Manski and Molinari 2010). This rounding behavior implies that individuals are uncertain about their financial position (Jansen and Pollmann 2001; Krifka 2002; Binder 2015). Ormerod and Ritchie (2007) argue that individuals who give round estimates are more likely to have insufficient knowledge or documentation. In addition, rounding occurs due to the lack of individuals' incentive to undertake the effort needed to acquire exact information (Dechow and You 2012). Moreover, borrowers could be strategically rounding their income in order to look more attractive to users (Carslaw 1988; Das and Zhang 2003; Garmaise 2015). This implies that individuals who lack sufficient financial knowledge and those who are unwilling to exert effort experience worse economic outcomes (Garmaise 2015).

In this chapter, we examine the effect of rounding behavior on borrower's credit performance and the associated consequences in peer-to-peer lending. The analysis shows that borrowers who report round income figures are more likely to experience delinquency or default on their loans than those who provide income figures that are more accurate. Furthermore, borrowers who exhibit rounding behavior experience higher fluctuations in their credit score. These borrowers are more likely to encounter negative changes in their credit score than those who were more accurate while reporting their income level. Lastly, we find that borrowers benefit from rounding their income. Borrowers who exhibit rounding behavior are significantly charged lower interest rate than those who do not report rounded income figures. However, this implies that investors are not compensated for the increased risk associated with rounding behavior. Overall, the results of this chapter show that borrowers who are uncertain about their financial position have consistently worse credit performance.

This chapter provides consistent evidence that the presence of rounding behavior in online lending marketplaces is associated with worse economic outcomes. Accordingly, it contributes to the current literature that focuses on the impact of misreporting and information falsification by borrowers on loan performance (Jiang et al. 2014; Garmaise 2015, Piskorski et al. 2015, Griffin and Maturana 2016). We provide evidence on the impact of the behavior patterns in misreporting income in a fast-growing industry that suffers from a lack of regulation. In addition, this chapter directly contributes to the strand of literature that focuses on the performance of loans in peer-to-peer lending. Most studies focus on the impact of loan attributes, borrowers' characteristics, and platform mechanisms on loan performance (Lin et al. 2013; Emekter et al. 2015; Everett 2015; Miller 2015; Iyer et al. 2016).

1.3. Research Context and Data

This thesis employs data from Lending Club, the largest online lending marketplace in the U.S. As of 2016, Lending Club has issued loans of value around $24 billion. Moreover, Lending Club is one of the first online marketplaces to be listed on the New York Stock Exchange. Lending Club's IPO was at the end of 2014 with a valuation of $5.4 billion. Moreover, Lending Club sold more than 57 million shares at IPO, raising around $900 million.

The data enable us to observe loans funded by investors through Lending Club throughout their monthly credit cycle. The dataset provides information regarding borrower's credit characteristics (e.g., credit score, debt-to-income ratio, and the number of credit accounts) and borrower's financial position at the time of loan application. Moreover, it provides detailed information about loan characteristics and monthly performance. Borrowers need to comply with certain requirements in order to qualify for a loan through Lending Club. Lending Club borrowers must be above 18 years old and meet the platform's credit criteria. Normally, Lending Club requires that applicants have a minimum credit score of 660, a debt-to-income ratio of not more than 40% and a credit history for a minimum of 36 months. Moreover, applicants must have been the subject of no more than five inquiries in the last six months and have at least two revolving accounts in their credit profile.

When borrowers meet the eligibility criteria, Lending Club offers them a fixed interest rate based on the assigned credit grade. The loan grades on Lending Club range from A1 to E5 with a base interest rate between 6.46% and 27.27%. Additionally, the maximum amount of loan that a borrower can apply for is $40,000 and the minimum amount is $1,000. The loan terms are either 36 or 60 months. If the borrower accepts the loan conditions, the loan is posted online for investors to fund.[3] Potential investors may decide to fund parts of the loan, usually in increments of $25, based on their assessment of the loan's characteristics and borrower's credit history. Lending Club investors are usually able to view each borrower's credit history online. Investors on Lending Club can be either individuals or institutional ones. In order to qualify as an investor in Lending Club, one must have either at least an annual gross income of $70,000 and a net worth of at least $70,000 or "just" a net worth of $250,000.[4] If enough investors are willing to fund the loan, an intermediate bank originates the loan in agreement with the platform. In the final step of the lending process, the borrower's monthly payment less servicing and other associated fees are distributed across investors.[5]

1.4. Structure of the Thesis

The remainder of this thesis is structured as follows. Chapter 2 studies the relationship between the structure of the local credit market and the local growth of online lending marketplaces. Chapter 3 examines the benefits of social capital for borrowers in peer-to-peer lending. Chapter 4 investigates the relationship between income rounding behavior and borrower credit outcomes. Lastly, Chapter 5 provides a summary of this thesis and its implications for future research.

[3] Lending Club charges borrowers one-time origination fees that range between 1% and 6.00%, which is paid when the loan is issued.
[4] These are for investors residing in states other than California. In California, investors must have either at least an annual gross income of $85,000 and a net worth of $85,000 or "just" a net worth of $250,000.
[5] Lending Club charges investors 1% service fee of any borrower's payment.

Chapter 2

Online Financial Inclusion and Its Implications for Borrowers: Evidence from Peer-to-Peer Lending

2.1. Introduction

The financial market is witnessing rapid changes with the emergence of online marketplaces that provide various types of credit to a wide range of consumers without needing to have a bank acting as an intermediary. Online lending marketplaces do not necessarily offer new financial products; rather they revolutionize the current lending process with their innovative edge. Furthermore, online lending marketplaces provide consumers with low-cost and convenient financial products as alternatives to bank's credit products. The process of lending through these marketplaces occurs entirely online; different types of borrowers are listed for many kinds of lenders to fund.

Peer-to-peer consumer lending has been developing rapidly in the United States financial market as an alternative finance model. In 2016, peer-to-peer lending generated around $21 billion worth of consumer loans in the U.S., increasing by 17% from 2015 and by 176% from 2014 (Ziegler et al. 2017).[6] However, this rapid growth comes with some challenges; lack of clear regulatory oversight, fraud, and uncertainty during economic downturns. On the other hand, one of the major benefits from the growth of peer-to-peer lending is that it has the opportunity to expand access to finance to underserved segments of the population (U.S. Department of Treasury 2016). Furthermore, online marketplaces might strengthen the stability of the financial system by creating a more diverse and less homogenous financial landscape (Boot 2017).

In this chapter, we explore the extent to which the emerging online marketplaces can satisfy the needs of those who are underserved by the traditional banking system in the U.S. financial market. More specifically, we test whether the local growth of peer-to-peer lending is driven by the lack of access to traditional banking. Unlike banks, online lending marketplaces make great use of technology, big data, and the lack of capital requirements in their models. This enables online lending marketplaces to provide individuals with quick access to cash and diverse investment opportunities at a low cost. Consequently, these unique features of online marketplaces might allow them to reach segments of the population that the traditional banking system is unable or unwilling to serve. Additionally, we explore whether the local growth of peer-to-peer lending mitigates or exacerbates market frictions, which could result from the shortage of bank branch networks in the local market. The absence of bank branch networks tends to amplify local market frictions[7] and thus influence the process of bank lending (Degryse and Ongena 2005; DeYoung et al. 2008; Agarwal and Hauswald 2010; Hollander and Verriest 2016). Furthermore, increased distance

[6] Peer-to-peer consumer lending amounted to $18 billion in 2015 and $7.6 billion in 2014 (Ziegler et al. 2017).
[7] Berger et al. (2005) argue that bank geographical proximity might help in mitigating information asymmetries.

between banks and borrowers weaken the informational advantage that banks have over competitors in the local market (Agarwal and Hauswald 2010). This, in turn, allows other lenders to compete for borrowers as they face fewer adverse selection problems (Hauswald and Marquez 2006; Agarwal and Hauswald 2010).

Online marketplaces utilize their low operating costs to attract customers by offering lower lending rates. Lower lending rates, in turn, allow individuals to consolidate high-interest debt and improve their overall risk profile. Alternatively, the growth of peer-to-peer lending could exacerbate market frictions as information problems could lead unobserved low-quality borrowers to self-select into online marketplaces (Akerlof 1970; Miller 2015). This might result in moral hazard problems as borrowers could use this new channel of lending to engage in risky behavior *ex post* (Karlan and Zinman 2009).[8] To explore this issue, we study the relationship between the local growth of peer-to-peer lending and credit outcomes by measuring borrower risk of default *ex post*. The existence of information frictions in the credit market could be disruptive and have a negative effect on borrower default (Jaffee and Russell 1976; Broecker 1990; Miller 2015).

Peer-to-peer lending might mitigate market frictions by expanding credit to underserved segments and by allocating credit efficiently to safer borrowers. Therefore, it is critical to consider the welfare implications of mitigating frictions in the credit market (Karlan and Zinman 2009). On the one hand, borrowers might exploit the increased access to online marketplaces by over-borrowing or by engaging in risky activities. On the other hand, borrowers might effectively utilize the expanded access to finance to consolidate their current debt obligations and smooth their income. To

[8] For instance, after the loan origination borrowers may use the loan for another purpose other than stated which could be riskier.

investigate these possibilities, we relate the expansion of peer-to-peer lending in local markets to borrower credit welfare by measuring future changes in borrower's credit score.

Our results suggest that the local credit environment influences the outreach of online marketplaces. Using an instrumental variable approach, we find a negative and statistically significant relationship between access to bank financing and the growth of peer-to-peer lending in the local credit market. Peer-to-peer lending increases access to finance in local areas that are underserved by the traditional banking system. Furthermore, we find that the presence of small banks in the local market has a more pronounced negative effect on the expansion of online lending marketplaces than the presence of large banks. This could be due to the different roles that large and small banks have in the local market, as the latter tend to lend more to small and local borrowers and have more local knowledge (Berger et al. 2001; Berger et al. 2004). As online lending marketplaces mainly specialize in facilitating small personal loans, it is a closer substitute to small banks.

The findings of this chapter also show that the local growth of peer-to-peer lending is associated with a lower risk of borrower default *ex post*. This implies that online lending marketplaces might mitigate market frictions that occur due to the local absence of branch networks. In addition, the results indicate that the growth of peer-to-peer lending in the local market is significantly associated with improvement in borrower quality through enhancing borrower's credit score. Overall, the findings of this chapter suggest that online lending marketplaces are willing to meet the demands of financial market participants and fill the market gap created by the absence of bank branch networks in the local market. Additionally, online lending marketplaces can identify safer borrowers and help individuals gain access to broader financial services by building up their credit profile.

The remainder of this chapter is organized as follows. Section 2.2 provides the theoretical framework of this chapter. In Section 2.3, we provide data description and the measurement of variables. Section 2.4 presents the methods and the results of this chapter. Section 2.5 provides the main conclusion and implications.

2.2. Theoretical Motivation

2.2.1. The Role of Banks vs Peer-to-Peer Lending

Financial intermediaries exist to mitigate market frictions related to informational asymmetries and transaction costs (Leland and Pyle 1977; Boyd and Prescott 1986; Allen and Santomero 1998). As financial intermediaries, banks perform two fundamental roles in the economy: liquidity creation and risk transformation (Berger and Bouwman 2009). Banks create liquidity by financing illiquid assets (loans) with liquid liabilities (deposits) (Diamond and Dybvig 1983; Kashyap et al. 2002). Additionally, banks provide maturity transformation, where they transform shorter maturity deposits to meet borrowers' demand for relatively medium- and long-term loans (Bhattacharya and Thakor 1993). Banks also transfer risk by issuing riskless liquid deposits where savers are risk-averse to fund risky, illiquid loans where borrowers have the risk of default (Diamond 1984). Banks tend to minimize risk by diversifying their portfolios, pooling risks, and monitoring borrowers (Berger et al. 1995; Demsetz and Strahan 1997). Furthermore, banks hold capital and reserves as a buffer for unexpected losses (Cebenoyan and Strahan 2004; Bikker and Metzemakers 2005). By performing these intermediary functions, banks are capable of hedging any risk that arises from their services.

The financial landscape could be facing structural changes due to the entrance of technology-oriented players (Boot 2016). Online marketplaces are disintermediating most of the traditional banking functions with their big data analytics and innovative solutions (Morse 2015). Online lending marketplaces match up with banks' process of deposit-taking and granting loans by providing borrowers and investors with a platform to meet online. Online lending marketplaces screen loan applicants according to the platforms' credit criteria before posting loans online for potential investors to fund according to their investment preference. Unlike banks, online lending marketplaces do not pool the supply of money, but they allow investors to find loans by pooling borrowers with different credit risk to accommodate investors' various risk appetite. Also, online lending marketplaces facilitate transactions from the collection of loan payments, handling the collection processes in case of default, to enforcing charges (Wang et al. 2009). However, online lending marketplaces fail to achieve transformation regarding risk, maturity, and liquidity (Moenninghoff and Wieandt 2013). For peer-to-peer loans, lenders are the ones who bear the credit risk, as the loans are not insured. Additionally, the loan duration is the same as the duration of the investors' claim. Similarly, the liquidity of the loan is the same as of the claim.

Technology-based businesses face low barriers to enter the market (Einav et al. 2016). Therefore, online marketplaces can tap into the financial market without having to build local offices and without needing to have local agents. Hence, online lending marketplaces attain a momentous cost saving for borrowers and lenders by having low overhead costs, reducing costs related to applications screening, and cutting search costs. Contrary to banks, online lending marketplaces do not have capital requirements, and thus, it could exhibit a cost advantage over traditional banking. Borrowers and lenders benefit from this cost advantage by having lower interest rates and higher return. However, online marketplaces disintermediate most of the bank functions by conveying a large part of these functions to the platforms' users (Moenninghoff and Wieandt 2013). Therefore, they cannot perform the function of risk management carried out by banks. Consequently, participants in online lending marketplaces bear various types of risks arising from the financial transactions they are involved in. These risks vary from operational risk, default risk, to liquidity risk.

There are fundamental differences between the role and process of online lending marketplaces and commercial banks in facilitating loans as the latter have federal deposit insurance and regulations for bank risk taking. The Federal Insurance Corporation (FDIC) insures the money held by depositors in their bank accounts. Hence, FDIC guarantees depositors' funds in case of bank failure. On the other hand, depositors face the risk of losing their money if they invest in peer-to-peer loans. Another way to think about the difference between bank lending and peer-to-peer lending is that banks raise money in advance in the form of deposits and they give investors the confidence that they will perform an adequate job by diversifying their assets, maintaining their capital, and having regulatory oversight (Boot and Thakor 2000). Thus, in the traditional banking model, depositors are unaware of which investments the banks put their money in. On the contrary, peer-to-peer lending provides borrowers with the opportunity to get a loan. Subsequently, with the information provided on the loan application, borrowers try to convince investors that they have a good prospect and are a high-quality investment. In the peer-to-peer lending model, investors get to choose which loan to invest in and the investment amount according to their risk appetite. Furthermore, while banks make profits from the spread between the deposit rate and the interest rate they charge on loans, online lenders create their profits from the fees charged to borrowers and investors.

2.2.2. Borrower-lender Proximity

Distance can affect the strength of the borrower-lender relationship and, thus, affect lenders' capability to acquire and utilize soft information (Agarwal et al. 2011). Furthermore, borrower-lender proximity eases access to subjective information, which improves the credit screening process. Agarwal and Hauswald (2010) argue that subjective information is one of the important cores in local informational advantage. They state that banks have an informational advantage in the local market that diminishes by increasing distance. Furthermore, Dell'Ariccia and Marquez (2004) show that, to some extent, the informational advantage provides informed lenders with market power that allows them to capture borrowers, as adverse selection could make it more problematic for uninformed lenders to provide credit to borrowers. Consequently, strong bank-borrower relationship and proximity could mitigate the asymmetric information problem that occurs between borrowers and lenders (Sufi 2007; Hollander and Verriest 2016; Kysucky and Norden 2016). In transaction-oriented finance, banks might not have much incentive to acquire information compared to relationship-based finance. Nevertheless, markets could fail if the problems of asymmetric information are too high to overcome without the banks' acquisition and processing of information (Boot and Thakor 2015).

Information acquisition could increase the efficiency of the credit market as it plays a role in allocating funds to creditworthy borrowers (Alessandrini et al. 2009). Consequently, the loss of local knowledge could affect the precision of banks' credit screening and thus, make their lending decisions more susceptible to errors (Hauswald and Marquez 2006). Dell'Ariccia and Marquez (2006) show that the structure of information in the loan market has an important role in establishing banks' lending standards and hence is a significant indication of stability and the volume of credit contributed to the overall economy. Furthermore, the problem of asymmetric information could lead banks to engage in spatial discrimination through loan pricing (Degryse and Ongena 2005; Agarwal and Hauswald 2010; Bellucci et al. 2013), credit rationing (Stiglitz and Weiss 1981; DeYoung et al. 2008), and loan conditions (Hollander and Verriest 2016). As banks lose their informational advantage for more distant loan applicants, other lenders suffer less adverse selection problems and hence, allow them to compete aggressively for borrowers (Hauswald and Marquez 2006; Agarwal and Hauswald 2010).

Technological advances in communication and information processing have enabled banks to lend to distant borrowers (Petersen and Rajan 2002). Furthermore, due to its increased cost, soft information has started to play a less significant role in banks' lending decisions (Brevoort and Wolken 2009). However, in a credit market where there is an intensive information asymmetry problem (Leland and Pyle 1977; Dell'Ariccia 2001; Gorton and Winton 2003), soft information is critical for the inference of credit quality and successful lending decisions beyond credit scores and hard information (Petersen and Rajan 2002).[9] Furthermore, the extent to which financial institutions can take control of information asymmetries in their lending decisions is essential for access to credit (Beck and Brown 2015). Berger and DeYoung (2001) argue that, despite technological advances, physical distance still matters.

Contrary to traditional banks, online marketplaces do not suffer from economic frictions that arise from borrower-lender geographical distance (Agrawal et al. 2015), as the relationship between borrower and lender is a virtual one. Besides depending on hard information, online marketplaces make use of non-standard information and big

[9] Agarwal and Hauswald (2010) find that distance still plays a critical role in the acquisition of soft information despite the technological advances.

data in their lending decisions that are not available to banks (Morse 2015).[10] This non-standard information arises independently of the geographical distance between borrowers and lenders. Moreover, online marketplaces depend on the collective assessment of different lenders on non-standard and standard information to judge borrower's creditworthiness (Iyer et al. 2016). All of these provide online lending marketplaces with information that are not readily available to banks. Hence, this might give online marketplaces an advantage over banks in areas where the latter suffer from loss of local information. Iyer et al. (2016) report an increase in the online lending platforms' screening ability and in the accuracy in assessing borrowers. They argue that this is due to the effective utilization of non-standard information as the hierarchical distance between lender and borrower is lesser in the online market. Furthermore, some unusual soft factors might help in identifying creditworthy borrowers (Dorfleitner et al. 2016). Due to their expertise and economies of scale, financial intermediaries are viewed as the repositories of soft information (Fama 1985). However, Lin et al. (2013) show that soft information can be gathered and used without the need of a financial intermediary. The distance between borrowers and lenders could create a market gap as banks lose their local informational advantage. Consequently, this gives an opportunity to online marketplaces to meet customers' needs and fill this market gap.

2.2.3. Local Credit Market

Financial outreach is critical for economic development and growth by fostering access to finance (Beck et al. 2007). Local economic development is about creating opportunities for individuals who reside within a certain area, as well as improving

[10] This unusual or non-standard information can be friends' endorsement, loan description text, and the collective assessment of many investors (Lin et al. 2013; Morse 2015; Dorfleitner et al. 2016; Iyer et al. 2016).

human welfare and determining how the local economic structure influences the choices that individuals make (Shaffer et al. 2006). The efficiency of financial intermediaries and the services they offer is essential for economic growth and development (Schumpeter 1934; King and Levine 1993; Levine 1997; Demirgüç-Kunt and Maksimovic 1998; Beck et al. 2000). Furthermore, credit market imperfections, such as information asymmetries and transaction costs, might affect local economic and social outcomes (Garmaise and Moskowitz 2006). These imperfections could cause banks to lose their competitiveness more than when these imperfections do not exist (Degryse and Ongena 2004). Guiso et al. (2004) find that local market matters in financial development and that distance could segment local markets, which is consistent with Becker's (2007) findings that the capital market of banks is geographically segmented.

The extent to which individuals can access and utilize financial services could have an impact on economic development and welfare (Beck and Demirgüç-Kunt 2008; Beck et al. 2008; Butler and Cornaggia 2011; Demirgüç-Kunt and Klapper 2012; Allen et al. 2016). Accordingly, individuals might benefit (suffer) from the local presence (absence) of banks. Degryse and Ongena (2004) argue that the availability and pricing of credit depend on the local market conditions and that the banking market remains largely local. Using data on mortgage lending, Ergungor (2010) finds that high bank branch presence has a positive effect on the number of mortgages originated by financial intermediaries. Furthermore, he argues that the benefits of branch presence increases as bank branches get closer to the local market. Also, the benefits of screening borrowers are greater in markets with higher bank concentration (Dell'Ariccia and Marquez 2006). Hence, banks will be able to judge borrowers' creditworthiness adequately in the markets where they have a large presence. On the other hand, Nguyen (2014) finds that branch closings are more disruptive in disadvantaged areas and are associated with a reduction in local lending supply. Moreover, a decrease in the capacity of local intermediaries due to the failure of one intermediary will limit borrower access to finance, which might lead borrowers to pass up investment or purchases opportunities resulting in local activity failure (Rajan and Ramcharan 2016).

2.2.4. Relation to Existing Literature

The main contribution of this chapter is to provide evidence on the role of emerging online marketplaces in the local credit market. Furthermore, this chapter directly contributes to the growing literature on peer-to-peer lending. Most of the literature focuses on loan performance in peer-to-peer lending related to different borrower characteristics and platform mechanisms (Lin et al. 2013; Emekter et al. 2015; Everett 2015; Miller 2015; Dorfleitner et al. 2016; Iyer et al. 2016). Another strand of the literature focuses on biases in the lending process in online marketplaces (Pope and Sydnor 2011; Duarte et al. 2012; Ravina 2012). However, this chapter attempts to provide an overall understanding of how online lending marketplaces fit into the financial process and draws a causal relationship between local access to finance and the expansion of peer-to-peer lending.

This chapter also contributes to the strand of literature that focuses on how online marketplaces relate to the current traditional banking system. Butler et al. (2016) show that borrowers in competitive financial markets are less willing to pay a high interest rate on peer-to-peer loans. Wolfe and Yoo (2018) look at the other side of the story and study how peer-to-peer lending affects banks' personal loan volumes and quality. In contrast to these studies, this chapter investigates whether online marketplaces meet the needs of individuals who lack access to finance. Furthermore, we identify the implications of the local growth of online marketplaces and whether they increase market frictions or not. A final implication of this study is that there can be a wider financial setting where banks and online marketplaces can co-exist by serving different financial needs. Achieving a balanced relationship between banks and the FinTech industry will benefit financial market users as banks and online marketplaces have something to offer each other, banks with their experience and online marketplaces with their innovative edge.

2.3. Data

The primary two datasets used in this study are about commercial banks and peer-to-peer lending local outreach. The data about commercial banks comes from the federal deposit insurance corporation (FDIC). The summary of deposit data (SOD) from the FDIC provides information on the exact physical address of bank branches and other branch-level data, such as the amount of deposits held by individual branches and the year of branch incorporation. For the online lending data, we use loan applications data from Lending Club. Lending Club is the largest online lending marketplace in the U.S. with a loan issuance value of greater than $23 billion at the end of 2016 (since inception). We match these two datasets at the three-digit ZIP code area level. Our data are on an annual frequency from 2012 to 2015 covering around 884 three-digit ZIP codes areas.

2.3.1. Main Variables Measurement

We construct two measures of local financial outreach by banks and online marketplaces. Local bank branch outreach is our main independent variable. Similar to Butler and Cornaggia (2011), Cornaggia (2013), Beck et al. (2014), and Butler et al. (2016), we use the number of bank branches per 1,000 people in a three-digit ZIP code area. This reflects the local presence of branch networks and the distance between traditional lenders and borrowers. Moreover, this measure indicates traditional lenders ability to capture soft information about the areas they operate in, which in turn could affect their local lending decisions and informational advantage (Hauswald and Marquez 2006; Ergungor 2010). As the distance between borrowers and banks increase, banks might lose their local advantage, which allows other lenders to penetrate the local credit market and compete for borrowers.

For robustness, we use local deposits held by bank branches to measure access to finance and proxy for local lending capacity. Bank supply of local deposits has a positive impact on local loan supply, which affects local economic activity and access to finance (Becker 2007; Butler and Cornaggia 2011). In addition, the level of deposits held by bank branches could proxy the actual use of bank's services (Beck et al. 2007).

We adopt similar measures for our dependent variable, the outreach of online marketplaces. We employ the number and amount of loans issued by Lending Club per 1,000 people at the three-digit ZIP code level. Higher online intensity indicates greater access to the financial services offered by online marketplaces. Furthermore, this allows us to capture how online marketplaces penetrate the local credit market and how it interacts with existing bank branch networks.

2.3.2. Control Variables

We compile our control variables from several sources at the three-digit ZIP code and state level. We control for local market concentration by including the Herfindahl-Hirschman Index (HHI) based on branch deposits within the three-digit ZIP code area. Guzman (2000) shows that credit rationing is more prevalent in monopolistic banking systems than in competitive ones. Also, we control for the bank's local experience and branding by including the median age of bank branches in the local market. This proxy for how long banks have been operating in the local market, which could affect consumer loyalty to traditional banking. Furthermore, we add measures of bank performance by controlling for the median return on assets (ROA) and the median allowance for loan and lease losses ratio (ALLL) for banks operating within the three-digit zip code area. These measures are associated with the likelihood of bank failure, which in turn could affect bank's expansion (Wheelock and Wilson 2000; Jin et al. 2017).[11] We control for the area net worth by using annual three-digit ZIP codes House Price Index (HPI) from the Office of Federal Housing Finance Agency. Price appreciation increases individuals' net worth, which might attract lenders to certain local areas (Dell'Ariccia et al. 2012; Ramcharan and Crowe 2013).

Local economic conditions and demographic characteristics might affect individuals' decision to use peer-to-peer lending and the presence of bank branches in a certain area. Therefore, we control for a number of demographic characteristics at the three-digit ZIP code level. We also control for the percentage of the white population and the percentage of the male population. To control for the education level in the local area, we include the percentage of the population aged 25 years old

[11] ROA is negatively associated with bank failure while ALLL is positively associated with bank failure (Jin et al. 2017).

and over who hold a bachelor degree (Cornaggia 2013). Furthermore, we control for local economic conditions with the percentage of the labor force that is unemployed and the share of the population living below the poverty line (Butler et al. 2016). Measures of local demographics, economic conditions, and population come from the American Community Survey 5-year estimates.[12] Moreover, we control for local economic development by including the number of business establishments[13] in the three-digit ZIP code area per 1,000 people. We obtain establishments data from ZIP Code Business Patterns issued by the U.S. census bureau.

Lastly, we include a number of state-level control variables. We control for real GDP per capita obtained from the Bureau of Economic Analysis. We follow Butler (2016) and control for state's credit demand and quality in order to account for each state financial conditions. The different financial condition of states where the borrowers reside could have an effect on the presence of bank branches and the usage of alternative sources of finance. We do so by including states' auto debt balance per capita, credit card balance per capita, and mortgage debt balance per capita. We also include the percentage of auto debt, credit card debt, and mortgage debt balances that are ≥90 days delinquent. These data come from the New York Fed/Equifax Consumer Credit Panel. Appendix 2.1 provides a detailed description of the variables used and their sources.

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[12] American community survey is published by the U.S. Census Bureau. The Census Bureau employ ZIP code tabulation area (ZCTA) that is a close approximation of U.S. ZIP codes.

[13] This excludes institutions that carries lending activities and any other activities related to finance and insurance.

2.3.3. Summary Statistics

Table 2.1 presents the summary statistics of the variables used in this study. The number of branches varies from less than 0.032 per 1,000 people to a maximum of around three branches per 1,000 people. The mean number of branches per 1,000 people is 0.34. For online marketplaces, the maximum number of loans issued per 1,000 people is about three online loans with a mean value of 0.62. On average, bank branches have an average deposit value of $34,864 per 1,000 people in a three-digit ZIP code area. On the other hand, individuals in a three-digit ZIP code area borrow $9,123 per 1,000 people from online marketplaces. The value of online loans originated might be deemed little compared to the value of deposits held at banks. However, this might indicate the growth opportunity for online marketplaces.

[Insert Table 2.1 here]

The mean Herfindahl-Hirschman Index (HHI) is 0.0694 for bank deposits with a minimum value of 0.004. The average age of branches operating in a three-digit ZIP code is 32.5 years and varies between 8 and 113 years. The rest of the descriptive statistics of other control variables employed in this study at a three-digit ZIP code and state level are given in Table 2.1.

2.4. Methods and Results

2.4.1. Main Specification

To assess how the local presence of mainstream banking and hence local access to finance affects the outreach of online marketplaces, we estimate the following model:

$$\mathrm{Ln}(Online\ Outreach_{z,t}) = \alpha + \beta\ \mathrm{Ln}(Branch\ Outreach_{z,t}) + \gamma Z_t + Year_t\ + State_s + \varepsilon_{z,t} \qquad (2.1)$$

$\mathrm{Ln}(Online\ Outreach_{z,t})$ is the natural logarithm of the total number of online loans issued per 1,000 people at the level of three-digit ZIP code z in year t. Similarly, our main independent variable $\mathrm{Ln}(Branch\ Outreach_{z,t})$ is the natural logarithm of the total number of bank branches per 1,000 people. For robustness, we use the natural logarithm of the total amount of online loans issued per 1,000 people and the natural logarithm of the total amount of deposits held by bank branches per 1,000 people at the three-digit ZIP code level as our dependent and independent variables, respectively. Z is a vector of controls that include three-digit ZIP code level and state-level variables. One possible issue of our study is that some unobservable state-level variables might affect the presence of online marketplaces and correlate with local branch networks. Additionally, time varying macroeconomic factors that influence the level of local loans issued by online marketplaces could be unobserved. In order to address these concerns, we include $Year_t$ and $State_s$ to capture year and state fixed effects, respectively.

2.4.1.1. Identification Strategy

A possible issue that we encounter is establishing the causal effects of local branch networks on the local peer-to-peer lending activities due to reverse causality. The growth of online marketplaces can cause banks to close their branches as fewer people are going to banks and are using online facilities instead. Therefore, we address this concern by implementing an instrumental variable (IV) approach as ordinary least squares (OLS) estimates could bias our results. For an instrument to be valid, it has to be strongly correlated with local branch outreach (instrument relevance) and only affect peer-to-peer lending activities through local branch outreach (exclusion restriction).

The first instrument that we use for local branch outreach is the average distance to the nearest three-digit ZIP code area.[14] This proxy for the average travel distance to the nearest market. A large distance between the local market and the nearest alternative market increase the importance of local market accessibility and convenience as customers face higher transportation costs to find alternative markets. This, in turn, will increase the number of local bank branches considering that there is a higher demand for the local bank branches. On the other hand, online marketplaces occur entirely in a virtual environment. Therefore, it arises independently of the physical distance to other markets. The second instrument that we use is the local branch outreach in the year 2000 per 1,000 people. Past local presence of bank branches is strongly related to the current presence of bank branches. However, it is unlikely that past bank branch networks will have a direct impact on the current outreach of online marketplaces since the year 2000 in which we use the branch

[14] We obtain this measure by taking the average distance between each five-digit ZIP code for each three-digit ZIP code. ZIP code distance data is obtained from National Bureau of Economic Research.

outreach as an instrument is before the year 2005 in which the online marketplaces is launched.

2.4.2. Main Results

2.4.2.1. The Effect of Branch Outreach on the Expansion of Online Lending

Table 2.2 presents the main instrumental variable estimates for the effect of the current local presence of bank branches on the outreach of online marketplaces.[15] Model 1 reports the instrumental variable estimates for local branch outreach. Model 2 reports the instrumental variable estimates for local branch deposit as a proxy of local lending capacity.

[Insert Table 2.2 here]

Column (1) of Table 2.2 shows the first-stage estimates that relate the average distance to the nearest three-digit ZIP code and branch outreach in the year 2000 to the current branch outreach. Similarly, column (3) of Table 2.2 shows the first-stage estimates that relate the average distance and branch deposit level in the year 2000 to the current branch deposit. The results confirm that the instruments used are significantly and positively correlated with the local number of bank branches and deposits level. The first-stage F-statistics are 644 and 411, respectively. Based on Stock and Yogo (2005)'s rule of thumb ($F > 10$), we can verify the strength of our instruments.

[15] We provide the OLS results in Appendix 2.2.

Columns (2) and (4) of Table 2.2 present the second stage results for both models, which support our initial hypothesis that online marketplaces increase access to finance in areas that lack access to mainstream banking. The coefficient estimates of local branch presence and local branch deposits are negative and statistically significant at the 1% level. This finding indicates that the local absence of traditional banks influences the expansion of peer-to-peer lending. As shown in column (2) of Table 2.2, a 1% decrease in the local presence of bank branches leads to about 0.10% increase in the local outreach of peer-to-peer lending. In column (4), we find a similar relation between bank branches local deposits and the amount of online loans issued per 1,000 people. This suggests that the local lending capacity of bank branches affect the local lending levels of peer-to-peer lending. Specifically, there is a high supply of loans issued by online marketplaces in areas where there could be high demand for credit due to the absence of banks. A 1% decrease in the local lending capacity measured by bank deposits level leads to a 0.09% increase in the amount of loans issued by online marketplaces. Overall, these results suggest that individuals turn to peer-to-peer lending when there is lower access to local bank financing. Moreover, these results relate to the main research question of this chapter that is to which extent the emerging online marketplaces can satisfy the needs of those who are underserved by the banking system. The results suggest that online lending marketplaces meet the financial needs of underserved segments of the population.

Our results are consistent with Butler et al. (2016), who find that the local finance capacity of traditional banking affects consumers' borrowing decisions on online marketplaces. They state that borrowers who reside in an area with a greater competitive presence of bank branches are less willing to pay for online loans. Additionally, our findings are in line with the findings of Kim and Hann (2017) who observe that online crowdfunding platforms serve borrowers who lack access to finance from traditional banks. Furthermore, these results are consistent with the argument that banks reduce their loans funding in markets where they have less local informational advantage due to their local absence (Cortés and Strahan 2017). Furthermore, the local absence of banks creates a market gap and thus gives competitors the opportunity to start poaching customers, which in our case is what online marketplaces are doing. Although the coefficient estimate of the bank market concentration (HHI) is only significant in the second model, it has a positive sign in both models. This suggests that higher market concentration and thus lower degree of competition among banks is associated with higher levels of peer-to-peer lending activities. This reinforces our initial conclusion that online marketplaces penetrate markets that could be underserved by mainstream banking. Other results from the first stage of Table 2.2 shows the relation between bank performance controls and the presence of bank branches. Although they are insignificant, the results show that banks with worse performance have a lower presence of bank branches in the local market.

In all specifications, we include year and state dummies to control for unobserved changes in economic conditions (e.g., business cycles, interest rates, and uneven developments across different regions). Furthermore, we provide additional tests in Table 2.2 that our instruments are valid. The Kleibergen-Paap rk LM test rejects the null hypothesis that the equation is under-identified (P-value < 0.05), confirming that the instruments are significantly correlated with the endogenous variable. Moreover, the two instruments pass the Hansen's J-test for over-identifying restrictions. The null hypothesis is that the instruments are valid. We fail to reject the null hypothesis in all model specifications (P-value > 0.05). The Hansen's J-test has a P-value of 0.34 for the first model and is 0.12 for the second model. This test implies that the excluded instruments are correctly excluded from the equation and are valid.

One of the potential concerns for our results is that the average distance to the nearest alternative market is correlated with some economic outcomes or local demand for credit and household credit quality, perhaps driving peer-to-peer borrowing. To address these concerns, we control for local economic conditions and development by including GDP, poverty rate, unemployment rate and the number of business establishments per 1,000 people. In addition, we control for local demand for credit by including debt levels and delinquencies for different debt products, which is similar to Butler et al. (2016) and Wolfe and Yoo (2018). Another potential explanation for our results is that regions with a high average distance to the nearest alternative market are large and expanse land with relatively low economic growth. If this is the case, the instrument of average distance should be negatively associated with branch outreach. However, we find that the instrument of average distance is positively related to branch outreach as a large distance between the local market and the nearest alternative market increases the demand for the local bank branches (banking services). It is unlikely that the average distance to the nearest adjacent region could affect peer-to-peer lending through channels other than the number of bank branches per 1,000 people.

2.4.2.2. The Role of Small Banks in the Local Market

Small banks tend to have a stronger relationship with their local borrowers and have more local knowledge compared to large banks (Berger et al. 2001). Also, because small banks are more likely to serve local and small customers, they play a greater role in the local credit environment (Berger et al. 2004). Small banks are perceived as the repository of soft information due to their decentralized structure, and they tend to act on soft information better than large banks (Berger and Udell 2002; Stein 2002; Berger et al. 2005; Liberti and Mian 2009; Canales and Nanda 2012; Kysucky and Norden 2016). This might give small banks a comparative advantage over large banks in sustaining longer relationships with local borrowers. Moreover, small banks invest in building personal relationships with customers by having geographically concentrated operations (Yeager 2004). With their local knowledge and lower monitoring costs, small banks can be more effective at promoting local economic growth and alleviating credit constraints (Stein 2002; Hakenes et al. 2015), whereas large banks might not alleviate credit constraints as effectively as small banks. In addition, large banks have an impersonal relationship with their customers due to their centralized decision-making structure (Berger et al. 2005; Canales and Nanda 2012). Therefore, we differentiate between small and large banks as they have different roles in the local credit market. We classify small banks based on the bank's size; banks with assets less than $1 billion are considered small (DeYoung et al. 2004; Berger et al. 2017). For robustness, we use $300 million to differentiate between small and large banks (Strahan and Weston 1998; Black and Strahan 2002).

Table 2.3 provides the results of the instrumental variable regressions for small and large banks. The two main independent variables are the total number of large banks and small banks within the three-digit ZIP code area per 1,000 people. The dependent variable in columns (1) and (2) of Table 2.3 is the number of online loans per 1,000 people. Employing the same instruments used in Eq. (2.1) for small and large banks, we find that small banks have a significantly negative effect on the outreach of online marketplaces, while large banks do not have a significant effect. This suggests that online lending marketplaces compete more with small banks than large banks. This is because both peer-to-peer lending platforms and small banks specialize in small loans. A lower existence of small banks, and hence loss of local informational advantage, might result in having underserved small borrowers, leading to greater online marketplaces expansion. The p-value related to the Wald test for equality shows that the difference between the coefficient of small and large banks are significant.

[Insert Table 2.3 here]

In Table 2.4, we compare the average online outreach measured by the number of online loans per 1,000 people across the quintiles of the distribution of branch outreach measured by the number of branches per 1,000 people. For all banks, we observe a decreasing trend of online outreach as we move from the smallest quintile of branch outreach to the largest branch outreach. This is consistent with our first hypothesis that overall peer-to-peer lending activities increase as the local presence of bank branches decrease. Additionally, we compare the difference between large and small banks. The average online outreach increases as the outreach of small bank branches decreases. However, for large banks, the average outreach of peer-to-peer lending increases as the outreach of large bank branches increases. Large banks do not invest in relationships with local borrowers as much as small banks do and they tend to have a centralized decision-making structure that could make it more difficult for local borrowers to access credit; therefore, borrowers will be more inclined to use peer-to-peer lending as a financing alternative. This suggests that the negative relation between the outreach of online lending marketplaces and local branch networks could be driven mainly by the presence of small banks, which, compared to large banks, have greater local knowledge and comparative advantage in relationships with local and small borrowers. The p-values associated with the Wald tests show significant differences in levels of online outreach between the lowest quintile of the distribution of bank branches outreach and the highest quintile.

[Insert Table 2.4 here]

2.4.3. Does Online Outreach Affect Borrower's Default?

In the previous section, we find that the outreach of peer-to-peer lending has an inverse relationship with the local branch network of banks, and hence local access to finance. The absence of banks in the local market could increase market frictions as they lose their local information and monitoring advantage over competitors (Gilje et al. 2016). Peer-to-peer lending might either mitigate or exacerbate these market frictions. On the one hand, online marketplaces might mitigate market frictions by utilizing big data models and non-standard information that is not available to banks in their credit allocation (Morse 2015). On the other hand, online marketplaces might amplify market frictions if lower quality borrowers self-select to online marketplaces (which might have fewer restrictions than banks). This might result in a moral hazard problem as borrowers have greater incentives to engage in risky activities *ex post*, as online loans are not secured by any type of collateral. To identify this issue, we study borrower's creditworthiness by analyzing the performance of online loans *ex post* in relation to the expansion of online marketplaces in the local credit market.

In this model, we use monthly loan-level data of 396,504 loans originated between 2012 and 2015 by Lending Club. We employ only completed loans: loans that borrowers either pay off or default. We define a loan as failed in a given month when a borrower default on their payment. Since our data is a monthly discrete-time panel, we estimate our empirical model using a Complementary log-log model (cloglog), which is equivalent to the Cox proportional hazard model. Allison (1982) defines a discrete-time hazard rate by:

$$P_{it} = \Pr[T_i = t \mid T_i \geq t, X_{it}] \qquad (2.2a)$$

where T is the discrete random variable giving the uncensored time of failure and P_{it} is the conditional probability that a borrower will default at month t given that the borrower has not already defaulted. We employ piece-wise constant specification of the hazard function (i.e., the baseline hazard is constant within each duration interval).[16] We track each loan (borrower) i issued between the year 2012 and 2015 for each month in their credit cycle until it is either paid off or defaulted. This method could partially mitigate the reverse causality issue, as borrower's monthly decision to pay back the loan or default should not directly affect the current local outreach of online marketplaces. More specifically, we use the Complementary log-log function as:

$$\log(-\log(1 - P_{it})) = \alpha_j + \beta' X_{it} \qquad (2.2b)$$

The main independent variable is the natural logarithm of the total number of loans issued by online marketplaces per 1,000 people in a three-digit ZIP code area. For robustness, we use another measure of the outreach of online marketplaces, which is the natural logarithm of the total amount of online loans issued per 1,000 people. In addition to the main independent variable, we include both monthly-varying covariates and monthly-invariant covariates. Monthly-varying covariates include borrower's credit score and the remaining loan balance at the beginning of each month. Monthly-

[16] The reason of dividing survival time at a particular point is to ensure that there is a failure event within each duration interval.

invariant covariates include borrower's debt-to-income ratio, annual income, and the number of open credit accounts. Additionally, we include three-digit ZIP code and state control variables, as in Eq. (2.1). Similarly, we add state and loan origination year dummies.

We report the estimated coefficients of the relationship between the explanatory variables and the risk of borrower default in Table 2.5. Overall, our results suggest that the greater outreach of peer-to-peer lending is significantly and negatively correlated with borrower risk of default. To put the results into economic perspective, the results in column (1) of Table 2.5 show that a 1% increase in the local outreach of online marketplaces is associated with around [exp(0. 0.0702)−1] × 100 = 7% decrease in the hazard rate of borrower default. In column (3) of Table 2.5, we use the total amount of online loans per 1,000 people as a measure of the local outreach of online marketplaces, and our results are consistent. Additionally, our monthly-variant and -invariant control variables' estimates are consistent across different models. The higher the remaining loan balance in each month, the higher the risk of borrower default. Similarly, a high debt-to-income ratio and a high number of open credit account at the time of the loan origination is associated with an increase in borrower's risk of default. On the other hand, an increase in borrower's credit score of each month and a high reported income is associated with a decrease in the risk of borrower default.

[Insert Table 2.5 here]

Our results so far show that online lending marketplaces expand in areas with low presence of traditional banks. Furthermore, the results imply that online lending marketplaces do not exacerbate market frictions and extend credit to lower risk borrowers. Our interpretation of this finding is that low presence of traditional banks will lead to financial frictions and that peer-to-peer lending tends to mitigate these market frictions by expanding in areas with weak lending conditions and by identifying creditworthy borrowers. To confirm that the relationship between local branch networks outreach and the expansion of online marketplaces is not driven by unobserved borrower quality, we include measures of local bank branches outreach to our models of borrower default. If local branch outreach is correlated with unobserved borrower quality, it should have strong predictability power of borrowers' probability of default (Butler et al. 2016). We find that there is an insignificant relationship between branch outreach and the quality of online borrowers in all of our estimated models, suggesting that the baseline results are less likely to be biased by omitted borrow quality variables.

In Table 2.6, we measure the default rate for peer-to-peer lending in the local credit market. We define the local default rate as the share of defaulted borrowers at a three-digit ZIP code level. Additionally, we include a number of online borrower characteristics at a three-digit ZIP code level by including the median of debt-to-income ratio, credit score, number of open accounts, annual income, and loan amount. The aggregated results in columns (1) and (3) of Table 2.6 show that the growth of online marketplaces is associated with lower online default rate in the local credit market. Columns (2) and (4) of Table 2.6 repeat the above analysis, but with adding the branch outreach measures to our models. Consistent with our previous findings, branch outreach measures show an insignificant relationship with the local default rate.

The findings of this section suggest that the increased outreach of peer-to-peer lending is not associated with having lower borrower quality or lower creditworthiness. Peer-to-peer lending platforms meet the needs of safer borrowers and do not increase market frictions in the local market that suffers from the absence of banks. Additionally, peer-to-peer lending utilizes non-standard information and big data models in identifying borrowers, which could give them a comparative advantage in markets where banks lose their local advantage due to their absence.

[Insert Table 2.6 here]

2.4.4. Does the Local Growth of Online Marketplaces affect Borrowers' Financial Welfare?

In this section, we examine to what extent the expansion of peer-to-peer lending in the local market affects borrowers' financial welfare by looking at future changes in borrowers' credit score. If peer-to-peer lending is effective at mitigating market frictions by expanding access to finance to underserved segments and identifying safer borrowers, we should expect an improvement in borrowers' financial welfare (i.e., borrowers' credit score). Individuals might utilize this increased access to credit to consolidate their current debt obligations and hence improve their overall financial position (Bhutta 2014). However, if borrowers are enticed by peer-to-peer lending to over-borrow or if they misestimate the cost of such credit, increased access to credit by online marketplaces might exacerbate individuals' debt problems (Stango and Zinman 2009; Stango and Zinman 2011). Consequently, borrowers' financial position might suffer in the future due to increased debt burdens and thus we should expect a deterioration in their credit scores.

To this end, we use 396,504 completed online loans to test whether the increased expansion of online marketplaces is associated with improvement or deterioration in borrower's financial position by estimating the following equation:

$$FICO\ Change_{\ i,t}\ \% = \alpha + \beta\ \mathrm{Ln}(Online\ Outreach_{z,t}) + \gamma Z_t + Year_t + State_s + \varepsilon_{i,t} \quad (2.3)$$

we track changes in borrower's credit quality by measuring the percentage change in borrower's credit score (FICO) at the end of the loan (i.e., borrower paid off or defaulted on a loan). Therefore, we define $FICO\ Change_{\ i,t}\ \%$ as $[(FICO\ last - FICO\ start)/\ FICO\ start] \times 100$ for borrower i whose online loan is originated at year t. $FICO\ start$ is the borrower's credit score at loan origination and $FICO\ last$ is the borrower's credit score at the end of the loan. Using this measure of borrower welfare should partially address the reverse causality issue since the future changes in borrower's credit score should not directly affect the current local online outreach.

The main independent variable $\mathrm{Ln}(Online\ Outreach_{z,t})$ is the natural logarithm of the outreach of online marketplaces in the three-digit ZIP code area z measured by the aggregated number and amount of online loans issued per 1,000 people. We control for borrower characteristics as in Eq. (2.2b): debt-to-income ratio, annual income, and the number of open accounts. Additionally, we add the credit grade assigned by Lending Club to control for borrower's quality at the time of loan origination. We include three-digit ZIP code and state control variables as usual. Origination year and state dummies are also included. We present the OLS and logit results in Table 2.7.

[Insert Table 2.7 here]

In the first two columns of Table 2.7, we provide the OLS results using the total number of online loans in three-digit ZIP code per 1,000 people as the measure of local online outreach. The results suggest that the increased outreach of online marketplaces is associated with positive changes in borrower's financial position. More specifically, column (1) of Table 2.7 shows that a 1% increase in the local lending activities of online marketplaces is associated with a 0.25% increase in borrowers' credit score at the end of the loan. This implies that the expansion of credit by online marketplaces is not destructive, rather it might be beneficial to individuals' credit position. Borrowers might be effectively using the increased local outreach of peer-to-peer lending and thus eliminating moral hazard problems. Subsequently, this could make borrowers better off and thus help them to gain wider access to the financial system. For robustness, we use a logit model and define the dependent variable as a dummy if the borrower experienced a positive change in their credit scores or not. We present the results of the marginal effects of the logit model in the last two columns of Table 2.7. By this approach, we find similar results to the OLS model. Greater local outreach of online marketplaces is associated with a higher probability that the borrower will experience a positive change in their credit scores at the end of their loan and hence better credit conditions. Our results are consistent for the OLS and logit models when we use the amount of online loans per 1,000 people to measure online marketplaces outreach (See details in Appendix 2.3). Similar to our analysis of borrower default, we add the measure of bank branches outreach to our models in columns (2) and (4) of Table 2.7 and find that it is insignificantly associated with future changes in borrower's credit score. This confirms our suggestion that local branch outreach is uncorrelated with unobserved borrower quality.

In Table 2.8, we aggregate the data at a three-digit ZIP code level to measure the overall impact of the local growth of online marketplaces on borrower's financial welfare. We include the median percentage of change in credit scores at a three-digit ZIP code level as our dependent variable. The results are consistent with our findings of credit improvement on the borrower-level. We find that a greater outreach of peer-to-peer lending in the local credit market is associated with higher overall improvements in the local credit conditions.

[Insert Table 2.8 here]

2.5. Conclusions

This chapter presents evidence on online financial inclusion in underserved areas and its implications for borrowers. Being an alternative solution to bypass banks and borrow directly from investors, peer-to-peer lending can provide access to finance to borrowers who are underserved by mainstream banks. The innovative structure of online marketplaces could reduce information asymmetry through financial disintermediation and the use of non-standard information (Everett 2015; Dorfleitner et al. 2016; Gao and Lin 2016; Freedman and Jin 2017). One possible outcome of this is a reduction of credit rationing, and thus some previously credit-constrained borrowers could be able to access credit (Balyuk 2017). Furthermore, this disintermediation of online marketplaces has some additional implications. By being a low-cost source of credit, online marketplaces might reduce frictions in facilitating access to financial products and can increase efficiency through disintermediation.

The local absence of bank branches affects borrower-lender proximity, which in turn could result in market frictions related to the loss of banks' local informational advantage and increased operating costs. Therefore, this study investigates the relationship between the local growth of online marketplaces and local branch networks. We find that there is an inverse causal relationship between the presence and lending capacity of bank branches and the growth of online marketplaces. This suggests that online marketplaces expand access to finance in underserved areas by providing financial users with a convenient and low-cost lending channel. Second, this study attempt to offer insights into whether such an expansion of peer-to-peer lending in the local market aggravates market frictions that occur due to the absence of banks. If this is the case, the local absence of banks could lead low-quality borrowers to self-select into online loans, thus resulting in moral hazard problems. However, peer-to-peer lending is considered an innovative solution that mitigates market frictions. Specifically, we find that the local growth of online marketplaces is associated with lower borrower risk *ex post*. Additionally, the results suggest that the growth of peer-to-peer lending has positive implications on borrowers' credit welfare.

Online lending marketplaces can be a potential game-changer that revolutionizes the financial market. These marketplaces optimally use technology, big data analytics, and online social data to offer credit products. This innovative industry provides individuals with credit alternatives to banks' credit products. Furthermore, they enable individuals to access finance at a lower cost and provide investors with the opportunity to get a higher return. Due to their unique functions and regulatory oversight, banks will continue to be essential to the financial landscape. However, online marketplaces are structurally transforming the financial market by creating greater diversity. This can benefit users by providing different financial market players and offering different services to fulfill various financial needs.

2.6. Policy Implications

This chapter has several implications for policymakers. In the wake of the financial crisis, banks have significantly reduced their credit supply and closed down branches to cut down costs. This has left consumers looking for an alternative that can meet their financial needs. The findings of this thesis show that online lending marketplaces meet the needs of underserved segments of the population and increase access to finance. Moreover, online lending marketplaces do not exacerbate market frictions. This suggests that policymakers should regard online lending marketplaces as a valid alternative finance that is not destructive but one that can make individuals improve their financial position. This does not necessarily mean that online marketplaces can entirely replace banks. However, they both can co-exist in a wider financial market that can serve different market demands. Overall, this implies that achieving a balanced relationship between banks and online marketplaces is crucial.

2.7. Study Limitations and Areas for Future Research

The literature on online lending marketplaces is relatively new and is growing at an increased pace. This chapter provides several opportunities for future research. One important area is to examine the impact of bank competition in the local credit market on the growth of online lending marketplaces. This chapter focuses on the impact of online lending marketplaces on individuals. Therefore, future research could examine whether the growth of online lending marketplaces as an alternative source of finance is beneficial to small businesses as well. Furthermore, the findings of this chapter suggest that online lending marketplaces compete more with small banks. It would be interesting to further examine the impact of such competition between online lending marketplaces and small banks on the performance of small banks.

Table 2.1: Summary Statistics

VARIABLES	(1) Mean	(2) SD	(3) Min	(4) Max	(5) N
Branch outreach (per 1,000)	0.3396	0.1635	0.0318	2.7972	3,535
Branch deposit (per 1,000)	34,864	285,228	551.03	881,162	3,535
Online outreach (per 1,000)	0.6169	0.4592	0.0017	2.9739	3,310
Online amount (per 1,000)	9,123	7,195	5.8412	51,553	3,310
HHI	0.0694	0.1032	0.0044	1	3,535
Median branch age	32.4987	16.4627	8	113	3,535
Median return on assets	0.0047	0.0009	0.0010	0.0090	3,535
Median ALLL	0.0095	0.0019	0.0036	0.0171	3,535
Three-digit ZIP code level controls:					
House price index	401.23	230.7643	101	2,011	3,508
Percentage of white population	0.7961	0.1596	0.0310	0.9866	3,535
Percentage of male population	0.4948	0.0175	0.4265	0.8805	3,535
Poverty rate	0.1580	0.0556	0.0362	0.4203	3,535
Business establishments (per 1,000)	24.0840	26.4358	3.2724	949.915	3,535
Unemployment rate	0.0863	0.0277	0	0.2508	3,535
Percentage of over 25 population with bachelor degree	0.1625	0.0569	0.0305	0.4384	3,535
State Level controls:					
Credit card delinquency rate	8.1235	2.07	3.5	17	3,535
Auto delinquency rate	3.2342	1.1248	1	7	3,535
Mortgage delinquency rate	3.2071	2.2303	0.5	16	3,535
Credit card per capita	2,699	449.3	1,650	3,980	3,535
Auto loans per capita	3,622	654.1494	2,280	6,070	3,535
Mortgage per capita	29,927	10,350	14,340	58,930	3,535
GDP	48,306	9,875	31,337	163,270	3,535

This table provides the following summary statistics of the main and control variables used in this study: the average value (Mean), the standard deviation (SD), the minimum value (Min), the maximum value (Max), number of observations (N). All the variables are defined in Appendix 2.1.

Table 2.2: Online Outreach and Bank Branches Outreach

	Model (1)		Model (2)	
VARIABLES	(1) First stage	(2) Online Outreach	(3) First stage	(4) Online Amount
Average Distance	0.0013***		0.0008*	
	(0.0003)		(0.0005)	
Branch Outreach in 2000 (ln)	0.5947***			
	(0.0182)			
Branch Deposit in 2000 (ln)			0.6237***	
			(0.0219)	
Branch Outreach (ln)		-0.1027***		
		(0.0367)		
Branch Deposit (ln)				-0.0917***
				(0.0316)
HHI	-0.0934***	0.0494	2.9171***	0.3520***
	(0.0340)	(0.0606)	(0.1657)	(0.1194)
Median Branch Age	0.0022***	0.0005	0.0013	0.0003
	(0.0008)	(0.0008)	(0.0008)	(0.0010)
Median Return on Assets (ln)	0.0048	-0.1214***	0.0995	-0.0666
	(0.0275)	(0.0448)	(0.0614)	(0.0532)
Median ALLL (ln)	-0.0313	0.1141*	-0.2486***	0.0888
	(0.0345)	(0.0669)	(0.0673)	(0.0795)
Observations	3,278	3,278	3,278	3,278
Three-digit ZIP code level controls	Yes	Yes	Yes	Yes
State Level controls	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
IV tests				
F-Statistics	644.47		411.38	
Under-identifcation test (Kleibergen-Paap rk LM statistic P-value)		0.0000		0.0000
Hansen's Over-identification test (P-value)		0.3407		0.1221

This table provides the main instrumental variable regression of this study using 2SLS. In Model 1, the dependent variable is the natural logarithm of the total number of loans issued by online marketplaces in a three-digit ZIP code area per 1,000 people and the main independent variable is the natural logarithm of the total number of branches in a three-digit ZIP code area per 1,000 people. The first and second columns provide the first and second stage results of Model 1, respectively. In Model 2, the dependent variable is the natural logarithm of the sum of online loans' amount within three-digit ZIP code area per 1,000 people and the main independent variable is the natural logarithm of the sum of banks' branch deposits per 1,000 people. The last two columns report the first and second stage results of Model 2, respectively. Robust standard errors in parentheses.
* and *** indicate significance at the 10% and 1% levels, respectively.

Table 2.3: Online Outreach and Branch Outreach by Bank Size (Small and large Banks)

VARIABLES	(1) Online Outreach	(2) Online Outreach
Small Bank Branches Outreach $1B (ln)	-0.2017***	
	(0.0756)	
Large Bank Branches Outreach $1B (ln)	0.1811	
	(0.1562)	
Small Bank Branches Outreach 300 M (ln)		-0.1784***
		(0.0545)
Large Bank Branches Outreach 300 M (ln)		0.1542
		(0.1214)
HHI	0.0519	0.0456
	(0.0693)	(0.0673)
Median Branch Age	-0.0003	0.0007
	(0.0010)	(0.0010)
Median Return on Assets (ln)	-0.1033*	-0.1455***
	(0.0538)	(0.0535)
Median ALLL (ln)	0.0874	0.1164*
	(0.0795)	(0.0696)
Observations	2,684	2,893
Difference (Wald test)	0.091*	0.049**
Three-digit ZIP code level controls	Yes	Yes
State Level controls	Yes	Yes
State Dummies	Yes	Yes
Year Dummies	Yes	Yes

This table provides the instrumental variable regression using 2SLS. In this table, we separate the outreach of the banking system into small and large banks outreach. The dependent variable is the natural logarithm of the total number of online loans per 1,000 people. The two main independent variables are the natural logarithm of the total number of small and large bank branches using assets thresholds of $1B and $300M, reported respectively. Difference is the p-value of the Wald test for the equality of large bank outreach and small bank outreach. Robust standard errors in parentheses.
*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.4: Distribution of Average Online Outreach by Bank Branches Outreach Quintiles

		(1) = Lowest Branch Outreach	(2)	(3)	(4)	(5) = Highest Branch Outreach	T-test
All Banks (Obs.: 3,535)	Online Outreach (Mean)	.7094	.6768	.6124	.5490	.5176	0.000***
Small Banks (Obs.: 3,535)	Online Outreach (Mean)	.7408	.6847	.6069	.5435	.4835	0.000***
Large Banks (Obs.: 3,535)	Online Outreach (Mean)	.4965	.5594	.5862	.6565	.7729	0.000***

This table provides the mean of the number of online loans per 1,000 people (online outreach) across the quintiles of the distribution of bank branches outreach measured by the number of bank branches per 1,000 people. Where (1) is the lowest quintile and (5) is the highest quintile of bank branches outreach. Small and large banks are defined using assets thresholds of $1B. The t-test shows a significant difference in the mean between the lowest and highest quartile of bank outreach.
*** indicates significance at the 1% level.

Table 2.5: Online Outreach and Borrower Risk

VARIABLES	(1) Clog-log	(2) Clog-log	(3) Clog-log	(4) Clog-log
Online Outreach (ln)	-0.0702**	-0.0654**		
	(0.0282)	(0.0284)		
Branch Outreach (ln)		0.0192		
		(0.0258)		
Online Amount (ln)			-0.0603**	-0.0558**
			(0.0267)	(0.0264)
Branch Deposit (ln)				0.0164
				(0.0101)
Loan Beginning Balance (ln)	0.4043***	0.4043***	0.4045***	0.4044***
	(0.0066)	(0.0066)	(0.0066)	(0.0066)
Last FICO	-0.0373***	-0.0373***	-0.0373***	-0.0373***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Debt-to-income Ratio	0.0054***	0.0054***	0.0054***	0.0054***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Annual Income (ln)	-0.0326***	-0.0327***	-0.0323***	-0.0325***
	(0.0118)	(0.0119)	(0.0119)	(0.0119)
Open Accounts	0.0093***	0.0093***	0.0093***	0.0093***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Observations	7,718,011	7,718,011	7,718,011	7,718,011
Three-digit ZIP code level controls	Yes	Yes	Yes	Yes
State Level controls	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes

This table provides the results of the complementary log-log model. In column (1&2), the main independent variable is the natural logarithm of the total number of online loans per 1,000 people. In column (3&4), the independent variable is the natural logarithm of the total amount of online loans per 1,000 people. The dependent variable is a dummy variable equal to one if a borrower default on the loan in a given month, zero otherwise. Debt-to-income ratio, annual income, and open accounts are winsorized at the 1st and 99th percentile. Standard errors are clustered at the three-digit ZIP code level in parentheses.
** and *** indicate significance at the 5%, and 1% levels, respectively.

Table 2.6: Local Online Default Rate and Online Outreach

VARIABLES	(1) Default Rate	(2) Default Rate	(3) Default Rate	(4) Default Rate
Online Outreach (ln)	-0.0344**	-0.0344**		
	(0.0150)	(0.0151)		
Branch Outreach (ln)		-0.0017		
		(0.0081)		
Online Amount (ln)			-0.0295**	-0.0296**
			(0.0135)	(0.0135)
Branch Deposit (ln)				-0.0022
				(0.0030)
Median Debt-to-income Ratio	0.0037***	0.0037***	0.0037***	0.0037***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Median FICO	-0.0018***	-0.0018***	-0.0019***	-0.0019***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Median number of Open Accounts	0.0045*	0.0045*	0.0045*	0.0045*
	(0.0026)	(0.0026)	(0.0026)	(0.0026)
Median Income (ln)	-0.0557**	-0.0559**	-0.0505*	-0.0506*
	(0.0279)	(0.0280)	(0.0276)	(0.0276)
Median Loan Amount (ln)	0.1014***	0.1015***	0.1139***	0.1140***
	(0.0197)	(0.0197)	(0.0228)	(0.0228)
Observations	3,259	3,259	3,259	3,259
Three-digit ZIP code level controls	Yes	Yes	Yes	Yes
State Level controls	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes

This table provides the results of OLS regressions. In this table, we show the results for the relation between the growth of online marketplaces and default risk at the three-digit ZIP code level. The dependent variable is the local online default rate measured by the number of borrowers who defaulted on their loans over the total number of borrowers in a three-digit ZIP code. In column (1&2), the main independent variable is the natural logarithm of the total number of online loans per 1,000 people. In column (3&4), the main independent variable is the natural logarithm of the total amount of online loans per 1,000 people. Other independent variables are the aggregated online borrower characteristics on a three-digit ZIP code level. Debt-to-income ratio, annual income, and open accounts are winsorized at the 1st and 99th percentile Standard errors are clustered at the three-digit ZIP code level in parentheses.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.7: Online Outreach and Borrower's Financial Welfare

	Model (1)		Model (2)	
VARIABLES	(1) Change in FICO %	(2) Change in FICO %	(3) Positive FICO change	(4) Positive FICO change
Online Outreach (ln)	0.2502**	0.2149**	0.0146***	0.0143***
	(0.1088)	(0.1077)	(0.0053)	(0.0054)
Branch Outreach (ln)		-0.1479		-0.0013
		(0.1102)		(0.0056)
Debt-to-Income Ratio	-0.0956***	-0.0956***	-0.0036***	-0.0036***
	(0.0026)	(0.0026)	(0.0001)	(0.0001)
Annual Income (ln)	0.6043***	0.6046***	0.0073***	0.0073***
	(0.0401)	(0.0400)	(0.0021)	(0.0021)
Open Accounts	-0.0278***	-0.0279***	-0.0012***	-0.0012***
	(0.0038)	(0.0038)	(0.0002)	(0.0002)
Credit Grade:				
Grade B	-0.5470***	-0.5472***	0.0028	0.0028
	(0.0412)	(0.0412)	(0.0026)	(0.0026)
Grade C	-2.2192***	-2.2200***	-0.0549***	-0.0549***
	(0.0432)	(0.0432)	(0.0026)	(0.0026)
Grade D	-3.7159***	-3.7165***	-0.1061***	-0.1061***
	(0.0572)	(0.0572)	(0.0029)	(0.0029)
Grade E	-5.2770***	-5.2780***	-0.1579***	-0.1579***
	(0.0718)	(0.0719)	(0.0037)	(0.0037)
Grade F	-6.5045***	-6.5058***	-0.1985***	-0.1985***
	(0.1095)	(0.1094)	(0.0049)	(0.0049)
Grade G	-7.3595***	-7.3610***	-0.2240***	-0.2240***
	(0.2211)	(0.2212)	(0.0089)	(0.0089)
Observations	396,504	396,504	396,504	396,504
Three-digit ZIP code level controls	Yes	Yes	Yes	Yes
State Level controls	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes

This table reports the results of Eq. (2.3). In Model 1, we provide the results of the OLS regression using the natural logarithm of the total number of online loans as the main independent variable. The main dependent variable is the percentage change in borrower's FICO at the end of the loan. In Model 2, we present the marginal effects of the logit regression. The dependent variable is whether a borrower experienced a positive credit score change at the end of the loan. The base category for credit grade is grade A. Debt-to-income ratio, annual income, and open accounts are winsorized at the 1st and 99th percentile. Standard errors are clustered at the three-digit ZIP code level in parentheses.
** and *** indicate significance at the 5%, and 1% levels, respectively.

Table 2.8: Average Local Change in FICO and Local Online Outreach

VARIABLES	(1) Change in FICO % (Median)	(2) Change in FICO % (Median)	(3) Change in FICO % (Median)	(4) Change in FICO % (Median)
Online Outreach (ln)	1.0413***	1.0315***		
	(0.3260)	(0.3279)		
Branch Outreach (ln)		-0.2188		
		(0.2063)		
Online Amount (ln)			1.0076***	1.0070***
			(0.2818)	(0.2822)
Branch Deposit (ln)				-0.0268
				(0.0706)
Median Debt-to-income Ratio	-0.0507	-0.0510	-0.0549	-0.0551
	(0.0382)	(0.0381)	(0.0380)	(0.0379)
Median FICO	0.0068	0.0072	0.0079	0.0079
	(0.0120)	(0.0121)	(0.0114)	(0.0114)
Median number of Open Accounts	-0.1238	-0.1248	-0.1263	-0.1263
	(0.0786)	(0.0788)	(0.0793)	(0.0793)
Median Income (ln)	0.6563	0.6381	0.2422	0.2425
	(0.7760)	(0.7781)	(0.7438)	(0.7437)
Observations	3,259	3,259	3,259	3,259
Three-digit ZIP code level controls	Yes	Yes	Yes	Yes
State Level controls	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes

In this table, we show the results for the relation between the growth of online marketplaces and local credit improvement on a three-digit ZIP code level using OLS regression. The dependent variable is the median percentage change for borrowers in a three-digit ZIP code. In column (1&2), the main independent variable is the natural logarithm of the total number of online loans per 1,000 people. In column (3&4), the main independent variable is the natural logarithm of the total amount of online loans per 1,000 people. Other independent variables are the aggregated online borrower characteristics at the three-digit ZIP code level. Debt-to-income ratio, annual income, and open accounts are winsorized at the 1st and 99th percentile. Standard errors are clustered at the three-digit ZIP code level code in parentheses.

*** indicates significance at the 1% level.

Appendix 2.1: Variables Definitions

Variable	Description	Source
Branch outreach	The total number of banks branches in a three-digit ZIP code area per 1,000 people.	FDIC
Branch Deposit	The sum of banks branches deposits in a three-digit ZIP code area per 1,000 people.	FDIC
Online Outreach	The total number of online loans applications in a three-digit ZIP code area per 1,000 people.	Lending Club
Online Amount	Sum of the total amount of online loans application in a three-digit ZIP code area per 1,000 people.	Lending Club
Herfindahl-Hirschman Index (HHI)	The local market concentration based on branch deposits within the three-digit ZIP code area.	FDIC
Median ROA	The median return on assets ratio of banks within the three-digit ZIP code area (Ratio of net income to total assets).	Consolidated Report of Condition and Income.
Median ALLL	The median allowance for loan and lease losses of banks within the three-digit ZIP code area (Ratio of allowance for loan and lease losses to total assets).	Consolidated Report of Condition and Income.
Median Branch Age	The median age of branches within the three-digit ZIP code area at the reporting year (reporting year - branch year of incorporation).	FDIC
Panel A: Three-digit ZIP code Controls		
House-price Index (HPI)	Annual House price index.	Office of Federal Housing Finance Agency
White population %	The percentage of the white population.	American Community Survey 5-year estimates (census bureau)
Male population %	The percentage of the male population.	American Community Survey 5-year estimates (census bureau)

Percentage of over 25 population who hold at least a bachelor's degree	Percentage of the population aged 25 years and over with at least a bachelor's degree.	American Community Survey 5-year estimates (census bureau)
Unemployment rate	The number of unemployed individuals as a percentage of the labor force.	American Community Survey 5-year estimates (census bureau)
Poverty rate	Below poverty level population as a percentage of total population for whom poverty status is determined.	American Community Survey 5-year estimates (census bureau)
Business establishments per 1,000 people	The total number of business establishments within a three-digit ZIP code area per 1,000 people except for institutions that carry lending activities and perform any other activities related to finance and insurance.	ZIP code Business Patterns from U.S census bureau
Panel B: State-level controls		
Real GDP per capita	Real per capita GDP.	Bureau of Economic Analysis
Credit Card delinquency rate	Percent of Credit Card Debt Balance 90+ Days Delinquent.	New York Fed/Equifax Consumer Credit panel
Auto delinquency rate	Percent of Auto Debt Balance 90+ Days Delinquent.	New York Fed/Equifax Consumer Credit panel
Mortgage delinquency rate	Percent of Mortgage Debt Balance 90+ Days Delinquent.	New York Fed/Equifax Consumer Credit panel
Credit card per capita	Credit Card Debt Balance per Capita.	New York Fed/Equifax Consumer Credit panel
Auto loans per capita	Auto Debt Balance per Capita.	New York Fed/Equifax Consumer Credit panel

Mortgage per capita	Mortgage Debt Balance per Capita (excluding HELOC).	New York Fed/Equifax Consumer Credit panel
Panel C: Instrumental Variables		
Average Distance	Average distance to the nearest three-digit ZIP code area in miles.	National Bureau of Economic Research
Branch outreach in 2000	Total number of banks branches in a three-digit ZIP code area per 1,000 people in the year 2000.	FDIC
Branch Deposit in 2000	Sum of banks branches deposits in a three-digit ZIP code area per 1,000 people in the year 2000.	FDIC
Panel D: Lending Club loan applications variables		
Loan beginning balance	The remaining loan balance at the beginning of each month.	Lending Club
Last FICO	The last pulled Credit score at the beginning of each month.	Lending Club
Debt-to-income ratio	A ratio calculated using the borrower’s total monthly debt repayments on the total debt obligations, excluding mortgage and the requested LC loan, divided by the borrower’s self-reported monthly income.	Lending Club
Annual Income	The self-reported annual income provided by the borrower.	Lending Club
Open Accounts	The number of open credit lines in the borrower's credit file.	Lending Club
Credit Grade	Credit grade assigned by Lending Club.	Lending Club

Appendix 2.2: Online Outreach and Bank Branches Outreach (OLS Results)

VARIABLES	(1) Online Outreach	(2) Online Amount
Branch Outreach (ln)	-0.0724**	
	(0.0315)	
Branch Deposit (ln)		-0.0209
		(0.0203)
HHI	0.0549	0.1309
	(0.0816)	(0.1039)
Median Branch Age	0.0004	0.0001
	(0.0008)	(0.0010)
Median Return on Assets (ln)	-0.1243**	-0.0733
	(0.0487)	(0.0563)
Median ALLL (ln)	0.1170	0.1022
	(0.0734)	(0.0856)
Observations	3,286	3,286
Three-digit ZIP code level controls	Yes	Yes
State Level controls	Yes	Yes
State Dummies	Yes	Yes
Year Dummies	Yes	Yes

This table provides the OLS results of our main model. In Column (1), the dependent variable is the natural logarithm of the total number of loans issued by online marketplaces in a three-digit ZIP code per 1,000 people and the main independent variable is the natural logarithm of the total number of branches in three-digit ZIP code per 1,000 people. In Column (2), the dependent variable is the natural logarithm of the sum of online loans' amount within three-digit ZIP code per 1,000 people and the main independent variable is the natural logarithm of the sum of banks' branch deposits per 1,000 people. Standard errors are clustered at the three-digit ZIP code level in parentheses.
** indicates significance at the 5% level.

Appendix 2.3: Online Amount and Borrower's Financial Welfare

	Model (1)		Model (2)	
VARIABLES	Change FICO %	Change FICO %	Positive FICO change	Positive FICO change
Online Amount (ln)	0.2174**	0.2206**	0.0151***	0.0154***
	(0.1010)	(0.1010)	(0.0050)	(0.0051)
Branch Deposit (ln)		0.0146		0.0017
		(0.0431)		(0.0021)
Debt-to-Income ratio	-0.0956***	-0.0957***	-0.0036***	-0.0036***
	(0.0026)	(0.0026)	(0.0001)	(0.0001)
Annual Income (ln)	0.6026***	0.6023***	0.0072***	0.0072***
	(0.0400)	(0.0400)	(0.0021)	(0.0021)
Open Accounts	-0.0278***	-0.0278***	-0.0012***	-0.0012***
	(0.0038)	(0.0038)	(0.0002)	(0.0002)
Credit Grade:				
Grade B	-0.5470***	-0.5470***	0.0028	0.0028
	(0.0412)	(0.0412)	(0.0026)	(0.0026)
Grade C	-2.2193***	-2.2192***	-0.0549***	-0.0549***
	(0.0432)	(0.0433)	(0.0026)	(0.0026)
Grade D	-3.7160***	-3.7159***	-0.1061***	-0.1061***
	(0.0572)	(0.0572)	(0.0029)	(0.0029)
Grade E	-5.2774***	-5.2773***	-0.1580***	-0.1580***

	(0.0718)	(0.0718)	(0.0037)	(0.0037)
Grade F	-6.5049***	-6.5046***	-0.1986***	-0.1985***
	(0.1095)	(0.1095)	(0.0049)	(0.0049)
Grade G	-7.3602***	-7.3600***	-0.2241***	-0.2240***
	(0.2211)	(0.2212)	(0.0089)	(0.0089)
Observations	396,504	396,504	396,504	396,504
Three-digit ZIP code level controls	Yes	Yes	Yes	Yes
State Level controls	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes

This table reports the results of Eq. (2.3). In the first model, we provide the results of the OLS regression using the natural logarithm of the total amount of online loans as the main independent variable. The main dependent variable is the percentage change in borrower's FICO at the end of the loan. In Model 2, we present the results of the logit regression. The dependent variable is whether a borrower experienced a positive change in credit score at the end of the loan. The base category for credit grade is grade A. Debt-to-income ratio, annual income, and open accounts are winsorized at the 1st and 99th percentile. Standard errors are clustered at the three-digit ZIP code level in parentheses.
** and *** indicate significance at the 5%, and 1% levels, respectively.

Chapter 3

Does Social Capital Matter? Evidence from Peer-to-Peer Lending

3.1. Introduction

Along with human and physical capital, social capital has received much attention as these three forms of capital are critical to community growth and the promotion of productivity (Ostrom 2000; Iyer et al. 2005). In general, social capital refers to the norms and networks that arise from social interactions and which facilitate cooperative actions (Woolcock and Narayan 2000; Woolcock 2001). Social capital affects economic outcomes by easing the dissemination of information through social relations, effective norms, cooperative behavior, and effective sanctions (Grootaert and Van Bastelar 2002). In addition, social capital constrains opportunistic behavior and fosters altruistic inclinations by both individuals and firms (Coleman 1988; Knack and Keefer 1997). This can mitigate information asymmetry and reduce the free-rider problem as the trust between parties increases (Durlauf and Fafchamps 2004; Guiso et al. 2011; Gupta et al. 2018), which in turn reduces transaction costs. Financial contracts are considered the ultimate trust-intensive contracts (Arrow 1972). Hence, as social capital is an important determinant of trust, it has a major impact on financial market development and financial transactions (Guiso et al. 2004).

In this chapter, we examine the impact of region's social capital on lending conditions and individual economic outcomes using data from Lending Club, a leading online lending marketplace in the U.S. where borrowers and investors are connected directly online. Marketplace lending is increasingly growing as an innovative alternative form of consumer finance. According to TransUnion, FinTech loans counted for 38% of the total U.S. unsecured personal loan balances at the end of 2018 increasing from only 5% in 2013.[17] On the other hand, there is growing evidence on the benefits of social capital at both the macro and individual levels (Knack and Keefer 1997; La Porta et al. 1997; Knack 2002; Hong et al. 2004; Brown et al. 2008; Jha and Cox 2015; Javakhadze et al. 2016).

To be more specific, we explore whether the economic benefits of social capital transmit to the online environment by producing better lending conditions. We examine the impact of regions' social capital on borrowers' interest rates and the likelihood of failure in peer-to-peer lending.[18] Individuals in high social capital communities tend to trust each other more and individuals' trusting behavior and his or her own trustworthiness are highly correlated (Glaeser et al. 2000; Jiang and Lim 2018). Furthermore, social connection is strongly related to individuals' trustworthiness (Glaeser et al. 2000). Therefore, social capital can act as an informational cue that signal borrower's trustworthiness. Furthermore, economic transactions can be achieved at a lower cost in higher trust regions as information

[17] For details, see https://newsroom.transunion.com/fintechs-continue-to-drive-personal-loans-to-record-levels/

[18] We provide an illustration of this relationship in Appendix A.

asymmetry and adverse selection is reduced (Knack and Keefer 1997). Given that social capital signals individuals' trustworthiness, borrowers in regions with high social capital should be more likely to receive lower interest rates ex ante. Ex post, these borrowers should be less likely to default as social capital constrains opportunistic behavior. There could be concerns that local economic and social characteristic is irrelevant in online lending. However, gathering information beyond hard information is critical in financial markets (Petersen and Rajan 2002; Lin et al. 2013). Durate et al. (2012) find that impressions of trustworthiness are important in online lending. Furthermore, the findings of Butler et al. (2016) suggest that local economic conditions affect online lending decisions. This implies that the characteristics of local markets still play an important role in online marketplaces.

We compute the social capital index for U.S. three-digit ZIP code prefix areas by following Rupasingha et al.'s (2006) method. In this method, social capital is divided into two components: norms and networks. Norms comprise the voter turnout rate in the latest presidential election and the U.S. census response rate. This component reflects social values such as altruism, civic cooperation, and mutual trust (Knack 2002; Guiso et al. 2004; Guiso et al. 2011). The existence of effective norms results in internal and external sanctions that constrain individuals' opportunistic behavior (Coleman 1988; Elster 1989). On the other hand, networks comprise social associations and non-profit organizations. These represent the density of social networks and interactions that could facilitate communication, the flow of information, and the enforcement of civic norms (Putnam 1993). Moreover, social and civic associations create social capital by increasing the possibility of learning about civic values and norms through social interactions (Stolle 2003). Using four variables, we employ a principal component analysis to compute a three-digit ZIP code social capital index.

Our empirical analysis shows that social capital has a negative and statistically significant relationship with the interest rates charged on online loans after controlling for borrower attributes, loan characteristics, three-digit ZIP code demographic controls, state-level factors, and state and year fixed effects. To have a better understanding of the role played by social capital, we consider that borrowers could have different levels of moral hazard. Our results show that the effect of social capital on interest rates is stronger for borrowers who have higher levels of moral hazard. Specifically, the negative impact of social capital on interest rates is stronger for borrowers with lower credit scores, lower income levels, and higher debt-to-income ratios. This implies that social capital could convey information about borrowers beyond hard information. Moreover, if social capital constrains individuals' opportunistic behavior, we should find a negative association between social capital and borrower default. Using different definitions of default, we find that borrowers in high social capital regions are less likely to default on their loans. The reason behind this is that individuals in high social capital communities have stronger norms and hence are more likely to repay their debts on time, as they feel obligated to behave in an altruistic manner (Portes 1998; Guiso et al. 2004).

Our main results are robust to several robustness tests. We find that social capital reduces interest rates when we implement an instrumental variable approach to account for the endogeneity problem due to omitted variables that are correlated with both our social capital index and the interest rates on online loans. In addition, our results are robust to using alternative definitions of social capital. We use organ donation at the state level and a dummy for regions with high social capital.

Furthermore, the results are consistent when we use social associations and non-profit organizations separately as alternative measures of social capital. Overall, the findings of this study indicate that borrowers in high social capital regions incur lower interest rates and are less likely to default than borrowers in regions with low social capital.

The remainder of this chapter proceeds as follows. In section 3.2, we provide the theoretical framework of this study. Section 3.3 provides a description of data and the construction of variables. Section 3.4 presents the main results of this chapter and a number of robustness tests. Section 3.5 provides additional results. Lastly, Section 3.6 concludes the chapter.

3.2. Literature Review

3.2.1. Social Capital

The theory of social capital has become popular among sociologists, economists, and political scientists (Arrow 2000). Social capital complements the concepts of physical and human capital and the three forms of capital are essential for the growth of society (Ostrom 2000). While physical capital has to do with the materials that facilitate production (Coleman 1988), human capital is concerned with the skills and knowledge acquired by individuals (Schultz 1961; Becker 1994). Broadly speaking, social capital can be understood as the social relations and networks that affect personal interactions and the norms and trust that arise from them. While physical and human capital are regarded as individual assets, social capital is considered a collective asset that resides in social relations and networks (Hooghe and Stolle 2003).

Despite the increased attention to social capital and its impact, the definition of social capital has remained elusive. One of the first authors to formally define social capital is Coleman (1988, p. 98), who defines it in terms of its function, stating that "it is not a single entity but a variety of different entities, with two elements in common: they all consist of some aspect of social structures, and they facilitate certain actions of actors within the structure." Furthermore, Coleman (1990, p. 304) state that social capital facilitates the accomplishment of certain aims that could not be achieved without its presence or that could only be attained at an increased cost. The seminal work of Putnam (1993) popularized the notion of social capital among policymakers by transforming the concept into an attribute of larger social units: communities and societies (Portes and Vickstrom 2011). Putnam (1993, p. 167) defines social capital as "features of social organization, such as trust, norms, and networks, that can improve the efficiency of society by facilitating coordinated actions." Thus, Putnam focuses on networks of civic engagement[19] and trust as an essential form of social capital. He argues that by fostering norms of reciprocity and improving the flow of information and communication, civic engagement generates social trust. Trust, in turn, facilities cooperation among members of the community. Woolcock and Narayan (2000), Woolcock (2001) argue that there is an emerging consensus on defining social capital as the norms and networks that facilitate collective action.

3.2.2. Characteristics of Social Capital

One main feature that distinguishes social capital from human and physical capital is that it is considered a public good. Social capital exists in the structure of social relations among individuals and hence it is available to all members of the community (Coleman 1988). Consequently, social capital is less tangible than human and physical capital. Given that it is a public good, social capital depends on individuals' will to sustain it and to not be free riders (Lin 1999). Furthermore, Lin (1999) provides

[19] According to Putnam (1993), examples of networks of civic engagement are sports clubs, choral societies, cooperatives, and neighborhood associations.

several elements that may explain why social capital functions in ways that are not accounted for by economic or human capital. First, social capital facilitates *the flow of information* in imperfect markets. This provides individuals with more sources of information about opportunities and choices that otherwise would not be available to them. Second, social ties can be perceived as indications of individuals' *social credentials*, i.e. individuals can access resources through their social relations. Finally, social relations provide individuals with recognition and *reinforcement*, which are critical for their mental health.

Surveying the social capital literature, Durlauf and Fafchamps (2004, p. 5) conclude that the presence of social capital produces positive externalities for all members of a group, whether it is a community or a social group. These externalities are obtained through shared trust, norms, and values and their subsequent effects on individuals' behavior. In turn, informal types of organization based on social networks and associations result in shared trust, norms, and values. In addition, social capital deteriorates with disuse. Therefore, continued interaction, reciprocity, and trust are essential to maintain social capital (Ostrom 2000). On the other hand, Uphoff (2000) proposes that social capital can be distinguished into two interrelated categories: cognitive and structural. The structural category pertains to social organization, such as civic associations and engagement. The cognitive category relates to the mental processes that are reinforced by norms, values, and beliefs.

3.2.3. Social Capital and Economic Outcomes

Social capital provides an approach to integrating the perspectives of sociologists and economists by establishing that the social interactions of communities and institutions can shape economic development (Woolcock and Narayan 2000). There is considerable evidence confirming that societies with high levels of social capital and trust experience enhanced economic outcomes (Knack and Keefer 1997; Zak and Knack 2001; Francois and Zabojnik 2005; Algan and Cahuc 2010; Bjørnskov 2012). Measuring social capital in terms of the social trust, Whiteley (2000) argues that its impact on economic growth is as strong as that of human capital. Social capital fosters economic growth by reducing transaction costs, mitigating principal-agent problems and promoting innovative and entrepreneurial activities (Knack and Keefer 1997; Rupasingha et al. 2000; Whiteley 2000). Bjørnskov (2012) points out that social trust reduces the complexity of society (Luhmann 1979) and thus makes it steadier and more predictable, which in turn lowers transaction costs. On the other hand, a lack of social capital requires more external control and legal enforcement, which can discourage innovation and investment (Knack and Keefer 1997; Rupasingha et al. 2000). Using measures of civic norms and social trust from the World Values Survey, Knack and Keefer (1997) find that these measures contribute to GDP growth, national investment levels, and lower rates of corruption. Also using indicators from the World Values Survey, La Porta et al. (1997) report a similar relationship between social trust and economic outcomes. Lastly, Zak and Knack (2001) show that social trust is negatively related to income inequality.

A number of studies establish that stock market participation is higher in more sociable and more trusting communities (Hong et al. 2004; Brown et al. 2008; Guiso et al. 2008; Georgarakos and Pasini 2011; Changwony et al. 2014). They conclude that social interactions generate social capital, which facilitates the accessibility of information regarding the stock market. Furthermore, individuals in high social capital regions will have more trust in the financial system and thus have higher participation rates. Using data from the Health and Retirement study, Hong et al. (2004) find that social households are four percent more likely to participate in the stock market than non-social households. Guiso et al. (2008) report that trusting individuals have a higher probability of buying stocks and are more likely to invest in risky assets. In addition, Guiso and Jappelli (2005) find that households' financial awareness is positively associated with social interaction. Guiso et al. (2004) investigate the various links between social capital and financial development by studying households' financial choices. They document that households in high social capital areas are more likely to invest in stocks, obtain credit, and hold less cash.

Another strand of the literature studies the benefits of social capital for corporations. These studies propose that social capital limits risk-taking and opportunistic behavior by firms through imposing social and behavioral norms. Jha and Cox (2015) argue that social capital is the most accurate concept to explain altruistic inclinations. Examining the relationship between social capital in U.S. counties and firms' corporate social responsibility, Jha and Cox (2015) find that firms located in high social capital counties are more inclined to be socially responsible. Hoi et al. (2018) find a similar positive relationship between social capital and corporate social responsibility activities. In addition, Lins et al. (2017) find that during the financial crisis firms with high social capital experienced higher stock returns, greater profitability, and better growth than firms with low social capital. Levine et al. (2018) report that during banking crises social trust facilitates firms' access to informal credit channels and that firms in high-trust countries do not suffer as much reduction in profits and employment as firms operating in lower-trust countries. They argue that social trust reduces the adverse effects of banking crises on firms. Furthermore, social capital decreases firms' cost of equity by reducing information asymmetry and agency problems (Ferris et al. 2017; Gupta et al. 2018). In addition, firms located in high social capital regions hold less cash and pay lower audit fees (Jha and Chen 2014; Habib and Hasan 2017). Hasan et al. (2017a) find that social capital is negatively associated with corporate tax avoidance practices. Lastly, social capital enables firms to incur lower interest rates and looser non-price loan terms (Hasan et al. 2017b).

3.2.4. Relation to Existing Literature

This study extends the growing body of literature that documents the economic benefits of social capital at the macro and individual levels by highlighting the significant value of social capital for online borrowers, in particular for borrowers who are more susceptible to moral hazard problems. In addition, this study contributes to the group of studies that focus on the impact of the social environment on debt contracting. While most studies examine the debt-contracting outcome for corporations in high social capital regions (Cheng et al. 2017; Hasan et al. 2017b), we investigate how community social capital affects individuals' economic outcomes.

Regarding the online marketplace context, most studies examine the role of online social networks and online friendships in peer-to-peer lending (Lin et al. 2013; Freedman and Jin 2017). However, we focus on the role of community social capital in online marketplaces. Lin et al. (2013) report that borrowers with online friends are more likely to obtain funding and receive lower interest rates on their loans. Duarte et al. (2012) find that borrowers who appear more trustworthy are more likely to be funded and have lower interest rates. Lin and Pursiainen (2018) study the impact of the social capital of the county where the entrepreneur resides on the performance of crowdfunding campaigns. They find that social capital has a positive impact on crowdfunding campaigns.

3.3. Data Description and Construction of the Variables

3.3.1. Main Specification

We employ the following model to investigate the individual benefits of social capital in online lending marketplaces.

$$Interest\ Rate_{i,t} = Social\ capital_{z,t} + Borrower\ Charactersitcs_{i,t} + Loan\ Charactersitcs_{i,t} + Demographic\ Controls_{z,t} + State\ Controls_{s,t} + Year_t + State_s + \varepsilon_{i,t} \qquad (3.1)$$

where the dependent variable $Interest\ Rate_{i,t}$ is the borrower's interest rate and the main independent variable $Social\ capital_{z,t}$ is the three-digit ZIP code area's social capital in a specific year. Providing that the benefits of social capital transfer to individuals, we expect a negative relation between the social capital of the region where the borrower resides and the interest rate charged on online loans. Following previous literature (Durate et al. 2012; Lin et al. 2013; Emekter et al. 2015; Iyer et al. 2016), we control for borrower-specific and loan-specific variables that can determine the interest rate charged. Iyer et al. (2016) show that online lenders evaluate borrowers credit risk based on hard and soft information about borrowers. Similarly, Herzenstein et al. (2008) show that borrower's demographic characteristics, financial strength, and loan characteristics have a significant impact on borrower's likelihood to obtain credit in peer-to-peer lending. While determining the impact of online social connection on online loans outcomes, Lin et al. (2013) control for borrower's hard credit information (e.g., Debt-to-income ratio, length of credit history, and loan purpose). Furthermore, borrowers with higher credit risk have a higher probability of default which in turn affect the interest rate charged (Emekter et al. 2015). Therefore, it is important to control for borrower's credit history and demographic characteristics while evaluating the impact of social capital on interest rate. For $Borrower\ Charactersitcs$, we include the borrower's credit score at the time of the loan application (*FICO*), debt-to-income ratio (*DTI*), revolving line utilization rate (*Revol Util*), number of open credit accounts (*Open accounts*), and the length of credit history in months (*Credit age*). In addition, we include the natural logarithm of the borrower's annual income (*Ln(Income)*) and homeownership status (*Homeownership*). For $Loan\ Charactersitcs$, we incorporate the following variables: the natural logarithm of the loan amount (*ln(Loan amount)*) and the duration of the loan (*Loan term*). We also add loan purpose fixed effects to our specification.

There could be concerns that our measure of social capital might be correlated with other demographic variables that in turn could affect the interest rate charged. In order to address these concerns, we add a number of demographic and geographical characteristics at the three-digit ZIP code level. For instance, Helliwell and Putnam (2007), and Putnam (1995) argue that education is a key predictor of civic engagement due to the inclinations, resources, and skills that highly educated individuals acquire. Therefore, we control for educational attainment in the three-digit ZIP code area measured by the percentage of 25 years old and over population with a bachelor's degree. In addition, we include the unemployment rate, the percentage of the male population, the percentage of the population that are married, and the percentage of the population that are native-born in order to isolate the potential effects of local demographic characteristics on the production of social capital (Putnam 1995;

Rupasingha et al. 2006; Hasan et al. 2017b). For instance, married people are more trusting and engage more in civic activates than single people (Putnam 1995). $Demographic\ Controls_{z,t}$ reflects all the demographic controls at the three-digit ZIP code area level. We obtain our demographic measures from the American Community Survey 5-year estimates.

We control for credit demand and credit quality at the state level in order to account for state-level differences that could affect interest rate (Butler et al. 2016). We include states' per capita auto debt balances, per capita credit card balances, and per capita mortgage debt balances. In addition, we control for the percentage of auto debt, credit card debt, and mortgage debt balances that are more than or equal to 90 days overdue. These data are available from the New York Fed/Equifax Consumer Credit Panel. We control for the state's real GDP per capita obtained from the Bureau of Economic Analysis. All the state-level control variables are included in $State\ Controls_{s,t}$. Lastly, to control for unobserved macroeconomic characteristics that vary with time, we include $Year_t$ and $State_s$ to capture year and state fixed effects, respectively.

3.3.2. Construction of the Social Capital Index

Social capital is the main independent variable of interest in this study. To construct our measure of social capital, we adopt an approach that has commonly been used in previous studies (Putnam 2007; Chetty et al. 2014; Jha and Cox 2015; Jin et al. 2017; Hasan et al. 2017a; Hasan et al. 2017b; Lin and Pursiainen 2018). This measure is based on Rupasingha et al. (2006), who use a range of secondary data to construct a proxy of social capital. Our social capital indicator consists of two measures of *norms* and two measures of *social networks*. The *norms* measures are voter turnout in the most recent U.S. presidential election[20] and the response rate to the U.S. Census Bureau's decennial census (Alesina and La Ferrara 2000; Knack 2002).[21] These measures reflect reciprocity and civic cooperation, as there is no legal obligation or direct benefit from voting or participating in the census (Knack 2002; Guiso et al. 2004; Guiso et al. 2011). Instead, these acts could be driven by individuals' loyalty and sense of duty to society (Knack 1992). Moreover, the benefits of voting and census participation accrue to the whole community or society.

The second measure, *social network,* is comprised of the number of social associations[22] and the number of tax-exempt non-profit organizations.[23] Social associations include religious organizations, bowling centers, golf courses and country clubs, physical fitness facilities, sports clubs, political organizations, labor organizations, business associations, professional organizations, and civic and social organizations. We normalize both variables by the three-digit ZIP code area population (per 1,000). The measures of social networks represent horizontal social interactions among individuals. A high density of social networks promotes social cooperation and solidarity among members (Putnam 1993). In addition, in regions with dense social and civic associations, there are more opportunities to learn cooperative values and norms, providing a setting for the development of social trust (Stolle 2003). We use principal component analysis (PCA) to calculate our index on an annual basis from 2012 until 2016 using the above-mentioned four measures. PCA derives linear combinations of the original variables that contain most of the variables' variance.[24]

[20] We use the voter turnout in the 2016 presidential election. Our results are robust to using the voter turnout in the 2012 presidential election.

[21] These two variables are available at the county level. We transform them to three-digit zip code using an allocation method based on the residential ratio for each year. We obtain this data from the U.S. Department of Housing and Urban, available at https://www.huduser.gov/portal/datasets/usps_crosswalk.html

[22] The data on the number of social and civic associations are obtained from ZIP code Business Patterns issued by the U.S. census bureau.

[23] We obtain the data on non-profit organizations from the National Center for Charitable Statistics (NCCS).

[24] Appendix 3.2 provides the eigenvalues and the proportion of each component.

The first component is the linear combination that explains the maximal overall variance. Hence, we define our social capital index as the first principal component for each three-digit ZIP code area in a given year.

3.3.3. Summary Statistics

The data employed in this study are extracted from various sources and cover the period from 2012 to 2016. Data on online loans come from a leading peer-to-peer lending platform in the U.S.: Lending Club. These data provide us with details regarding individuals who received loans from investors using the online marketplace. They include information about the borrower's credit history at the time of the loan application and information regarding the loan received. Lending Club is one of the first online lending marketplaces to be listed on the New York Stock Exchange (NYSE) with a market valuation of $5.4 billion. We employ a number of control variables at the three-digit ZIP code area and state levels from different sources. Table 3.1 provides summary statistics of the main and control variables. Panel A shows the borrower- and loan-specific characteristics of more than a million borrowers/loans, Panel B contains the demographic characteristics at the three-digit ZIP code area level and Panel C presents summary statistics for the state-level controls. The summary statistics for the main variables of interest show that the average interest rate charged for online loans is 13.21. The mean social capital index is -0.70, which is roughly in line with the summary statistics in Jha and Cox (2015) and Hasan et al. (2017b). Appendix 3.3 provides a more detailed description of all the variables used in the chapter and their sources.

[Insert Table 3.1 here]

3.4. Empirical Results

3.4.1. Baseline Regression Results

Table 3.2 presents the results of our main specification using an OLS regression analysis with robust standard errors clustered at the three-digit ZIP code area level. In all the models, the dependent variable is the interest rate and the main independent variable is the social capital index at the three-digit ZIP code area level, where a higher social capital index implies better social capital. In Model 1, we only include borrower-level characteristics. In Model 2, we add borrower-level and loan-level controls. Model 3 includes borrower-level characteristics, loan-level controls, three-digit ZIP code area demographic factors, and state-level controls. Model 4 is the baseline specification. It comprises of borrower-level characteristics, loan-level controls, three-digit ZIP code area demographic factors, state-level controls, and state fixed effects. We control for year fixed effects in all the models to account for unobserved time-varying factors.

This set of analysis addresses our first research question on the impact of social capital on borrower's interest rate. The coefficients estimated for the social capital index are negative and statistically significant for all the models. The results suggest that a higher level of social capital is associated with a lower interest rate. Model 4 shows that a one standard deviation increase in social capital is associated with a decrease in the borrower's interest rate of around 0.02. This supports our initial prediction that social capital provides individuals with better lending conditions by reducing information asymmetry and adverse selection problems. Furthermore, the findings of this study suggest that social capital mitigates financial market inefficiencies through information sharing and trust which in turn helps individuals receive better lending conditions. Overall, the results confirm the economic benefits of social capital at the individual level.

[Insert Table 3.2 here]

These results are in line with signaling and adverse selection theory which posits that adverse selection problems can be mitigated by using signals to convey borrower quality (Akerlof 1970; Spence 2002). Social capital signals borrower's trustworthiness and thus reduces the information gap between borrowers and lenders. This, in turn, lower interest rate as social capital mitigates information asymmetry. Accordingly, our results confirm the significance of signaling in markets that could have higher information asymmetry problems. Our results are consistent with the findings of Hasan et al. (2017b) and Cheng et al. (2017), who find that corporations headquartered in high social capital regions incur a lower cost of bank loans. Our findings are also in line with those of Lin and Pursiainen (2018), who observe a positive relationship between social capital and the performance of crowdfunding campaigns using data from Kickstarter. Table 3.2 also shows that the control variables generally have the expected effect on the interest rate. For example, borrowers with a higher credit score, a higher income level, and longer credit history have lower interest rates, which implies that borrowers with a good credit history and in a good financial position incur lower interest rates. Revolving utilization rate and debt-to-income ratio are positively associated with the interest rate. Regarding loan characteristics, larger loan amounts and longer-term loans are associated with higher interest rates.

3.4.2. Robustness Checks

3.4.2.1. Instrumental Variable approach

Although our baseline specification controls for borrower attributes, loan characteristics, and three-digit ZIP code area and state demographic factors, there might still be unobservable factors that affect social capital and the interest rate. Individuals might self-select into communities based on observed and unobserved characteristics and these same characteristics could be correlated with social capital and the interest rate. This may result in a spurious relationship between social capital and the interest rate. In order to overcome this endogeneity issue, we employ an instrumental variable approach as our identification strategy.

We identify two instruments for our social capital index. The first instrument we employ is racial fragmentation, which has commonly been used in previous studies as an instrument for social capital (Hasan et al. 2017a; Hasan et al. 2017b; Gupta et al. 2018). A number of studies propose that racial and ethnic fragmentation challenge and inhibit social capital (Knack and Keefer 1997; Alesina and La Ferrara 2000; Alesina and La Ferrara 2002; Costa and Kahn 2003; Hero 2003; Delhey and Newton 2005; Putnam 2007; Stolle et al. 2008). Communities that feature high levels of ethnic, racial, and socio-economic fragmentation face more difficulties in creating social capital, trust, and cooperation (Stolle et al. 2008). The negative link between community fragmentation and social capital might be attributable to the argument that trust and cooperation depend on the perceived similarity between oneself and others in the community (Vigdor 2004). A shared identity is accompanied by shared loyalty, shared experiences, and closeness, which in turn facilitate trust and cooperative behavior as the social distance between people decreases (Miller 1995; Alba and Nee 2003; Putnam 2007).

Alesina and La Ferrara (2002) investigate the determinants of social capital. They report that racial fragmentation has a significant negative effect on the degree of participation in social activities. Costa and Kahn (2003) find that racial fragmentation is a significant predictor of lower civic engagement in the form of volunteering and group membership. In addition, their findings show that increased ethnic fragmentation is associated with lower voter turnout. They argue that community fragmentation explains trends in social capital over time. Furthermore, Vigdor (2004) reports that there is a significantly lower census response rate in more heterogeneous counties.

We follow Alesina and La Ferrara (2000) and Alesina and La Ferrara (2002) and define our *racial fragmentation* index as:

$$\text{Racial fragmentation}_z = 1 - \sum_K S_{KZ}^2 \qquad (3.2)$$

This index reflects the likelihood that two individuals randomly drawn from a three-digit ZIP code area belong to different races. S_{KZ} is the share of each race K in the population of three-digit ZIP code area Z and K represents the following races: 1) White; 2) Black or African American; 3) Asian; 4) American Indian or Alaska Native; 5) Native Hawaiian or Other Pacific Islander; 6) other. A higher index indicates increased racial fragmentation. Racial diversity is considered exogenous as the share of each group is relatively stable and it is highly unlikely that there will be a significant shift between groups in a short period of time (Alesina et al. 2003). Therefore, we do not expect racial fragmentation to have a direct relationship with individuals' interest rates.

The second instrument we employ in this chapter is the occurrence of school shootings in the three-digit ZIP code area. School shootings are considered unique and rare events that are unpredictable, but their occurrence has a negative impact on individuals and communities (Muschert 2007; Rocque 2012; Flannery et al. 2013; Wallace 2015). In addition, rampage school shootings challenge the beliefs about community, home, and childhood (Newman et al. 2004). A number of studies argue that school shootings result in fear, insecurity, and moral panics, which are usually fueled by intense media coverage (Burns and Crawford 1999; Altheide 2009; Kupchik and Bracy 2009; Schildkraut et al. 2015). Fear of crime, in turn, could ruin community social cohesion and social trust and raise concerns about the stability of social organization (Hummelsheim et al. 2011). Moreover, fear of crime could result in people avoiding certain areas or changing their routine activities, thus constraining social interactions, and diminishing the chances of participating in social activities (Liska et al. 1988; Stafford et al. 2007). Therefore, we expect the consequences of school shootings in terms of fear, insecurity, and mistrust to negatively affect communities' social capital as they disrupt local social networks and norms. We obtain data on school shootings from the Washington Post.[25] The Washington Post provides data on shootings that have occurred in primary and secondary schools during school hours since the Columbine High School massacre in 1999. We define our instrument *shoot* as a dummy taking the value of 1 if at least one school shooting occurred in the three-digit ZIP code area in a given year. The occurrence of school shootings is random and rare so it is highly unlikely that their occurrence will directly affect individuals' interest rates. Moreover, school shootings are unpredictable so they will only affect individuals' interest rates through their impact on social capital.

Table 3.3 reports the instrumental variable estimates for the impact of region's social capital on borrowers' interest rate in peer-to-peer lending. We include all the

[25] These data are available at https://github.com/washingtonpost/data-school-shootings

control variables specified in the baseline specification. Column (1) reports the coefficients from our first-stage regression of social capital on the racial fragmentation index and on the indicator of the occurrence of a school shooting. The estimated coefficients for both instrumental variables are consistent with our expectation regarding the significance and direction of the relationships. The estimated coefficient for racial fragmentation is highly significant at the 1% level and is negatively associated with social capital, which indicates that the more heterogeneous the community, the lower the social capital index is (Alesina and La Ferrara 2000; Alesina and La Ferrara 2002; Putnam 2007). Similarly, our indicator of school shootings is statistically significant and negatively associated with social capital, which is in line with our prediction that occurrences of school shootings have a negative impact on community social cohesion and social interaction. Generally, the first-stage results confirm that our instruments are strongly related to our endogenous variable.

[Insert Table 3.3 here]

Column (2) in Table 3.3 presents the results of the second-stage regression. As expected, the results show a negative and statistically significant estimate of social capital, indicating that individuals in high social capital regions have a lower interest rate. A one standard deviation increase in the social capital index leads to a reduction of about 0.42 in borrowers' interest rates. The instrumental variable results are in line with our OLS estimation, which indicates a robust negative relationship between social capital and the cost of online loans.[26] Overall, these results suggest that social capital

[26] The IV estimates could be larger than the OLS estimates due to heterogeneous effects. The estimated effects of the instrumental variable model is the local average treatment (LATE), meaning that the IV estimates capture the average effect for those who receive the treatment by the instrument (Imbens and Angrist 1994). On the other hand,

mitigates market frictions, thus benefiting individuals through having lower interest rates in peer-to-peer lending.

The diagnostic tests in Table 3.3 provide further proof that our instruments are valid and relevant. The Kleibergen-Paap rk LM test rejects the null hypothesis that the equation is under-identified (P-value < 0.05), this verifies that the two instruments are strongly correlated with the endogenous variable. The Hansen's J-test has a P-value of 0.33 and so we fail to reject the null hypothesis that the instruments are valid (P-value > 0.05). This test confirms that our instruments are correctly excluded from the equation and are valid. One potential concern is that our instruments could be correlated with other local economic characteristics that could, in turn, affect the interest rate. We believe this is highly unlikely as we control for local economic conditions and development by adding the unemployment rate, GDP, education, and the region's demographic variables to our model. In addition, we control for local financial structure by including variables related to regional debt levels and overdue payment rates. Lastly, our data allows us to control for borrowers' credit profiles and financial positions.

3.4.2.2. Alternative Measures of Social Capital

We explore whether our results are robust to using alternative measures of social capital. First, we use organ donation as an alternative measure (Guiso et al. 2004; Buonanno et al. 2009; Hasan et al. 2017a; Hasan et al. 2017b). Organ donation is an altruistic action as there is no obligation or direct benefit from donating. We obtain organ donation data from the Organ Procurement and Transplantation Network

the OLS model estimates the average treatment effect for the entire population (ATE). This could lead to the IV estimates being larger than the population average treatment (Jiang 2017).

(OPTN).[27] Unfortunately, OPTN only releases organ donation data at the state-level. Therefore, *organ donation* is the number of organ donors per 1,000 people at the state level. We adjust our main specification and use organ donation instead of the index of social capital. Furthermore, we modify our baseline model with an indicator variable for high social capital communities. *High SC* is a dummy that takes the value of 1 if the three-digit ZIP code area's social capital is higher than or equals the median social capital index for a given year. Lastly, we use social associations per 1,000 people and non-profit organizations per 1,000 people, separately.[28]

Table 3.4 reports the results of the modified specification using alternative measures of social capital. Model 1 in Table 3.4 uses organ donations and Model 2 uses the indicator of three-digit ZIP code areas with high social capital. Model 3 and Model 4 use the number of social associations and the number of non-profit organizations per 1,000 people, respectively. For most of the models, the estimated coefficient for the alternative proxies for social capital is statistically significant and negative. This suggests that the negative relationship between social capital and borrowers' interest rates in online marketplaces still holds after using different proxies for social capital.

[Insert Table 3.4 here]

[27] The organ donation data is obtained from https://optn.transplant.hrsa.gov/data/view-data-reports/. This measure includes both deceased and living donors. OPTN defines a donor as any individuals from whom at least one organ is recovered for transplantation.

[28] We do not include either the voting turnout or the census response rate as alternative measures of social capital as both variables are consistent across the years.

3.5. Additional Results

3.5.1. Evidence from Subsamples

In this section, we examine the extent to which social capital can mitigate market frictions. Different borrowers can have different levels of moral hazard, so the impact of social capital can vary across borrowers. Lin and Pursiainen (2018) argue that the benefits of social capital in mitigating market inefficiencies should increase as the severity of moral hazard increases. Similarly, Ferris et al. (2017) find that the benefit of high social capital in reducing the firm's cost of equity is stronger when market frictions are greater. Moreover, Guiso et al. (2004) report that the impact of social capital is stronger for less educated individuals and when legal enforcement is lower. Accordingly, we expect the impact of social capital to be more significant for borrowers who are more likely to have greater moral hazard. We identify a number of borrower characteristics that are more susceptible to show a higher risk of moral hazard. To identify these borrowers, we employ three sorting variables: credit score, income level, and debt-to-income ratio. These borrowers are more likely to be financially constrained as they have greater information asymmetry and agency problems.

We re-estimate our baseline specification and report the results for the subsamples in Table 3.5. The sample is split into three groups based on credit score, income, and debt-to-income ratio, respectively. A borrower is classified as having a low credit score if borrower's credit score is below or equals the median credit score for the three-digit ZIP code area in a given year. Similarly, a borrower is considered to have a low income if borrower's annual income is lower or equals the median annual income. Lastly, a borrower falls in the high debt-to-income group if borrower's debt-to-income ratio is higher or equals the median debt-to-income ratio in our sample.

[Insert Table 3.5 here]

We present the results of the regressions for the subsamples in Table 3.5. Model 1 is based on the credit score, Model 2 is based on annual income, and Model 3 presents the results for the subsample based on the debt-to-income ratio. As expected, the results presented in Table 3.5 show that the estimated coefficients for social capital are negative and statistically significant for borrowers with greater moral hazard. The effect of social capital is most pronounced for borrowers with a lower credit score, a lower income, and a higher debt-to-income ratio. For instance, Column (1) of Model 1 shows that a one standard deviation increase in the social capital index for the subsample of borrowers with a low credit score is associated with a 0.02 decrease in the interest rate. We find similar magnitudes of social capital for borrowers with low income and those with a high debt-to-income ratio in Model 2 and Model 3, respectively. On the other hand, for borrowers with a higher credit score, a higher income, and a lower debt-to-income ratio, social capital is insignificant or only marginally affects the interest rate. Moreover, the magnitude of social capital is greater for the subsample of borrowers with greater moral hazard. Our results are relatively consistent when we use alternative measures of social capital. We provide the results for the subsamples using different measures of social capital in Appendix 3.4.

In Table 3.6, we categorize borrowers into two groups: high and low risk. Borrowers are classified as high risk if they have a low credit score, a low income, and a high debt-to-income ratio at the same time. The low risk category refers to borrowers with a high credit score, a high income, and a low debt-to-income ratio simultaneously. We observe that the negative impact of social capital on the interest rate is more significant for borrowers with high risk. Column (1) shows that a one standard deviation increase in social capital for borrowers with higher risk is associated with a decrease in the interest rate of around 0.04. In addition, the magnitude of social capital is significantly greater for borrowers with high risk than borrowers with low risk. Overall, our results confirm that the effect of social capital is stronger for borrowers who are more susceptible to moral hazard. Moreover, our results are in line with previous literature. They are consistent with the findings of Guiso et al. (2004), Ferris et al. (2017), Lin and Pursiainen (2018), who find that the benefits of high social capital are significantly stronger when market frictions are greater.

[Insert Table 3.6 here]

3.5.2. Evidence from Default

The norms in high social capital communities such as altruism and social sanctions encourage individuals to pay their debts on time (Costa and Kahn 2003; Guiso et al. 2004). Moreover, Guiso et al. (2013) argue that moral considerations might mitigate the likelihood of mortgage default. They report that individuals who believe that it is morally wrong to default are significantly less likely to default. In addition, Jin et al. (2017) find that banks in high social capital regions were less likely to fail during the financial crisis and are more financially stable. They argue that social capital limits banks' risk-taking behavior and that it acts as an informal monitoring mechanism.

Similarly, Ostergaard et al. (2015) show that banks in high social capital regions have higher survival rates and that savings banks in these regions raise more deposits and are more altruistic.

Based on the preceding discussion, if social capital encourages altruistic behavior it should have a negative effect on borrowers' likelihood of default. In Table 3.7, we regress our social capital index on different measures of borrower default using a logit model. As in our baseline specification, we control for borrower characteristics, loan characteristics[29], three-digit ZIP code area demographic factors, state-level factors, state fixed effects, and year fixed effects. Table 3.7 provides the average marginal effects of the logit regression. In Model 1, we define default as a dummy that equals 1 if the borrower is 31-120 days late in payment or the loan is in default (zero otherwise). In Model 2, borrower default is specified if only the loan is in default. Lastly, in Model 3 we restrict our sample to only completed loans and define default as a dummy that equals 1 if the loan is in default (zero if the loan is paid off). The coefficient estimates for social capital are negative and statistically significant, implying that an increase in the social capital index is associated with a lower probability that a borrower will default on his/her loan in a given month. Across all the models, a one standard deviation increase in social capital is associated with a decrease of around 0.2 in the borrower's likelihood of default. Moreover, our results are robust to using different classifications of default. These findings suggest that social capital might mitigate moral hazard problems and limits opportunistic behavior.

[Insert Table 3.7 here]

[29] However, we control for the loan age instead of the loan term as how far the borrower is in the loan could affect the likelihood of default. The older the loan gets, the less likely it is that the borrower will default.

For robustness, we split the borrowers into two groups: high and low risk, as before, to ascertain whether social capital mitigates moral hazard. If the benefits of social capital are realized through mitigating market frictions, we should find that the negative association between social capital and the likelihood of default is stronger for higher risk borrowers, who might have greater levels of moral hazard. We present the results of the relationship between social capital and borrower likelihood of default for the subsamples in Table 3.8. These results are the average marginal effects of a logit regression for the subsamples. We observe statistically significant effects of social capital on nearly all the different measures of borrower default for high risk borrowers. In contrast, the coefficient estimates for social capital are insignificant or only marginally significant for borrowers with low risk. These results further confirm that the impact of social capital is most evident among individuals with higher levels of moral hazard.

[Insert Table 3.8 here]

3.6. Conclusions

In this chapter, we examine the impact of high social capital on individuals' economic outcomes in peer-to-peer lending. Social capital produces positive economic payoffs at the macro and individual levels (Guiso et al. 2011). Moreover, social capital has a significant impact on financial market development (Guiso et al. 2004). Social capital is considered a public good that everyone within a community can access and benefit from (Coleman 1988). In general, social capital refers to the norms and social networks in a society that enables cooperative behavior through shared trust, norms, and values.

In addition, social capital limits opportunistic behavior and promotes altruistic actions. Therefore, individuals in high social capital regions are less likely to violate social norms because of internal and external sanctions. These characteristics of social capital help mitigate market frictions. In this chapter, we try to understand the benefits of social capital in peer-to-peer lending context.

We first investigate whether high levels of social capital benefits individuals in peer-to-peer lending by having better lending conditions. The results show that individuals in high social capital regions are charged a lower interest rate on their online loans. In additional tests, we find that the impact of social capital on interest rate is stronger for borrowers with greater moral hazard. These results imply that social capital affects individuals' economic outcomes by mitigating moral hazard. Moreover, we find that higher levels of social capital are associated with a lower likelihood of borrower default. We perform multiple robustness checks to ensure the consistency of our main regression results. In all of these robustness tests, we find that our social capital index is negative and statistically significant. This suggests a consistent negative relationship between social capital and borrowers' interest rates. Overall, this study confirms the economic benefits of having higher social capital in online marketplaces. Moreover, the findings of this chapter imply that social capital is effective in mitigating market frictions. This is critical for a fast-growing industry like online marketplaces, which are transforming the financial landscape. Therefore, maintaining satisfactory levels of social capital is essential for online lending marketplaces.

3.7. Policy Implications

The analysis of Chapter 3 suggests that social capital mitigates market frictions in online marketplaces and provides evidence on the economic payoffs of having high social capital. This indicates that the economic benefits of having high levels of social capital transmit to the online environment. Therefore, policymakers should take into consideration the importance of maintaining satisfactory levels of social capital even when everything is shifting online. Furthermore, these findings provide significant implications for social capital theory as they suggest that the community's social capital is important for the online environment and it can mitigate market frictions.

3.8. Study Limitations and Future Research

The analysis of Chapter 3 focuses on the benefits of the community's social network in peer-to-peer lending. Another strand of the literature examines the role of online social networks and friendship in online lending marketplaces (Lin et al. 2013; Freedman and Jin 2017). Further research could examine the interaction between online and community social network and whether online social network acts as an alternative to community's social network.

Table 3.1: Summary Statistics

VARIABLES	(1) Mean	(2) SD	(3) p25	(4) p50	(5) p75	(6) p95
Social capital	-0.7028	1.1590	-1.4682	-0.6516	-0.0313	0.9774
Panel A: Borrower and Loan Characteristics						
Interest rate	13.21	4.59	9.75	12.79	15.99	21.67
FICO	696.48	30.42	672	687	712	757
Credit age (in months)	198.28	90.59	137	180	244	373
Annual income	75,212	42,606	46,152	65,000	91,000	156,000
Debt-to-income ratio	18.49	8.36	12.19	18	24.45	33.14
Open accounts	11.68	5.27	8	11	14	22
Revolving line utilization rate	53.76	23.77	36.10	54.30	72.20	92
Loan amount	14,869	8,632	8,000	13,000	20,000	33,000
Panel B: Three-digit ZIP controls						
Percentage of over 25 population with bachelor degree	0.19	0.05	0.15	0.18	0.22	0.29
Unemployment rate	0.08	0.02	0.06	0.08	0.09	0.12
Percentage of male population	0.49	0.009	0.48	0.49	0.49	0.50
Percentage of native born population	0.85	0.11	0.78	0.88	0.94	0.97
Percentage of married population	0.48	0.06	0.43	0.49	0.52	0.56
Panel C: State level controls						
GDP	50,918	9,766	44,057	52,007	56,196	64,286
Credit card delinquency rate	7.84	1.73	6.50	8	8.5	11
Mortgage delinquency rate	2.60	1.95	1.5	2	3	7
Auto delinquency rate	3.40	1.06	2.50	3	4	5
Auto loans per capita	4,001	794	3,420	3,820	4,360	6,070
Mortgage per capita	33,264	11,038	23,770	30,220	43,910	51,890
Credit card per capita	2,914	410	2,640	2,940	3,220	3,540

This table provides the following summary statistics of the main and control variables used in this study: the average value (Mean), the standard deviation (SD), the 25th percentile (p25), the 50th percentile (p50), the 75th percentile (p75), and the 95th percentile (p95). All of the variables are defined in Appendix 3.3.

Table 3.2: Social Capital and Interest Rates

	Dependent variable: Interest rate			
VARIABLES	Model (1)	Model (2)	Model (3)	Model (4)
Social Capital	-0.0621***	-0.0616***	-0.0345***	-0.0169**
	(0.0136)	(0.0118)	(0.0094)	(0.0078)
Borrower Characteristics:				
FICO	-0.0529***	-0.0541***	-0.0541***	-0.0541***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Revol Util	0.0088***	0.0084***	0.0084***	0.0084***
	(0.0003)	(0.0002)	(0.0002)	(0.0002)
DTI	0.0924***	0.0648***	0.0657***	0.0656***
	(0.0009)	(0.0008)	(0.0006)	(0.0006)
Ln(Income)	-0.2540***	-1.1942***	-1.1899***	-1.1927***
	(0.0138)	(0.0150)	(0.0131)	(0.0127)
Open accounts	-0.0152***	-0.0091***	-0.0105***	-0.0102***
	(0.0011)	(0.0010)	(0.0011)	(0.0010)
Credit age	-0.0042***	-0.0039***	-0.0039***	-0.0039***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Homeownership Status (Owner)	-0.0376**	-0.2794***	-0.2579***	-0.2549***
	(0.0175)	(0.0136)	(0.0117)	(0.0118)
Loan Characteristics:				
Ln(Loan amount)		0.6356***	0.6342***	0.6354***
		(0.0087)	(0.0087)	(0.0088)
loan term		4.0697***	4.0724***	4.0722***
		(0.0114)	(0.0115)	(0.0115)
Three-digit ZIP controls:				
Unemployment Rate			1.6901***	2.8266***
			(0.4961)	(0.4496)
Married population per %			0.0114	0.1955*
			(0.1663)	(0.1143)
Native born population %			-0.6668***	-0.6716***
			(0.1036)	(0.0806)
Male population %			-3.5101***	-2.9225***
			(0.7898)	(0.6880)
Bachelor holders over 25 population %			-0.5219***	-0.2588*
			(0.1650)	(0.1374)
Loan Purpose Fixed Effects	No	Yes	Yes	Yes
Three-digit ZIP code level controls	No	No	Yes	Yes
State level controls	No	No	Yes	Yes
State Dummies	No	No	No	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	1,274,723	1,274,723	1,274,723	1,274,723
R-squared	0.2130	0.4418	0.4423	0.4426

This table reports the baseline regression results of borrowers' interest rates on the region's social capital index with a set of control variables. Model 1 includes borrower attributes where revol util, debt-to-income ratio, annual income, and open accounts are winsorized at the 1st and 99th percentile. Model 2 adds controls for loan characteristics. Model 3 includes additional controls for three-digit ZIP are demographic factors and state control variables. Model 4 presents the baseline specification. It controls for state fixed effects along with borrower attributes, loan characteristics, three-digit zip code, and state control variables. In all the models, we add year fixed effects. Standard errors are clustered at the three-digit ZIP code level in parentheses.
*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3.3: The Causal Effect of Social Capital: Instrumental Variable Approach

VARIABLES	(1) First stage	(2) Interest rate
Racial Fragmentation	-1.0004***	
	(0.0101)	
Shoot	-0.0300***	
	(0.0028)	
Social Capital		-0.4171***
		(0.0416)
Borrower Characteristics:		
FICO	0.0003***	-0.0540***
	(0.0000)	(0.0001)
Revol Util	0.0003***	0.0085***
	(0.0000)	(0.0002)
DTI	-0.0000	0.0656***
	(0.0001)	(0.0004)
Ln(Income)	-0.0120***	-1.1990***
	(0.0013)	(0.0081)
Open accounts	-0.0025***	-0.0113***
	(0.0001)	(0.0007)
Credit age	0.0001***	-0.0038***
	(0.0000)	(0.0000)
Homeownership status (Owner)	-0.0078***	-0.2581***
	(0.0011)	(0.0071)
Loan Characteristics:		
Ln(Loan amount)	0.0065***	0.6379***
	(0.0010)	(0.0061)
Loan term, 60 months	-0.0169***	4.0654***
	(0.0012)	(0.0080)
Loan Purpose Fixed Effects	Yes	Yes
Three-digit ZIP code level controls	Yes	Yes
State Level controls	Yes	Yes
State Dummies	Yes	Yes
Year Dummies	Yes	Yes
Observations	1,274,723	1,274,723
IV tests		
F-Statistics		
Under-identifcation test (Kleibergen-Paap rk LM statistic P-value)		0.0000
Hansen’s Over-identification test (P-value)		0.33

This table provides the instrumental variable regression results using 2SLS. Column (1) shows the first-stage regression, where the two instruments: racial fragmentation and shoot are regressed on social capital. Column (2) shows the second-stage regression results. The main independent variable is social capital and the dependent variable is the interest rate. Robust standard errors in parentheses.
*** indicates significance at the 1% level.

Table 3.4: Alternative Measures of Social Capital

	Dependent variable: Interest rate			
VARIABLES	Model (1)	Model (2)	Model (3)	Model (4)
Organ donation	-0.1719*			
	(0.0911)			
High SC		-0.0336**		
		(0.0145)		
Social density			-0.0515**	
			(0.0258)	
Nonprofit density				-0.0042
				(0.0038)
Borrower Characteristics:				
FICO	-0.0541***	-0.0541***	-0.0541***	-0.0541***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Revol Util	0.0084***	0.0084***	0.0084***	0.0084***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
DTI	0.0656***	0.0656***	0.0656***	0.0656***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Ln(Income)	-1.1929***	-1.1929***	-1.1929***	-1.1924***
	(0.0127)	(0.0127)	(0.0128)	(0.0127)
Open accounts	-0.0102***	-0.0102***	-0.0103***	-0.0102***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Credit age	-0.0039***	-0.0039***	-0.0039***	-0.0039***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Homeownership Status (Owner)	-0.2559***	0.2559***	-0.2549***	-0.2549***
	(0.0118)	(0.0118)	(0.0118)	(0.0118)
Loan Characteristics:				
Ln(Loan amount)	0.6355***	0.6355***	0.6354***	0.6353***
	(0.0088)	(0.0088)	(0.0088)	(0.0088)
loan term	4.0731***	4.0731***	4.0723***	4.0724***
	(0.0115)	(0.0115)	(0.0115)	(0.0115)
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes
Three-digit ZIP code level controls	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	1,277,828	1,277,828	1,274,723	1,274,723
R-squared	0.4427	0.4427	0.4426	0.4426

This table presents the results of the baseline specification using alternative measures of social capital. In Model 1, the alternative measure of social capital is the number of organ donors at the state level per 1,000 people. In Model 2, the main independent variable high social capital is an indicator of whether social capital is above or equals the median social capital in a given year. In Model 3 and Model 4, the independent variable is the number of social associations per 1,000 and the number of non-profit organizations per 1,000 people, respectively. In all the models, the dependent variable is the borrower's interest rate. Standard errors are clustered at the three-digit ZIP code level in parentheses.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3.5: Social Capital and Interest Rates: Evidence from Subsamples

	Dependent variable: Interest rate					
	Model (1)		Model (2)		Model (3)	
VARIABLES	Low FICO	High FICO	Low Inc	High Inc	High DTI	Low DTI
Social Capital	-0.0237***	-0.0180*	-0.0265***	-0.0141	-0.0229**	-0.0107
	(0.0087)	(0.0105)	(0.0099)	(0.0097)	(0.0111)	(0.0083)
Borrower Characteristics:						
FICO	-0.0667***	-0.0451***	-0.0515***	-0.0572***	-0.0578***	-0.0512***
	(0.0005)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Revol Util	0.0114***	0.0044***	0.0110***	0.0054***	0.0107***	0.0085***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
DTI	0.0686***	0.0678***	0.0671***	0.0673***	0.1139***	0.0041***
	(0.0007)	(0.0008)	(0.0007)	(0.0008)	(0.0013)	(0.0014)
Ln(Income)	-1.1011***	-1.2503***	-1.9158***	-0.4642***	-1.3263***	-1.1157***
	(0.0153)	(0.0156)	(0.0202)	(0.0202)	(0.0171)	(0.0136)
Open accounts	0.0108***	-0.0408***	-0.0089***	-0.0092***	-0.0065***	-0.0035***
	(0.0012)	(0.0013)	(0.0012)	(0.0012)	(0.0012)	(0.0013)
Credit age	-0.0048***	-0.0027***	-0.0040***	-0.0038***	-0.0037***	-0.0041***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Homeownership status (Owner)	-0.1990***	-0.2924***	-0.1102***	-0.3971***	-0.1364***	-0.3702***
	(0.0128)	(0.0162)	(0.0125)	(0.0168)	(0.0136)	(0.0145)
Loan Characteristics:						
Ln(Loan amount)	0.6648***	0.6333***	0.3740***	0.9282***	0.7246***	0.5709***
	(0.0108)	(0.0123)	(0.0114)	(0.0108)	(0.0112)	(0.0107)
Loan term, 60 months	4.1828***	3.9535***	4.2252***	4.0188***	4.1015***	4.0403***

	(0.0134)	(0.0144)	(0.0144)	(0.0132)	(0.0135)	(0.0143)
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Three-digit ZIP code level controls	Yes	Yes	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	681,848	592,875	650,252	624,471	638,832	635,891
R-squared	0.3622	0.4189	0.4081	0.4772	0.4306	0.4416

This table provides the results of the baseline specification for the subsamples. The dependent variable is the borrower's interest rate and the main independent variable is social capital. Model 1 presents the results of the subsample based on the credit score; we classify borrowers as having low fico if their credit score is below or equals the median credit score for the three-digit ZIP code in a given year. Model 2 is based on annual income; borrowers are classified as having a low income if their income is below or equal the median income for the three-digit ZIP code in a given year. Model 3 is based on debt-to-income ratio; borrowers fall in the high debt-to-income sample if their debt-to-income ratio is higher or equals the median debt-to-income ratio in our sample. Standard errors are clustered at the three-digit ZIP code level in parentheses.
** and *** indicate significance at the 5%, and 1% levels, respectively.

Table 3.6: Social Capital and Interest Rates: Evidence from Subsamples

	Dependent variable: Interest rate	
	(1)	(2)
VARIABLES	High Risk	Low Risk
Social Capital	-0.0363**	-0.0061
	(0.0148)	(0.0145)
<u>*Borrower Characteristics:*</u>		
FICO	-0.0599***	-0.0421***
	(0.0008)	(0.0004)
Revol Util	0.0160***	0.0038***
	(0.0004)	(0.0005)
DTI	0.1053***	0.0063***
	(0.0018)	(0.0023)
Ln(Income)	-1.7107***	-0.4328***
	(0.0342)	(0.0264)
Open accounts	0.0124***	-0.0277***
	(0.0018)	(0.0020)
Credit age	-0.0046***	-0.0028***
	(0.0001)	(0.0001)
Homeownership status (Owner)	-0.0242	-0.5014***
	(0.0191)	(0.0271)
<u>*Loan Characteristics:*</u>		
Ln(Loan amount)	0.4964***	0.8427***
	(0.0165)	(0.0181)
Loan term, 60 months	4.2474***	3.8786***
	(0.0221)	(0.0206)
Loan Purpose Fixed Effects	Yes	Yes
Three-digit ZIP code level controls	Yes	Yes
State level controls	Yes	Yes
State Dummies	Yes	Yes
Year Dummies	Yes	Yes
Observations	214,137	179,338
R-squared	0.3260	0.4390

This table provides the results of the baseline specification for the subsamples of high and low risk borrowers. The dependent variable is the borrower's interest rate and the main independent variable is social capital. The results for high risk borrowers are presented in the first column, where a borrower is classified as high risk if he/she has low fico, a low income, and a high debt-to-income ratio. Column (2) presents the results for low risk borrowers, who have high fico, a high income, and a low debt-to-income ratio. Standard errors are clustered at the three-digit ZIP code level in parentheses.

*** indicates significance at the 1% level.

Table 3.7: Social Capital and Borrower Default

	Dependent variable: Default		
VARIABLES	Model (1)	Model (2)	Model (3)
Social Capital	-0.0020**	-0.0020***	-0.0028***
	(0.0008)	(0.0008)	(0.0011)
Borrower Characteristics:			
FICO	-0.0015***	-0.0014***	-0.0019***
	(0.0000)	(0.0000)	(0.0000)
Revol Util	0.0000	0.0000*	0.0002***
	(0.0000)	(0.0000)	(0.0000)
DTI	0.0027***	0.0026***	0.0036***
	(0.0001)	(0.0001)	(0.0001)
Ln(Income)	-0.0636***	-0.0610***	-0.0849***
	(0.0012)	(0.0011)	(0.0016)
Open accounts	0.0013***	0.0013***	0.0017***
	(0.0001)	(0.0001)	(0.0001)
Credit age	-0.0001***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)
Homeownership status (Owner)	-0.0340***	-0.0324***	-0.0463***
	(0.0013)	(0.0013)	(0.0018)
Loan Characteristics:			
Ln(Loan amount)	0.0667***	0.0625***	0.0921***
	(0.0008)	(0.0007)	(0.0010)
Loan age	-0.0053***	-0.0056***	-0.0030***
	(0.0000)	(0.0000)	(0.0001)
Loan Purpose Fixed Effects	Yes	Yes	Yes
Three-digit ZIP code level controls	Yes	Yes	Yes
State level controls	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Observations	1,257,468	1,257,468	940,584

This table presents the results of the relation between social capital and borrower default. The table shows the average marginal effects of a logit regression. The main independent variable is social capital. In Model 1, the dependent variable is an indicator that equals 1 if the last observed loan status is that the borrower is 31-120 days late in payment or the loan is in default (0 otherwise). In Model 2, the dependent variable equals 1 if the last observed loan status is in default (0 otherwise). In Model 3, the data are limited to completed loans and the dependent variable is defined as 1 if the loan is in default (0 if paid off). Standard errors are clustered at the three-digit ZIP code level in parentheses.
*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3.8: Social Capital and Borrower Default: Evidence from Subsamples

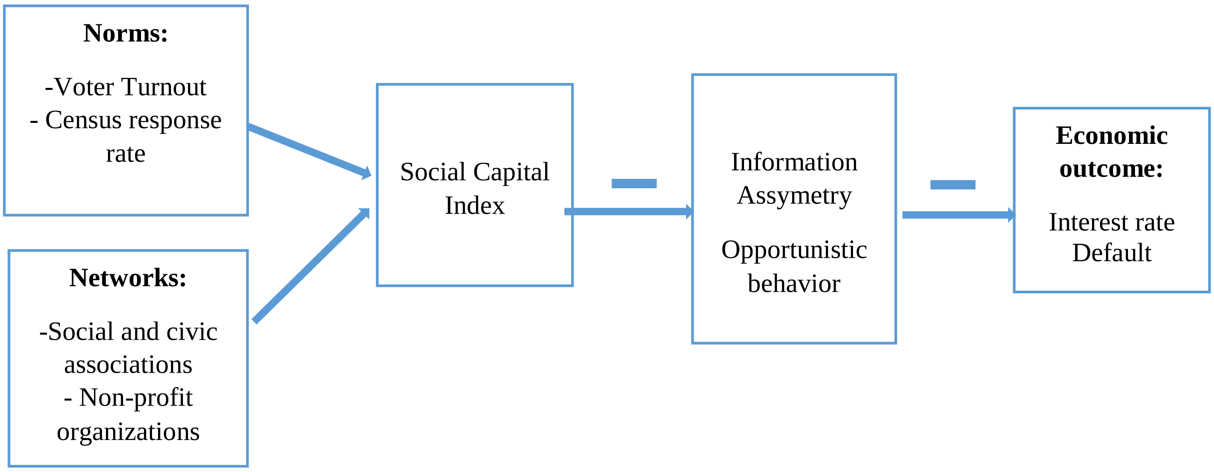
	Dependent variable: Default					
	Model (1)		Model (2)		Model (3)	
VARIABLES	High Risk	Low Risk	High Risk	Low Risk	High Risk	Low Risk
Social Capital	-0.0047***	-0.0020	-0.0052***	-0.0022*	-0.0072***	-0.0026
	(0.0017)	(0.0013)	(0.0018)	(0.0012)	(0.0022)	(0.0017)
Borrower Characteristics:						
FICO	-0.0019***	-0.0010***	-0.0018***	-0.0009***	-0.0023***	-0.0012***
	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Revol Util	0.0004***	-0.0003***	0.0004***	-0.0002***	0.0007***	-0.0002***
	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
DTI	0.0038***	0.0006***	0.0037***	0.0005***	0.0049***	0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Ln(Income)	-0.0784***	-0.0312***	-0.0761***	-0.0301***	-0.1017***	-0.0416***
	(0.0036)	(0.0022)	(0.0035)	(0.0021)	(0.0045)	(0.0029)
Open accounts	0.0025***	0.0004***	0.0023***	0.0004***	0.0032***	0.0005***
	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0003)	(0.0002)
Credit age	-0.0000	-0.0001***	-0.0000**	-0.0001***	0.0000	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Homeownership status (Owner)	-0.0486***	-0.0277***	-0.0471***	-0.0264***	-0.0636***	-0.0367***
	(0.0023)	(0.0016)	(0.0022)	(0.0016)	(0.0029)	(0.0022)
Loan Characteristics:						
Ln(Loan amount)	0.0887***	0.0468***	0.0838***	0.0437***	0.1192***	0.0639***
	(0.0019)	(0.0014)	(0.0019)	(0.0013)	(0.0025)	(0.0018)
Loan age	-0.0095***	-0.0021***	-0.0101***	-0.0024***	-0.0065***	-0.0008***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	211,899	176,341	211,899	176,341	160,436	132,027

Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Three-digit ZIP code level controls	Yes	Yes	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the results for the relation between social capital and borrower default for the subsamples of high and low risk borrowers. The main independent variable is social capital. The table shows the average marginal effects of logit regression. In Model 1, the dependent variable is an indicator that equals 1 if the last observed loan status is if the borrower is 31-120 days late in payment or the loan is in default (0 otherwise). In Model 2, the dependent variable equals 1 if the last observed loan status is default (0 otherwise). In Model 3, data are limited to completed loans and the dependent variable is defined as 1 if the loan is charged off (0 if paid off). Standard errors are clustered at the three-digit ZIP code level in parentheses.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix 3.1: An Illustration of the Relationship between Social Capital and Economic Outcomes



Appendix 3.1a: Summary statistics of the variables used to construct the social capital index

VARIABLES	(1) Mean	(2) sd	(3) p25	(4) p50	(5) p75	(6) p95
Voter Turnout	0.5461	0.0918	0.4930	0.5522	0.6070	0.6832
Census response rate	0.0183	0.0190	0.0071	0.0139	0.0226	0.0479
Social and civic associations density	1.1658	0.4392	0.8767	1.1286	1.3865	1.9648
Non-profit organizations density	5.4406	2.6474	3.8987	4.8755	6.2275	9.6883

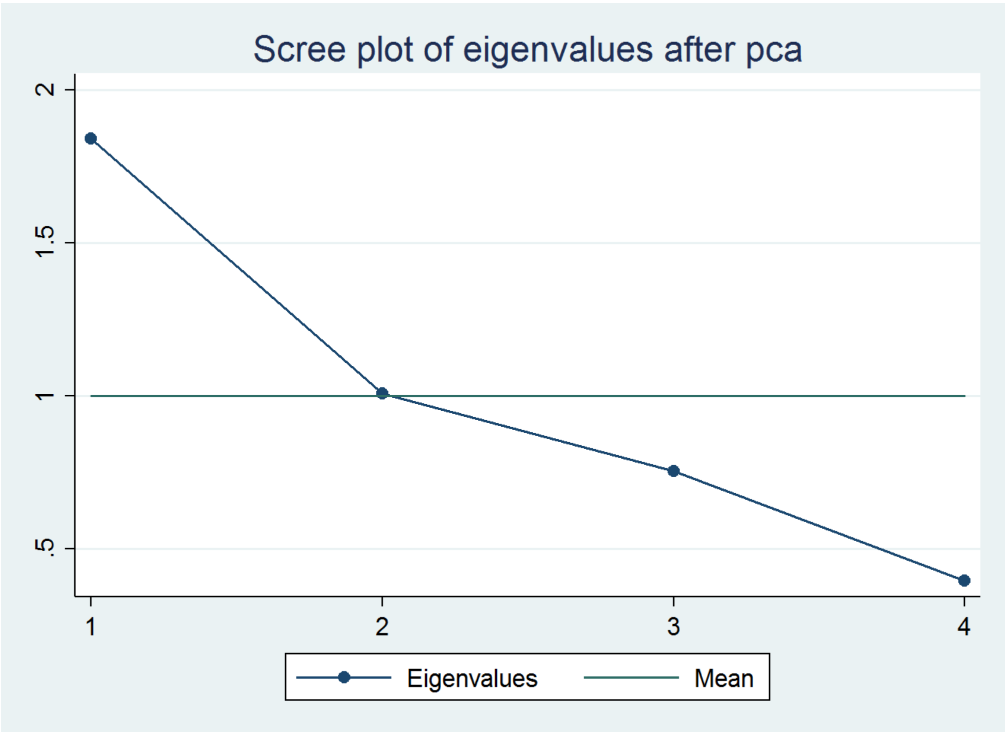
Pairwise correlations

Variables	Voter Turnout	Census response rate	Social and civic associatio ns density	Non-profit organizations density
Voter Turnout	1.000			
Census response rate	0.062	1.000		
Social and civic associations density	0.346	0.175	1.000	
Non-profit organizations density	0.291	-0.011	0.570	1.000

Appendix 3.2: Principal Component Analysis

Component	Eigenvalue	Proportion	Cumulative
Comp1	1.84007	0.4600	0.4600
Comp2	1.00749	0.2519	0.7119
Comp3	.754815	0.1887	0.9006
Comp4	.397622	0.0994	1.0000

This table shows the eigenvalues of the correlation matrix, ordered from the largest to the smallest. Proportion is how much of the total variance each component can explain.



This graph provides a visual illustration of the eigenvalues relative to each other. The component in the top part of the scree plot explains the most variance.

Appendix 3.3: Variables Definitions

Variable	Description	Source
Social capital	The social capital index based on PCA analysis. The four variables used in PCA are voter turnout, census bureau response rate, the number of non-profit organizations per 1,000 population, and the number of social organizations per1,000 people.	
The number of social organizations per 1,000	The number of social organizations per 1,000 people in each three-digit ZIP code area. These organizations include: - Religious organizations - Bowling centers - Golf courses and country clubs - Physical fitness facilities - Sports clubs - Business associations - Professional organizations - Political organizations - Labor organizations - Civic and social associations	ZIP code Business Patterns
The number of non-profit organizations per 1,000	The number of non-profit organizations per 1,000 people that are exempted from tax.	National Center for Charitable Statistics (NCCS)
Voter turnout	The total number of voters in the 2016 presidential election divided by the voting age population (population over 18).	These data are obtained from https://github.com/Presidential_Results_12-16
Census response rate	The 2010 census participation rate. According to the census bureau, it is defined as the percentage of questionnaires mailed back by households.	U.S. census bureau
Panel A: Borrower and loan characteristics		
FICO	The borrower's credit score at the time of the loan application	Lending Club
Debt-to-income ratio	A ratio calculated using the borrower's total monthly debt repayments on the total debt obligations, excluding mortgage and the requested LC loan divided by the borrower's self-reported monthly income.	Lending Club

Annual Income	The self-reported annual income provided by the borrower.	Lending Club
Open Accounts	The number of open credit lines in the borrower's credit file.	Lending Club
Revolving line utilization rate	The amount of credit that the borrower is utilizing compared to all the available revolving credit.	Lending Club
Homeownership status	An indicator that is equals 1 if the borrower owns a house and zero if he rents his/her house.	Lending Club
Credit age	The length of the borrower's credit history in months.	Lending Club
Loan amount	The amount of the loan applied for by the borrower.	Lending Club
Loan term	A dummy that equals 1 if the loan term is 60 months and zero if it is 36 months.	Lending Club
Loan age	The last observed month on the books for each loan.	Lending Club
Loan purpose	The purpose of the loan applied for by the borrower. The possible categories are debt consolidation, home improvement, credit card, car, house, major purchase, medical, moving, small business, vacation, and other.	Lending Club
Panel A: Three-digit ZIP code controls		
Male population %	The percentage of the male population.	American Community Survey 5-year estimates (census bureau)
Percentage of over 25 population who hold at least a bachelor's degree	Percentage of the population aged 25 years and over with at least a bachelor's degree.	American Community Survey 5-year estimates (census bureau)
Unemployment rate	The number of unemployed individuals as a percentage of the labor force.	American Community Survey 5-year estimates (census bureau)

Native born population %	The percentage of the population that are born in the United States.	American Community Survey 5-year estimates (census bureau)
Married population %	The percentage of the population that are married.	American Community Survey 5-year estimates (census bureau)
Panel C: State-level controls		
Real GDP per capita	Real per capita GDP.	Bureau of Economic Analysis
Credit card delinquency rate	Percentage of Credit Card Debt Balance 90+ Days Delinquent.	New York Fed/Equifax Consumer Credit panel
Auto delinquency rate	Percentage of Auto Debt Balance 90+ Days Delinquent.	New York Fed/Equifax Consumer Credit panel
Mortgage delinquency rate	Percentage of Mortgage Debt Balance 90+ Days Delinquent.	New York Fed/Equifax Consumer Credit panel
Credit card per capita	Credit Card Debt Balance per Capita.	New York Fed/Equifax Consumer Credit panel
Auto loans per capita	Auto Debt Balance per Capita.	New York Fed/Equifax Consumer Credit panel
Mortgage per capita	Mortgage Debt Balance per Capita (excluding HELOC).	New York Fed/Equifax Consumer Credit panel

Appendix 3.4: Social Capital and Interest Rate: Evidence from Subsamples using Alternative Measures of Social Capital

Panel A: subsamples based on credit score

	Model (1)		Model (2)		Model (3)		Model (4)	
VARIABLES	Low FICO	High FICO	Low FICO	High FICO	Low FICO	High FICO	Low FICO	High FICO
Organ donation	-0.3279**	0.0012						
	(0.1326)	(0.1335)						
High SC			-0.0367**	-0.0395**				
			(0.0167)	(0.0173)				
Social density					-0.0707***	-0.0510		
					(0.0274)	(0.0335)		
Nonprofit density							-0.0088**	-0.0022
							(0.0038)	(0.0051)
Observations	683,518	594,310	683,518	594,310	681,848	592,875	681,848	592,875

Panel B: subsamples based on Income

	Model (1)		Model (2)		Model (3)		Model (4)	
VARIABLES	Low Inc	High Inc	Low Inc	High Inc	Low Inc	High Inc	Low Inc	High Inc
Organ donation	-0.1702	-0.1723						
	(0.1228)	(0.1235)						
High SC			-0.0584***	-0.0218				
			(0.0192)	(0.0168)				
Social density					-0.1128***	-0.0113		
					(0.0324)	(0.0283)		
Nonprofit density							-0.0078*	-0.0040
							(0.0046)	(0.0048)
Observations	651,843	625,985	651,843	625,985	650,252	624,471	650,252	624,471

Panel C: subsamples based on debt-to-income ratio

VARIABLES	High DTI	Low DTI	High DTI	Low DTI	High DTI	Low DTI	High DTI	Low DTI
Organ donation	-0.2583*	-0.0507						
	(0.1378)	(0.1428)						
High SC			-0.0403**	-0.0277*				
			(0.0176)	(0.0166)				
Social density					-0.0812**	-0.0177		
					(0.0372)	(0.0249)		
Nonprofit density							-0.0057	-0.0027
							(0.0058)	(0.0035)
Observations	640,396	637,432	640,396	637,432	638,832	635,891	638,832	635,891

This table replicates Table 3.8 using alternative measures of social capital. The dependent variable is the borrower's interest rate. Model 1 uses organ donation as the main independent variable. Model 2 uses a dummy for high social capital. Model 3 and Model 4 uses the number of social organizations and the number of nonprofit organizations, respectively. Panel (A) provides the results of the subsamples based on the credit score. Panel (B) provides the results based on annual income. Panel (C) provides the results based on debt-to-income ratio. Standard errors are clustered at the three-digit ZIP code level in parentheses.
*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Chapter 4

The Prevalence of Income Rounding Behavior and Credit Performance in Peer-to-Peer Lending

4.1. Introduction

Peer-to-peer lending is an online process in which borrowers and lenders meet directly. Online marketplaces provide individuals with an alternative source of finance where they can shop freely for borrowing and investment opportunities with increased convenience and lower cost. However, this cost efficiency could result in a questionable credit check process and increased risk of fraud. The peer-to-peer lending industry started in 2005 and ever since online lending marketplaces are steadily becoming an important part of the credit market. Although online marketplaces are growing at an increased pace, there has not been a proper unified regulatory framework for the industry. Furthermore, the absence of a proper background check inherently increases the risk of information falsification. Online lending marketplaces might not be consistent in verifying self-reported data (e.g., income, employment status). Therefore, borrowers are more likely to misreport personal information either by mistake or intentionally.

This chapter offers an insight into the effect of the prevalence of income rounding on the credit performance of online borrowers using a dataset from Lending Club. Dechow and You (2012) argue that individuals tend to provide round numbers due to lack of incentives for reporting accurate information. Moreover, the existence of rounding has been established in self-reported data with extra spikes in the data observed at numbers ending in zero (Pudney 2008; A'Hearn et al. 2009; Manski and Molinari 2010). This could be explained by number preference, recall error, availability heuristic, or lack of information (Tversky and Kahneman 1973; Tarrant et al. 1993; Ormerod and Ritchie 2007; Wang and Heitjan 2008). Rosch (1975) argues that most natural categories have a cognitive reference point. Round numbers act as cognitive reference points (Bhattacharya et al. 2012), as they are easier to come to mind (Schindler and Kirby 1997). In addition, the occurrence of clustering or psychological barriers suggests that individuals attribute information into a particular digit or barrier (Mitchell 2001). This implies that rounding behavior indicates imprecision or uncertainty regarding the information provided (Jansen and Pollmann 2001; Krifka 2002; Dechow and You 2012; Binder 2015). Moreover, individuals could be strategically exceeding a reference point in order to look more attractive to users (Carslaw 1988; Das and Zhang 2003; Garmaise 2015). Overall, this suggests that individuals who have imprecise information regarding their financial position are more likely to round their income, as they are less willing to exert the effort needed to calculate their precise income level.

In order to understand the impact of rounding, we examine the relationship between self-reported income figures and associated loan outcomes. Borrowers could report rounded income figures due to lack of information about their current financial position. However, what kind of signals do borrowers with inaccurate financial information provide? Gerardi et al. (2010) and Garmaise (2015) suggest that less financially informed borrowers and cognitively constrained borrowers experience worse loan outcomes. This implies that borrowers who exhibit rounding behavior may have worse loan performance than those who do not. Moreover, borrowers who do not make an effort in calculating their exact income might not have the incentive to pay their debt on time. To measure loan performance, we define loans as delinquent if in a given month they are late in payment or default. Self-reported data do not usually give exact information about the extent of rounding (Manski and Molinari 2010). However, a significant number of applicants who round their income might distort the distribution of income (Czajka and Denmead 2008). This could result in several spikes in the reported income at rounded values. We observe extra spikes around income multiples of $5,000 in our sample; therefore, $5,000 is considered as our main rounding threshold.

Our results suggest that the presence of rounding is associated with worse loan outcomes. The occurrence of rounding is associated with a significant increase in the probability that a borrower experiences delinquency or default in a given month. In addition, we use the volatility of changes in monthly credit score to measure borrowers' uncertainty. Our findings suggest that borrowers who round their income figures experience higher monthly fluctuations in their credit score than those who have reported precise figures. Moreover, they are more likely to experience negative changes in their credit scores. We employ a multinomial logit model to complement our findings and to account for other possible loan outcomes. We find that rounding is significantly associated with worse outcomes. Borrowers who round their income are more likely to end up in delinquency or default than to stay up-to-date with their payments. One way to mitigate the consequences of rounding is to compensate investors for the extra risk. However, we find that loans are not priced in a way that reflects the risk associated with rounding. Borrowers who round their income have a lower interest rate than those who do not round.

The rest of this chapter proceeds as follows. In section 4.2, we discuss the related literature on the psychology of rounding and loan performance. Section 4.3 gives an overview of the data used with descriptive statistics. Section 4.4 illustrates the specification used in the course of the analysis. We discuss the main results in section 4.5. In section 4.6, we provide robustness tests. Section 4.7 provides additional tests of the impact of rounding. Finally, section 4.8 presents the main conclusions of this chapter.

4.2. Literature Review

4.2.1. The Psychology of Rounding and Misreporting

It is recognized that numbers ending in zero and five are more attractive to individuals than those with other rightmost digits (Tarrant et al. 1993; Schindler and Kirby 1997). Furthermore, most individuals tend to provide rounded responses to quantifiable questions even if an exact response is desired (Myers 1954). Round numbers are cognitively accessible without the need to perform complex algorithms (Schindler and Kirby 1997), particularly in the case of large numbers (Kaufman et al. 1949). Moreover, rounding behavior might be caused by recall error (Wang and Heitjan 2008) or due to lack of information about the subject matter (Ormerod and Ritchie 2007), suggesting that rounding behavior indicates imprecision or uncertainty (Jansen and Pollmann 2001; Krifka 2002; Binder 2015).

Rounding occurs predominantly in surveys or self-reported data (Pudney 2008; Manski and Molinari 2010). Rounding behavior could lead to unusual patterns in the observed data and consequently, result in erroneous inference about the subject matter. Development economists and demographers observe extra spikes around certain numbers when people report their age (Myers 1954; Gráda 2006; A'Hearn et al. 2009). They observe that rounding does not happen randomly. Nevertheless, individuals exhibit a preference for numbers ending in five or zero, which is explained by the "age heaping" phenomenon (A'Hearn et al. 2009). Binder (2015) finds that nearly half of the responses about expected inflation rates exhibit heaping behavior around multiples of five. Pudney (2008) demonstrates that the distribution of households' expenditure significantly shows extra spikes at round responses. Furthermore, most of the reported income data is rounded on one level or another (Schweitzer and Severance-Lossin 1996; Hanisch 2005). Zinn and Würbach (2016) show that heaping around multiples of 1,000 increases with higher income. Similarly, Schweitzer and Severance-Lossin (1996) find that there is variation in rounding within different income levels.

Rounding has also been predominant in the financial market (Niederhoffer 1966; Harris 1991; Grossman et al. 1997). Dechow and You (2012) argue that rounding occurs when financial analysts do not have enough motive to exert more effort to obtain accurate information. Bollen and Pool (2009) find that the distribution of hedge funds returns contains an apparent discontinuity around zero. They suggest that it is an indication of manipulation. Carhart et al. (2002) and Agarwal et al. (2011) present further evidence supporting manipulation in hedge and mutual funds. Herrmann and Thomas (2005) find that analysts' forecasts for earnings per share persistently use 5-cent intervals. Additionally, they find that analysts who show evidence of heaping behavior tend to provide less accurate predictions. Aitken et al. (1996) demonstrate that traders in the Australian Stock Exchange have a strong preference for prices ending in zero.

The prevalence of misreporting or manipulation should increase when it is associated with better outcomes for the individual. For instance, hedge fund managers might have a greater incentive to manipulate performance reports as investors evaluate funds based on their progress and managers' appraisal is usually based on the fund's performance (Asness et al. 2001; Ben-David et al. 2013). Ben-David et al. (2013) support this claim by finding a significant occurrence of manipulation in hedge funds that have more incentives to enhance their position compared to competitors. Moreover, managers might be motivated to manage corporate earnings upwards in order to maintain past performance, meet analysts' forecasts, and avoid losses (Degeorge et al. 1999). Similarly, individuals might manipulate information within loan applications such as rounding their income in order to increase the odds of receiving funding (Dorfleitner and Jahnes 2014).

The study currently closest to this study is Garmaise (2015). He shows that borrowers who systematically misreport personal assets above round number thresholds are more likely to become delinquent.[30] Moreover, the effect of misreporting is not reflected in the pricing of loans. In contrast to Garmaise (2015), we focus on the outcome of rounding rather than over-reporting. Furthermore, the set-up of the peer-to-peer market differs entirely from the mortgage market. Peer-to-peer lending is a virtual and highly unregulated market. Therefore, misreporting is more likely to occur in the online market than in the mortgage market.

[30] Piskorski et al. (2015), Griffin and Maturana (2016) find similar unfavorable performance for misreported borrowers in mortgage applications.

4.2.2. Loans Performance in Peer-to-Peer Lending

The first stream of literature investigates the performance of online loans relative to borrower's credit characteristics. The most critical aspect that concerns investors in the lending process is whether a loan will end up in default or not. Emekter et al. (2015) find a significant disparity in credit characteristics between defaulted and current loans. Furthermore, debt-to-income ratio, revolving line utilization, and credit score significantly predicts default. Comparing the calculated theoretical and assigned interest rate by Lending Club, Emekter et al. (2015) find that the price of high-risk loans is not enough to reimburse investors in case of default. Moreover, Serrano-Cinca et al. (2015) demonstrate that the credit score given by Lending Club is the most significant predictor of default. Theoretically, credit score should be the best predictor of borrower's default. However, using data from Prosper, Iyer et al. (2016) provide evidence that the predictability power of interest rate outperforms the credit score by 45 percent.

Besides the credit characteristics of debtors, the mechanism of the online platform could have an impact on the default rate. For instance, Prosper used to allow users to form online borrowing groups where members can endorse and invest in each other's loans. Freedman and Jin (2017) find that loans to groups are more likely to default or be late in payment than those to individuals. Moreover, they find that being a group member and getting an endorsement from friends is associated with lower interest rate and a higher likelihood of funding. Everett (2015) finds that loans listed with group affiliation tend to have a lower default rate than those without group links. Iyer et al. (2015) examine the efficiency of online marketplaces screening, they find that online lenders have greater accuracy in predicting default than borrowers' credit score.

Another strand of the literature focuses on analyzing the role of soft information in peer-to-peer lending and its impact on the success of loan funding. Soft information can be an important factor in investors' decision to fund a loan or not (Dorfleitner et al. 2016). Several findings support the existence of discrimination in online lending marketplaces. Pope and Sydnor (2011) use applicants' photographs from Prosper to determine applicants' demographic characteristics. They report that black borrowers are less likely to receive funding and that they are charged interest rate 60-80 points higher than white applicants. Moreover, they find that lenders discriminate against the elderly and give preference to female applicants. Lin et al. (2013) provide further evidence of discrimination against male applicants.[31] On the contrary, employing several proxies of funding success from a German platform, Barasinska and Schäfer (2014) failed to find such discrimination between female and male applicants. They argue that discrimination could be platform specific rather than market specific.

Information asymmetry could be a prevalent problem in the online market due to the anonymity of borrowers, which could put lenders' investment at risk (Yum et al. 2012; Emekter et al. 2015). However, the requirement for borrowers to share more financial and personal information can mitigate this risk (Feng et al. 2015). Accordingly, Freedman and Jin (2008) find that the average funding rate by Prosper has increased since it started asking borrowers to disclose more information. Social networking such as group borrowing could be another way of reducing information asymmetry in the online market; group leaders might act as an effective monitoring mechanism due to shared liability (Yum et al. 2012; Freedman and Jin 2017). Moreover, online friendship ties can act as a signal of the borrower's quality and thus,

[31] Ravina (2012) obtains similar results in support of taste-based discrimination, she conclude that there is presence of the beauty effect using data from Prosper.

might mitigate adverse selection and improve loan performance (Lin et al. 2013). However, Freedman and Jin (2017) find that this tool has drawbacks as investors misinterpret the borrower's quality due to being in a social network. Moreover, the virtual leadership of geographically dispersed teams poses challenges to the monitoring process (Bell and Kozlowski 2002; Hill and Bartol 2016).

4.2.3. Relation to Existing Literature

This chapter differs from existing studies that link between misreporting and loan performance as follows. First, this study is conducted in a fast-growing yet unregulated industry. Therefore, it is critical to understand the consequences of regulatory absence in terms of misreporting. Second, while previous research (e.g., Garmaise 2015) explores the performance of mortgage borrowers who over-report their asset level, we focus on the outcome of rounding income. The level of income can be a determining factor in lending decisions and it is most susceptible to misreporting. Third, rounding may be more profound in the data employed in this study, as online platforms do not provide exact guidelines during the application process regarding the required figure, if it is an actual or estimated one. Furthermore, we contribute to the growing peer-to-peer lending literature by providing empirical evidence on how the behavioral aspect of marketplace users might affect loan's performance. Most studies focus on the impact of borrower, loan characteristics, and platform mechanisms on the performance of loans in online lending marketplaces (Emekter et al. 2015; Miller 2015; Serrano-Cinca et al. 2015; Dorfleitner et al. 2016; Iyer et al. 2016). Another strand of literature focuses on the consequences of biases and discrimination in peer-to-peer lending (Pope and Sydnor 2011; Lin et al. 2013). However, this study identifies the presence of behavior patterns in misreporting income in online lending marketplaces and its impact on borrower credit position.

4.3. Data Description

In this chapter, we use a dataset of online loans that are originated between 2012 and 2015 by Lending Club.[32] The data enables us to observe around 757,623 online loans throughout their monthly credit cycle. Furthermore, it gives information about borrower's credit history at the time of loans issuance. The data allows us to examine the monthly performance of online loans. The monthly repayment status of each loan is disclosed (i.e. whether loans went into delinquency, default, or are still current). Additionally, we are able to consider borrowers' uncertainty by examining monthly changes in credit score.

Table 4.1 reports a detailed summary statistics of the variables used in the statistical analysis. Panel (A) of Table 4.1 reports the summary statistics of borrower and loan specific characteristics. The average loan size is $14,965 with an average interest rate of about 13.2%. On average, the loans' cycle lasted around 21 months. A typical borrower at Lending Club has at the time of the loan's origination an average debt-to-income ratio of 18.5%, a credit score of 696 and credit history length of 198 months. In the six months preceding the application, an average borrower has around 11 open credit lines. Moreover, borrowers at Lending Club have an average annual income of $74,266. Panel (B) and Panel (C) reports the summary statistics of the control variables at the three-digit ZIP code level and state level, respectively. Appendix 4.1 provides a detailed definition of the variables used in this study and their sources.

[Insert Table 4.1 here]

[32] Due to the data availability at the time of analyzing and writing this chapter, the sample period differs from the previous chapters.

4.4. Econometric Specification and Estimation

4.4.1. Main Specification

In order to estimate the relation between the presence of income rounding and loan outcomes we specify the following model:

$$Performance_{i,t} = \alpha + \ \beta\, \tilde{\mathrm{I}}_{i,t} + \gamma_1\, Borrower_{i,t} + \gamma_2 Demogtaphic\ Controls_{z,t} + \gamma_3 State\ Controls_{s,t} + Year_t\ + State_s + \varepsilon_{i,t} \tag{4.1}$$

where $Performance_{i,t}$ is a binary variable of whether loan i issued at time t goes into delinquency or default for the first time compared to loans that did not experience delinquency or default at any point. Following previous literature (Keys et al. 2010; Demyank and Hemert 2011; Garmaise 2015), we define loans as delinquent if they have a status of 31-120 days late in payment or in default. For robustness, we use the volatility of monthly changes in the credit score to measure borrower's credit performance; this measure can serve as an indicator of borrower's credit deterioration (Agarwal et al. 2006). The main independent variable $\tilde{\mathrm{I}}_i$ is an indicator of whether the reported annual income is rounded to the nearest multiples of 5,000. According to Binder (2015), a dummy variable of rounding can be a simple measure of uncertainty.

Lenders usually assign a credit grade for each loan based on a credit risk model that distinguishes between borrowers who are more likely to make payments on time and those who are more likely to default (Crook et al. 2007). This model is partially based on the borrower's credit report. Borrowers with good credit position are expected to have a low debt-to-income ratio, long credit history, and other previous successful credit lines. These borrowers are expected to be more prompt in their payments. In addition, a borrower's monthly decision whether to make the loan payment promptly or default depends on some observable factors like personal characteristics, loan characteristics and market conditions (Clapp et al. 2006).

Using a sample of subprime mortgage loans that originated between 1996 and 2003, Danis and Pennington-Cross (2008) find that the delinquency rate falls for loans with a better credit score. Moreover, Ambrose and Sanders (2003) find a positive relationship between the volatility of credit spreads and the probability of default in commercial mortgage-backed securities. In the peer-to-peer lending context, Emekter et al. (2015) find that borrower characteristics has a significant impact on loans default. They find that debt-to-income ratio and credit score significantly predict the default probability. Similarly, Serrano-Cinca et al. (2015) find that borrower characteristics like income, homeownership, and credit history highly explain borrower default in peer-to-peer lending. Therefore, it's important to control for borrower characteristics while examining the impact of rounding on borrower's default. Accordingly, $Borrower_{i,t}$ is a set of borrowers' credit characteristics. This includes borrower's credit score at the time of loan application (FICO), number of open credit accounts in the borrower's credit file at the time of loan application (Open accounts), and debt-to-income ratio (DTI). In addition, we control for the length of borrower credit history in months (Credit age), homeownership status (Homeownership), and borrower's annual income in natural logarithm (Ln(Income)). We also add loan purpose fixed effects to our specification.

While examining the impact of rounding on loan performance, we control for a number of demographic variables in order to account for the demographic and financial structure of different local markets (Demyank and Hemert 2011). Moreover, misreporting could be more prevalent in (Garmaise 2015). $Demogtaphic\ Controls_{z,t}$ is a vector of control variables at the three-digit ZIP code level that includes unemployment rate, the percentage of the male population, and the percentage of the white population. To control for the educational attainment in the local area, we include the percentage of the population aged 25 years and over who hold a bachelor degree. $State\ Controls_{s,t}$ includes state-level control variables to account for credit demand and credit quality in our specification. We control for state's real GDP per capita, auto debt balance per capita, credit card balance per capita, and mortgage debt balance per capita. Furthermore, we control for the percentage of auto debt, credit card debt, and mortgage debt balances that are more than or equal to 90 days delinquent. Lastly, we incorporate origination year fixed effects $Year_t$ to account for any variation in the performance of specific loan cohorts and state fixed effects $State_s$ to control for unobserved macroeconomic factors.

4.4.2. Rounding Estimation

If borrowers are cognitively constrained, one will find an overrepresentation of zero as number ending in numerical responses (Schindler and Kirby 1997; Kuo et al. 2015). Dehaene and Mehler (1992) attribute the overrepresentation of numbers ending in zeros to the saliency of round numbers. This overrepresentation distorts the distribution of income by creating extra spikes at rounded values (Czajka and Denmead 2008). Figure 4.1 shows that there is apparent heaping in the distribution of income around the multiples of \$5,000. Therefore, we use \$5,000 as our rounding level. This interpretation is common in studies concerned about heaping in the observed data (Pudney 2008; Binder 2015). Further, Pope et al. (2015) carry out a graphical analysis to determine round numbers as focal points. For robustness, we use \$10,000 as another rounding threshold.

[Insert Figure 4.1 here]

Based on the graphical interpretation, we adopt a modified specification of Garmaise (2015) model in order to identify borrowers with rounded income figures. Annual income is normalized to the nearest multiples of 5,000, as follows:

$$\mathrm{I} = Annual\ Income - round(Annual\ Income, 5{,}000) \tag{4.2}$$

$$\tilde{\mathrm{I}}_{(1,0)} \begin{cases} 1 & \text{If } \tilde{\mathrm{I}} = 0 \\ 0 & \text{If } \tilde{\mathrm{I}} \neq 0 \end{cases} \tag{4.3}$$

Where $\tilde{\mathrm{I}}$ is an indicator of whether the reported income is likely to be rounded to the nearest multiples of 5,000 or not. A normalized income of zero implies that the reported income is a rounded figure (Garmaise 2015). In our sample, around half of borrowers stated income amount that is rounded to the nearest multiple of $5,000.

4.5. Main Results

4.5.1. Income Rounding and Loan Performance

In this section, we estimate the consequences of rounding in terms of loans that went into delinquency for the first time compared with those that did not experience delinquency throughout their credit cycle. These tests take into consideration the previous argument that borrowers who round their income experience negative credit outcomes as they have imprecise financial information and do not show the effort needed to report accurate income figures compared to those who report a more accurate figure.

Table 4.2 presents the results of the main specification for the full sample and for only completed loans. Across all models, the main independent variable is an indicator of income rounding. In Model 1, we employ a logit model to estimate the likelihood of borrower delinquency and default. The first column provides the results for the full sample where the dependent variable is an indicator if the borrower is late in payment or default for the first time. We report the average marginal effects calculated around mean points using all loans in our dataset. As expected, the estimated coefficient for the indicator of rounding is positive and statistically significant. This suggests that the prevalence of rounding behavior is associated with adverse loan outcomes. Borrowers who report a rounded income are almost 0.76 percent more likely to be late in payment or default than those who report a more accurate figure, controlling for state and origination year fixed effects. The results for borrower's characteristics controls show the expected effect on borrower default. For instance, borrowers with higher credit score, higher income level, and longer credit history are less likely to experience delinquency. On the other hand, an increase in borrower's debt-to-income ratio and the number of open credit accounts are associated with an increase in borrower's likelihood to experience delinquency.

[Insert Table 4.2 here]

In the second column of Model 1, we re-estimate the main specification for completed loans, where the dependent variable is an indicator of whether the loan ended up in default or repaid in full. We observe the same negative effect of rounding indicator on borrower default. Borrowers who exhibit rounding behavior are more likely to end up in default than to repay the loan in full. The probability of a loan terminating through default for borrowers with rounded income is around 1.4 percent higher than borrowers who do not show rounding behavior.

The volatility of changes in monthly credit score can be a measure of borrowers' uncertainty. In Model 2, we use the volatility of credit score changes as a measure of borrower credit performance. The dependent variable is the standard deviation of monthly credit scores. The covariates are the same as in the first model. In the first column of Model 2, we report the results for the full sample and in the second column, we report the results for the completed loans sample. For the full and completed loans sample, the results show that borrowers with rounding tendency experience higher fluctuations in their monthly credit score. In Model 3, we identify whether the changes in borrower's credit score is positive or negative. In this model, the dependent variable is an indicator that equals to 1 if the borrower experiences a negative credit score change. This is measured by comparing borrower's credit score at the time of loan application and the last observed credit score. The results further confirm that borrowers who exhibit rounding behavior are more likely to have worse credit performance. Borrowers who exhibit rounding behavior are more likely to experience negative changes in their credit score. The results in the first column of Model 3 show that borrowers who round their income have a higher probability to have negative credit score change of around 1 percent. Credit score can serve as a monthly indicator of the borrower's willingness to repay their debt. Thus, our results imply that borrowers who tend to round face higher uncertainty in their ability to make payments promptly.

Overall, our findings suggest that borrowers who round their income figures have worse loan outcomes, experience higher monthly fluctuations in their credit score, and have negative changes in their credit scores. This supports our initial prediction that borrowers who have imprecise information regarding their financial position and who are less willing to exert effort to report their income accurately have worse financial performance. Moreover, they are in line with the literature concerning the occurrence of rounding (Myers 1954; Tarrant et al. 1993; Schindler and Kirby 1997; Pudney 2008; Manski and Molinari 2010). Previous literature suggests that rounding doesn't happen randomly and that it indicates imprecision and uncertainty regarding the information provided (Myers 1954; Jansen and Pollmann 2001; Krifka 2002; Gráda 2006; Binder 2015).

Our results are consistent with Garmaise's (2015) findings for the default predictability of misreporting in the mortgage market. In addition, they are in line with Jiang et al. (2014), who observe borrowers with income falsification have worse loan performance. They argue that lack of verification of reported information and in particular, income is a significant source of unobserved heterogeneity in loan quality. Furthermore, they are consistent with the findings of Gerardi et al. (2010) that less financially informed borrowers and cognitively constrained borrowers experience worse loan outcomes. As shown in Appendix 4.2, our results are robust when we use $10,000 as our rounding level.

4.5.2. Rounding and Loan Pricing

Borrowers might benefit from rounding their income figures, as they might seem more desirable to lenders. Jiang et al. (2014) show that borrowers' income, with a major effect on loan terms and qualification, is the figure most subject to falsification. Borrowers may take the opportunity to receive better loan terms or increase their funding likelihood by rounding their annual income (Dorfleitner and Jahnes 2014). Thus, borrowers may alter their income figures in the hope of having higher loan amounts or lower interest rates.

In this part of the analysis, we conduct several models to see if the negative impact of rounding is taken into account and if loans are adequately priced to reflect the increased risk associated with rounding. The price and non-price terms are normally used to manage and monitor borrower's risk (Strahan 1999). Furthermore, information asymmetry problems in risky lending practices could be mitigated by having restrictive terms (Ortiz-Molina and Penas 2008). For the pricing term, risky borrowers should be charged a higher interest rate to compensate lenders for the extra risk of default. In addition, risky borrowers could face tighter non-price terms by receiving a smaller amount of loans to limit investors' risk exposure.

Our main results suggest that rounding behavior is associated with severe adverse outcomes. Therefore, it is critical to analyze whether lenders are aware of such behavior ex ante and if loan pricing adequately reflects the increased risk. Table 4.3 addresses this by analyzing the pricing terms reflected in the interest rate and the non-pricing terms reflected in the loan's size. In Model 1, we report the OLS estimates of the relation between rounding behavior and loan interest rate. In Model 2, we present the OLS estimates of the association between rounding and loan size. We run both models for the full sample and completed loans. Similar to the main specification, we include borrower characteristics, three-digit ZIP code demographic controls, state-level controls, state fixed effects, and year fixed effects. The results in Model 1 show that borrowers who tend to round their income are charged a significantly lower interest rate than those who do not round. As shown in the first column of Model 1, the occurrence of rounding is associated with a decrease in borrowers' interest rate of around 0.09. On the other hand, we do not find a significant association between the existence of rounding and the size of loan granted. Overall, these results imply that online lenders are not aware of such behavior ex ante. Loans granted to borrowers who do not provide accurate information regarding their financial position are not priced in a way that compensates investors for the extra risk. Furthermore, this implies that borrowers might mislead lenders by rounding their income figures. This suggests a potential information asymmetry between borrowers and lenders as borrowers hide or misreport their financial information when there is an inconsistent verification process in order to get better lending conditions. Our results are consistent with previous studies that document that the occurrence of misreporting or manipulation is more significant when it's associated with better outcomes for the individual (Degeorge et al. 1999; Asness et al. 2001; Ben-David et al. 2013).

[Insert Table 4.3 here]

4.6. Robustness Checks

4.6.1. Survival Analysis

We employ a discrete survival analysis that allows us to observe borrower's monthly payment decision and control for variables that varies monthly to address partially the endogeneity problem. Moreover, it allows us to examine how the behavior of rounding affects time to default. We use only completed loans and define loan failure in a given month if a borrower default on their payment. We estimate our empirical model using a Complementary log-log model (cloglog). Allison (1982) defines a discrete-time hazard rate as follows:

$$P_{it} = \Pr[T_i = t \mid T_i \geq t, X_{it}] \quad (4.4a)$$

where T is the discrete random variable giving the uncensored time of failure and P_{it} is the conditional probability that a borrower will default at month t given that the borrower has not defaulted before. Each loan (borrower) i is tracked throughout their credit cycle until the borrower default on the loan or pay it back fully. More specifically, we use the Complementary log-log function as:

$$\log(-\log(1 - P_{it})) = \alpha_j + \beta' X_{it} \tag{4.4b}$$

The main independent variable is an indicator of the existence of rounding for a specific borrower. In addition, we include monthly-varying covariates and monthly-invariant covariates in our survival specification. Monthly-varying covariates consist of borrower's credit score and the remaining loan amount at the beginning of each month. Monthly-invariant covariates include borrower's debt-to-income ratio, annual income, and the number of open credit accounts. As in Eq. (4.1), we include three-digit ZIP code controls, state-level controls, state and year dummies.

We report the results of the complementary log-log model in Table 4.4. The results confirm our earlier findings of the negative consequences of rounding behavior. The coefficient estimates on the indicator of rounding show that borrowers who round have a higher hazard rate than those who do not round. The occurrence of rounding is associated with around [exp(0. 0.0193)−1] × 100 = 2% increase in borrower's hazard rate. The monthly-variant and -invariant control variables' estimates show the expected impact on borrower's risk of default. Monthly-variant variables show that an increase in borrower's credit score in each month is associated with a decrease in borrower's default risk. On the other hand, an increase in the remaining loan balance in each month increases the risk of borrower default in a given month. Invariant control variables indicate that an increase in debt-to-income ratio and the number of open credit account at the time of loan origination is associated with an increase in borrower's risk of default.

[Insert Table 4.4 here]

4.6.2. Other Possible Loan Outcomes

The second set of analysis takes into consideration that a loan does not necessarily fall in only two categories but can have various outcomes. Borrowers may show inconsistency in their transition from one status to another. They might fail to make payments on time at any given point in their life but may recover and get back on track with their payments. Danis and Pennington-Cross (2008) argue that it is critical for any predictive model to account for the different levels of delinquency and to identify their competing risk natures. Therefore, we employ a multinomial logit model to account for these different outcomes.[33] The multinomial specification does not only account for the probability of several events occurrence but also consider the competing risk feature of these outcomes (D'Addio and Rosholm 2005). Loans could be terminated through either paying off or default. These events are considered mutually exclusive events since the occurrence of one naturally prevents observing the other event (Calhoun and Deng 2002).

Therefore, Eq. (4.1) is re-estimated using a multinomial logit model, where the probability of observing outcome j for loan i is

$$P(Y_i = j|x_i) = \frac{e^{\beta'_j x_i}}{1+\sum_{k=1}^{J} e^{\beta'_j x_i}} \qquad for \quad j \in [State_1, State_2, State_3] \tag{4.5}$$

[33] Calhoun and Deng (2002) give a comparative analysis between different statistical models that are usually used in analyzing mortgage loan terminations and explain why a discrete choice model like multinomial logit model is the most appropriate for loan termination analysis.

where x_i is a vector of independent variables that are used in Eq. (4.1) for loan i and β_j' is a vector of coefficients for each state of j. For the full sample, the possible states are current, delinquency, and paid off, respectively. Loans that have current status are those that are up to date on their payments. Delinquent loans are those who are late in payment or in default. Last, loans that have paid off status are those that borrowers have fully repaid. For robustness, we limit our sample to only completed loans and estimate a number of alternatives for the above specification by observing other possible states than default and paying off the loan on time. We consider that a borrower may settle the loan and prepay it before the due date. Therefore, the possible states for the completed loans sample are default, prepayment, and paid off.

Delinquency can be a turning point in loan's performance: a loan that is late in payment may eventually survive or enter a worse status like default. In this model, we amend our previous definition of delinquency by adding a restrictive condition: loans that fall in the delinquency category are those that have experienced delinquency for the first time and failed to recover later. In contrast to the previous model, current and paid off loans include both borrowers who did not fail to pay at any point and those who experienced a discrepancy in their payment status at time t but recovered at $t + n$ where n is the last observed month for each loan. Given that we have three discrete possible outcomes for each loan, we estimate a multinomial logit specification with the same covariates used in Eq. (4.1).

The results for the multinomial logit model are consistent with the prediction that rounding behavior is associated more with inferior than with enhanced outcomes. The first model in Table 4.5 presents the results for the full sample. The three possible outcomes are delinquency, paid off, and current, where the last is the base category. The first column presents the results of the probability that borrowers have delinquency status compared to staying up to date on their payments. The second column shows the results of the probability that borrowers pay off their loans compared to staying up to date on their loan payments. Even after taking into consideration the volatility of transitions, borrowers with rounding behavior are more likely to be late in payment or default. Furthermore, they are significantly less likely to pay off loans than to stay up to date on their payments. In the second model of Table 4.5, the option of prepayment is evaluated, and the sample is limited only to completed loans. The three possible outcomes are paid off, default, and prepayment, where the last is the base category. The cost of prepayment is considered lower than default as investors only lose future interest payments. However, prepayment can imply that borrowers have enough liquidity to settle the loan. The first column of Model 2 shows the results of the likelihood that loans go into default status relative to prepayment. The second column presents the results of the likelihood that loans are paid off at the end of the term compared to prepayment. The likelihood that a loan will end up in default is significantly higher for borrowers who exhibit rounding behavior than it is for borrowers who are more accurate while reporting their income. They are significantly more likely to end their loan through default than prepaying the loan. Furthermore, they are more likely to repay the loan at its due date than prepay it before the end of the loan term. The multinomial logit model confirms our results for the binary outcome model. Furthermore, it proves that the occurrence of rounding is not only associated with an unfavorable loan outcome but also significantly lowers the likelihood that borrowers will pay back loans promptly.

[Insert Table 4.5 here]

4.7. Additional Tests

There could be concerns that the negative relationship between rounding and credit outcomes is due to the quality of borrowers rather than the occurrence of rounding. Therefore, we identify the impact of rounding among different categories of borrowers to see if the lower quality or risky borrowers drive the increased risk associated with rounding. Table 4.6 reports the impact of rounding on loan's performance by different groups of borrowers where the dependent variable is an indicator if the borrower is late in payment or default. We split borrowers into three groups based on homeownership status, credit score, and income, respectively.

[Insert Table 4.6 here]

In the first Model, we distinguish borrowers based on homeownership where the first column reports the results for renters and the second column provides the results for homeowners. In Model 2, we differentiate between borrowers according to their credit score. We define borrowers as having a low credit score if their credit score is less than or equals the median credit score of a three-digit ZIP code for a given year. In addition, Model 3 provides the results of the subsamples based on borrower's income. Borrowers fall in the subsample of low income if borrower's annual income is lower or equal the median annual income of three-digit ZIP code for a given year. Across the three models, we do not find a significant difference between lower and higher quality borrowers. The results show that rounding is significantly associated with worse loan performance for both lower and higher quality borrowers. Moreover, we do not find a significant difference in the magnitude of rounding across different groups of borrowers. For robustness, we estimate the impact of rounding on the changes in borrower's credit score for different groups of borrowers. We report the results in Table 4.7 where the dependent variable is an indicator if borrowers experience negative changes in their credit score. The results show that rounding is consistently associated with worse credit outcomes. Across different groups, borrowers who round their income are more likely to face negative changes in their credit score. Overall, our results indicate that rounding by different categories of borrowers is consistently associated with worse credit outcomes.

[Insert Table 4.7 here]

If the negative impact of rounding on loan's performance is driven by the quality of borrowers, we should observe a significant difference in the pricing of loans between lower and higher quality borrowers who round their income figures. In Table 4.8, we examine the relationship between rounding and interest rate for the subsamples. The estimated coefficients on rounding across all models are negative and statistically significant.[34] The results for different subsamples show that borrowers who round their income are charged a significantly lower interest rate than those who do not round their income. This further confirms that our results are not driven by lower quality borrowers. In addition, this implies that lower and higher quality borrowers benefit from rounding their income by having lower interest rates.

[Insert Table 4.8 here]

[34] As shown in Appendix 4.3, we find either a marginal significant or insignificant association between the existence of rounding and the size of loan granted for the subsamples.

4.8. Conclusions

It is apparent that borrowing and lending habits are changing at an unprecedented rate. Online lending marketplaces are becoming an important part of the credit market. However, there is an increased risk and higher chances of misreporting in marketplace lending due to the online nature of the process and the inconsistency in verifying the supplied personal information of users. In this chapter, we examine the consequences for loan outcomes of the tendency to round self-reported responses. The existence of rounding behavior could imply that borrowers are less financially informed. Moreover, cognitively constrained and financially uninformed borrowers are more likely to experience adverse financial performance (Gerardi et al. 2010; Garmaise 2015).

Our findings suggest that rounding behavior is prevalent in the online market and is associated with severe adverse loan outcomes. Around half of the borrowers in our sample report income that is rounded to the nearest multiple of $5,000. Furthermore, borrowers who report rounded income have higher chances of default compared to precise borrowers. Considering the volatility of changes in credit scores, we find that rounding is extensively associated with higher fluctuations in borrower's credit score. Furthermore, rounding is associated with an increased likelihood that borrower experiences negative credit score changes. Lastly, by examining the pricing terms of loan contracts, we show that investors are not compensated for the increased risk of rounding. Borrowers who round their income are charged a lower interest rate.

4.9. Policy Implications

Our results suggest that misreporting income by means of rounding might play a role in loans' delinquency and that this could expose investors to extra risk, for which they are not compensated. This suggests that there should be a more thorough check of the borrower’s application, specifically for self-reported data. Ignoring the occurrence of rounding in the reported data may result in an invalid judgment about borrowers’ creditworthiness. The findings of Chapter 4 imply that it is necessary that policymakers distinguish borrowers who show behavior patterns in their information reporting as the virtual aspect of online lending marketplaces. Finally, policymakers should consider having a unified verification process that tries to provide investors with as much accurate information as possible may help to secure the online lending process. This could be done by outsourcing the verification process to a third party similar to the credit scoring process. Lastly, using technology for process implementation can profoundly reduce the burdens for users.

4.10. Areas for Future Research

This chapter focuses on the prevalence of behavioral patterns in Lending Club, it would be interesting to see whether such behavioral patterns hold for other marketplaces. This will help identify whether the occurrence of rounding behavior is an industry problem or platform specific. This thesis uses data from Lending Club, which is one of the few online lending marketplaces to be listed on the New York Stock Exchange. Future research should focus on whether going public add value to the participants in online marketplaces. Another prospect for future research is examining the competition between different online lending marketplaces and the impact on the financial position of those marketplaces. This would enrich the current literature on online marketplaces and provide an overall understanding of the mechanisms of online lending marketplaces.

Figure 4.1: Frequency of Annual Income

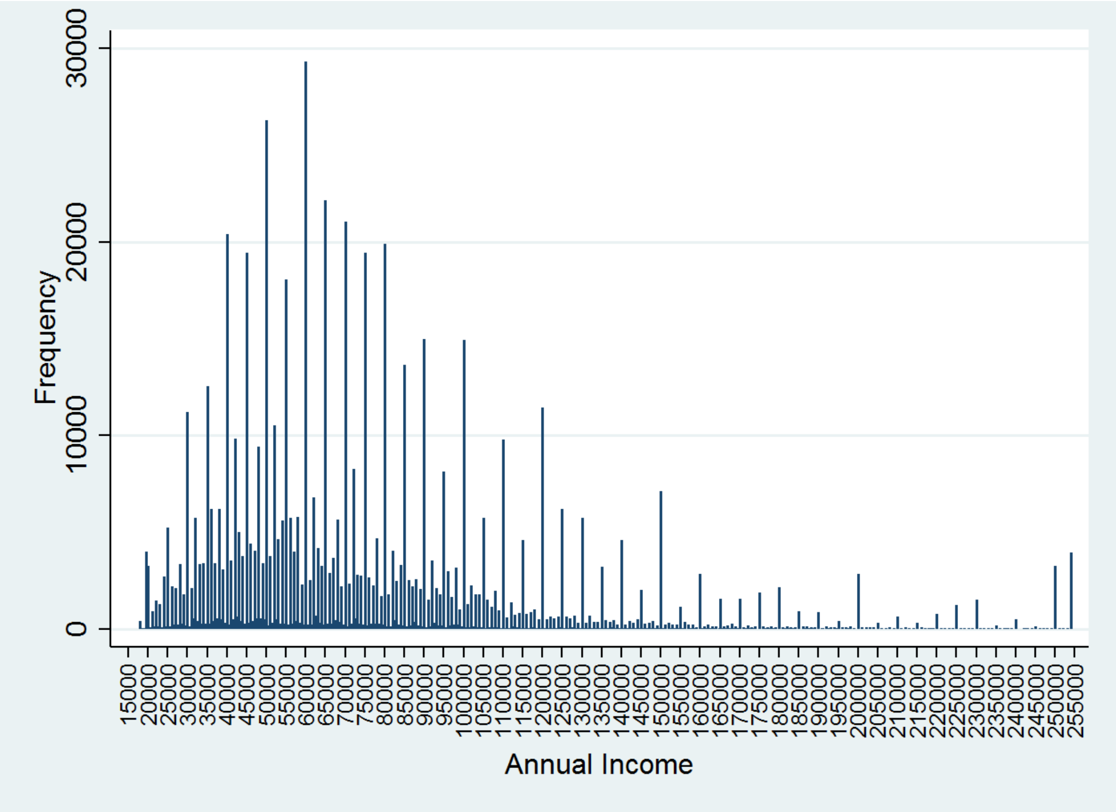


Table 4.1: Summary Statistics

VARIABLES	(1) Mean	(3) SD	(4) p25	(5) p50	(6) p75	(7) p95
Panel A: Borrower and Loan Characteristics						
Loan amount	14,965	8,425.86	8,400	13,500	20,000	32,000
Interest rate	13.20	4.38	9.99	12.99	15.99	20.99
Annual income	74,266	41,040	46,000	65,000	90,000	150,000
Debt-to-income ratio	18.46	8.27	12.21	17.97	24.34	33.02
Open accounts	11.69	5.18	8	11	14	22
Credit age (in months)	198.01	89.15	137	180	243	369
FICO	695.97	29.73	672	687	712	757
loan age	21.10	9.05	15	20	27	36
Panel B: Three-digit ZIP controls						
Percentage of over 25 population with bachelor degree	0.19	0.05	0.15	0.19	0.23	0.29
Unemployment rate	0.09	0.02	0.07	0.09	0.10	0.13
Percentage of male population	0.49	0.01	0.49	0.49	0.50	0.51
Percentage of white population	0.72	0.16	0.63	0.75	0.84	0.94
Panel C: State level controls						
GDP	50,498	9,735	43,216	51,844	55,247	63,390
Auto loans per capita	3,837	738.29	3,350	3,680	4,220	5,480
Mortgage per capita	33,371	11,084	23,410	30,790	43,980	51,850
Credit card per capita	2,862	401.18	2,600	2,830	3,180	3,460
Auto delinquency rate	3.28	1.04	2.50	3	4	5
Mortgage delinquency rate	3.02	2.12	1.50	2.50	3.50	7
Credit card delinquency rate	8.07	1.83	7	8	8.50	11

This table provides the following summary statistics of the main and control variables used in this study: the average value (Mean), the standard deviation (SD), the 25th percentile (p25), the 50th percentile (p50), the 75th percentile (p75), and the 95th percentile (p95). All the variables are defined in Appendix 4.1.

Table 4.2: Rounding and Loan Performance

	Model (1)		Model (2)		Model (3)	
	(1)	(2)	(1)	(2)	(1)	(2)
VARIABLES	Delinquency	Default	SD(FICO)	SD(FICO)	Negative change	Negative change
Round	0.0076***	0.0137***	0.4070***	0.5929***	0.0111***	0.0140***
	(0.0008)	(0.0012)	(0.0367)	(0.0554)	(0.0012)	(0.0016)
Borrower Characteristics:						
FICO	-0.0011***	-0.0017***	0.0018**	-0.0062***	0.0019***	0.0017***
	(0.0000)	(0.0000)	(0.0007)	(0.0010)	(0.0000)	(0.0000)
DTI	0.0028***	0.0055***	0.0838***	0.1891***	0.0043***	0.0057***
	(0.0001)	(0.0001)	(0.0026)	(0.0044)	(0.0001)	(0.0001)
Credit age	-0.0000***	0.0000	-0.0163***	-0.0146***	-0.0003***	-0.0002***
	(0.0000)	(0.0000)	(0.0002)	(0.0003)	(0.0000)	(0.0000)
Open accounts	0.0013***	0.0020***	0.0077**	0.0169***	0.0028***	0.0018***
	(0.0001)	(0.0001)	(0.0037)	(0.0063)	(0.0001)	(0.0002)
Ln(Income)	-0.0074***	-0.0176***	-0.5117***	-0.6871***	-0.0101***	-0.0198***
	(0.0011)	(0.0019)	(0.0464)	(0.0680)	(0.0018)	(0.0024)
Loan age	-0.0034***	-0.0003***	0.1276***	0.2187***	0.0031***	0.0040***
	(0.0001)	(0.0001)	(0.0028)	(0.0032)	(0.0001)	(0.0001)
Homeownership (rent)	0.0157***	0.0290***	0.5261***	0.9516***	0.0169***	0.0153***
	(0.0011)	(0.0021)	(0.0482)	(0.0735)	(0.0018)	(0.0023)
Observations	757,623	400,598	757,623	400,598	757,623	400,598
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Three-digit ZIP code level controls	Yes	Yes	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes	Yes	Yes

State Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Completed	Full	Completed	Full	Completed

This table presents the results of the baseline specification using different measures of borrower performance. Across all the models, the main independent variable is an indicator of rounding behavior. The first model shows the results of the average marginal effects of the logit regression. In the first column, the dependent variable is one if the loan experience delinquency or default for the first time at any point of their cycle and the base category is loans that did not encounter delinquency or default throughout their credit cycle. In the second column, we present the results for only completed loans. The dependent variable is one if the loan is terminated through default rather than paying back. The covariates include variables discussed in Eq. (4.1). The second model contains OLS estimates for the full and completed loans sample where the dependent variable is the standard deviation of monthly changes in borrower's credit score. In the last model, the dependent variable is an indicator if the borrower has experienced a negative change in their credit score at the last observed month. Model (3) shows the results of the average marginal effects of logit regression for the full and completed loan sample. DTI, annual income, and open accounts are winsorized at the 1st and 99th percentile. Standard errors are clustered at the three-digit ZIP code level in parentheses.
** and *** indicate significance at the 5%, and 1% levels, respectively.

Table 4.3: Rounding and Loan Terms

	Model (1)		Model (2)	
VARIABLES	Interest rate	Interest rate	Ln(loan amount)	Ln(loan amount)
Round	-0.0863***	-0.0697***	-0.0004	0.0004
	(0.0072)	(0.0100)	(0.0013)	(0.0017)
Borrower Characteristics:				
FICO	-0.0580***	-0.0634***	0.0016***	0.0015***
	(0.0001)	(0.0002)	(0.0000)	(0.0000)
DTI	0.0614***	0.0577***	0.0067***	0.0071***
	(0.0007)	(0.0009)	(0.0001)	(0.0001)
Credit age	-0.0031***	-0.0024***	0.0001***	0.0001***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Open accounts	-0.0181***	-0.0153***	0.0017***	0.0028***
	(0.0010)	(0.0014)	(0.0001)	(0.0002)
Ln(Income)	-0.6496***	-0.4923***	0.5589***	0.5670***
	(0.0125)	(0.0144)	(0.0020)	(0.0025)
Homeownership (rent)	0.1528***	0.2612***	-0.0295***	-0.0295***
	(0.0116)	(0.0137)	(0.0017)	(0.0022)
loan term (60 months)	4.3090***	4.7644***	0.4810***	0.4877***
	(0.0107)	(0.0134)	(0.0018)	(0.0022)
Observations	757,623	400,598	757,623	400,598
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes
Three-digit ZIP code level controls	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Sample	Full	Completed	Full	Completed

This table reports the OLS estimates of the relation between rounding and loan pricing and non-pricing terms. In Model 1, the dependent variable is the loan's interest rate. The first column of Model 1 provides the results of the full sample and the second column provide the results for completed loans. In Model 2, the dependent variable is the natural logarithm of the granted loan amount. The first column of Model 2 provides the results of the full sample and the second column provide the results for completed loans. DTI, annual income, and open accounts are winsorized at the 1st and 99th percentile. Standard errors are clustered at the three-digit ZIP code level in parentheses.
*** indicates significance at the 1% level.

Table 4.4: Survival Analysis

VARIABLES	cloglog
Round	0.0193**
	(0.0098)
Borrower Characteristics:	
Ln(Loan Beginning Balance)	0.3994***
	(0.0067)
Last FICO	-0.0374***
	(0.0001)
DTI	0.0041***
	(0.0006)
Credit age	0.0015***
	(0.0001)
Open accounts	0.0084***
	(0.0010)
Ln(Income)	-0.1034***
	(0.0130)
Homeownership (rent)	-0.0259**
	(0.0111)
Observations	7,787,208
Loan Purpose Fixed Effects	Yes
Three-digit ZIP code level controls	Yes
State level controls	Yes
State Dummies	Yes
Year Dummies	Yes
Sample	Completed

This table provides the results of complementary log-log model using only completed loans. The dependent variable is a dummy variable equal to one if a borrower default on loan in a given month, zero otherwise. The main independent variable is an indicator of whether the borrower rounds his/her income or not. Loan beginning balance and last FICO are control variables that vary monthly for each borrower. The rest of borrower characteristic variables do not vary monthly. DTI, annual income, and open accounts are winsorized at the 1st and 99th percentile. Standard errors are clustered at the three-digit ZIP code level in parentheses.
** and *** indicate significance at the 5%, and 1% levels, respectively.

Table 4.5: Multinomial Logit Model

	Model (1)		Model (2)	
	(1)	(2)	(1)	(2)
VARIABLES	Delinquency	Paid off	Default	Paid off
Round	0.0063***	-0.0116***	0.0138***	0.0021***
	(0.0007)	(0.0009)	(0.0012)	(0.0005)
Borrower Characteristics:				
FICO	-0.0011***	0.0008***	-0.0017***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
DTI	0.0028***	-0.0042***	0.0055***	-0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)
Credit age	-0.0000***	-0.0001***	0.0000	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Open accounts	0.0015***	-0.0003***	0.0020***	-0.0001*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Ln(Income)	-0.0111***	0.0043***	-0.0196***	-0.0180***
	(0.0012)	(0.0012)	(0.0019)	(0.0007)
Loan age	-0.0088***	-0.0286***	-0.0015***	0.0208***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Homeownership (rent)	0.0168***	-0.0186***	0.0285***	0.0018***
	(0.0012)	(0.0016)	(0.0021)	(0.0007)
Observations	757,623	757,623	400,598	400,598
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes
Three-digit ZIP code level controls	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes

State Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Sample	Full	Full	Completed	Completed

This table presents the results of the average marginal effects for the multinomial logit model. Observations are at loan level. The first model is estimated for the whole sample. The possible status for the first model is delinquency, paid off and continuous payment, where the latter is the base category. The second model is evaluated only for loans that are completed. The possible status is default, paid off and prepayment, where the latter is the base category. The list of covariates is the same as discussed in Eq. (4.1). DTI, annual income, and open accounts are winsorized at the 1st and 99th percentile. Standard errors are clustered at the three-digit ZIP code level in parentheses.
*, and *** indicate significance at the 10% and 1% levels, respectively.

Table 4.6: Rounding and Loan Performance: Evidence from Supsamples

	Dependent variable: Loan performance					
	Model (1)		Model (2)		Model (3)	
VARIABLES	Rent	Owner	low FICO	High FICO	low Inc	High Inc
Round	0.0090***	0.0067***	0.0081***	0.0073***	0.0068***	0.0082***
	(0.0014)	(0.0009)	(0.0012)	(0.0010)	(0.0011)	(0.0011)
Borrower Characteristics:						
FICO	-0.0012***	-0.0011***	-0.0006***	-0.0007***	-0.0011***	-0.0012***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
DTI	0.0034***	0.0023***	0.0034***	0.0021***	0.0028***	0.0028***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Credit age	0.0000*	-0.0001***	-0.0001***	0.0000	-0.0000	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Open accounts	0.0016***	0.0011***	0.0020***	0.0005***	0.0018***	0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Ln(Income)	-0.0050**	-0.0095***	-0.0022	-0.0133***	-0.0077***	0.0014
	(0.0020)	(0.0012)	(0.0017)	(0.0011)	(0.0021)	(0.0019)
Loan age	-0.0043***	-0.0029***	-0.0046***	-0.0022***	-0.0044***	-0.0024***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Homeownership (rent)			0.0187***	0.0119***	0.0150***	0.0163***
			(0.0015)	(0.0013)	(0.0014)	(0.0015)
Observations	298,902	458,710	403,840	353,765	386,590	371,021
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Three-digit ZIP code level controls	Yes	Yes	Yes	Yes	Yes	Yes

State level controls	Yes	Yes	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Full	Full	Full	Full	Full

This table presents the results of the baseline specification for the subsamples. The results show the average marginal effects of the logit regression. Across all the models, the dependent variable is one if the loan experience delinquency or default for the first time at any point of their cycle and the base category is loans that did not encounter delinquency or default throughout their credit cycle. The main independent variable is an indicator of rounding behavior. We divide the subsamples in Model 1 based on homeownership. Model 2 presents the results of the subsample based on credit score; we classify borrowers as having low fico if their credit score is below or equals the median credit score for a three-digit ZIP code in a given year. Model 3 is based on annual income; borrowers are classified as low income if their income is below or equals the median income for a three-digit ZIP code in a given year. The list of covariates is the same as discussed in Eq. (4.1). DTI, annual income, and open accounts are winsorized at the 1st and 99th percentile. Standard errors are clustered at the three-digit ZIP code level in parentheses.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4.7: Rounding and Credit Score Changes: Evidence from Subsamples

	Dependent variable: Negative Fico Change					
	Model (1)		Model (2)		Model (3)	
VARIABLES	Rent	Owner	low FICO	High FICO	low Inc	High Inc
Round	0.0119***	0.0107***	0.0104***	0.0117***	0.0112***	0.0097***
	(0.0019)	(0.0015)	(0.0017)	(0.0017)	(0.0017)	(0.0018)
Borrower Characteristics:						
FICO	0.0020***	0.0018***	0.0040***	0.0027***	0.0018***	0.0019***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
DTI	0.0043***	0.0042***	0.0035***	0.0053***	0.0041***	0.0048***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Credit age	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Open accounts	0.0032***	0.0025***	0.0041***	0.0013***	0.0028***	0.0028***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Ln(Income)	-0.0246***	-0.0013	-0.0209***	0.0032	-0.0476***	0.0383***
	(0.0027)	(0.0020)	(0.0022)	(0.0023)	(0.0035)	(0.0032)
Loan age	0.0027***	0.0034***	0.0018***	0.0048***	0.0025***	0.0037***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Homeownership (rent)			0.0171***	0.0151***	0.0151***	0.0168***
			(0.0021)	(0.0024)	(0.0021)	(0.0026)
Observations	298,913	458,710	403,854	353,769	386,590	371,028
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Three-digit ZIP code level controls	Yes	Yes	Yes	Yes	Yes	Yes

State level controls	Yes	Yes	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Full	Full	Full	Full	Full

This table presents the results of the baseline specification for the subsamples. The results show the average marginal effects of the logit regression. Across all the models, the dependent variable is an indicator if the borrower has experienced a negative change in their credit score at the last observed month. The main independent variable is an indicator of rounding behavior. We divide the subsamples in Model 1 based on homeownership. Model 2 presents the results of the subsample based on credit score; we classify borrowers as having low fico if their credit score is below or equals the median credit score for a three-digit ZIP code in a given year. Model 3 is based on annual income; borrowers are classified as low income if their income is below or equals the median income for a three-digit ZIP code in a given year. The list of covariates is the same as discussed in Eq. (4.1). DTI, annual income, and open accounts are winsorized at the 1st and 99th percentile. Standard errors are clustered at the three-digit ZIP code level in parentheses.
*** indicates significance at the 1% level.

Table 4.8: Rounding and Loan Pricing: Evidence from Subsamples

	Dependent variable: Interest rate					
	Model (1)		Model (2)		Model (3)	
VARIABLES	Rent	Own	Low credit	High credit	Low Inc	High Inc
Round	-0.0809***	-0.0908***	-0.0856***	-0.0867***	-0.0899***	-0.0988***
	(0.0119)	(0.0095)	(0.0098)	(0.0109)	(0.0103)	(0.0108)
Borrower Characteristics:						
FICO	-0.0588***	-0.0577***	-0.0607***	-0.0506***	-0.0572***	-0.0588***
	(0.0003)	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.0002)
DTI	0.0560***	0.0651***	0.0631***	0.0612***	0.0639***	0.0612***
	(0.0011)	(0.0007)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Credit age	-0.0034***	-0.0030***	-0.0043***	-0.0018***	-0.0034***	-0.0029***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Open accounts	-0.0246***	-0.0145***	0.0009	-0.0428***	-0.0199***	-0.0138***
	(0.0014)	(0.0011)	(0.0012)	(0.0014)	(0.0013)	(0.0014)
Ln(Income)	-0.7120***	-0.6124***	-0.5880***	-0.6980***	-1.4044***	0.1343***
	(0.0199)	(0.0139)	(0.0150)	(0.0168)	(0.0201)	(0.0232)
Loan Term	4.4101***	4.2601***	4.3502***	4.2809***	4.2712***	4.4241***
	(0.0172)	(0.0114)	(0.0128)	(0.0147)	(0.0147)	(0.0131)
Homeownership (rent)			0.1165***	0.1704***	0.0262**	0.2738***
			(0.0138)	(0.0161)	(0.0125)	(0.0180)
Observations	298,913	458,710	403,854	353,769	386,590	371,033
R-squared	0.4673	0.4932	0.3910	0.4814	0.4519	0.5133
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Three-digit ZIP code level controls	Yes	Yes	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Full	Full	Full	Full	Full

This table reports the OLS estimates of the relation between rounding and loan pricing for the subsamples. Across all the models, the dependent variable is the loan's interest rate and the main independent variable is an indicator of rounding. We divide the subsamples in Model 1 based on homeownership. Model 2 presents the results of the subsample based on credit score; we classify borrowers as having low fico if their credit score is below or equals the median credit score for a three-digit ZIP code in a given year. Model 3 is based on annual income; borrowers are classified as low income if their income is below or equals the median income for a three-digit ZIP code in a given year. The list of covariates is the same as discussed in Eq. (4.1). DTI, annual income, and open accounts are winsorized at the 1st and 99th percentile. Standard errors are clustered at the three-digit ZIP code level in parentheses.

** and *** indicate significance at the 5% and 1% levels, respectively.

Appendix 4.1: Variables Definitions

Variable	Description	Source
Round	An indicator of whether the borrower round his her income to the nearest multiples of $5,000.	Lending Club
Panel A: Borrower and loan characteristics		
FICO	The borrower’s credit score at the time of loan application.	Lending Club
Debt-to-income ratio	A ratio calculated using the borrower’s total monthly debt payments on the total debt obligations, excluding mortgage and the requested LC loan, divided by the borrower’s self-reported monthly income.	Lending Club
Annual Income	The self-reported annual income provided by the borrower.	Lending Club
Open Accounts	The number of open credit lines in the borrower's credit file.	Lending Club
Homeownership status	An indicator that equals to 1 if the borrower rents a house and zero if the borrower owns it.	Lending Club
Credit age	The length of borrower’s credit history in months; it is calculated as the time difference between borrower’s earliest credit line date and loan’s issue date.	Lending Club
Loan amount	The amount of the loan applied for by the borrower.	Lending Club
Loan term	A dummy that equals 1 if the loan term is 60 months and zero if it is 36 months.	Lending Club
Loan age	The last observed month on the books for each loan.	Lending Club
Loan purpose	The purpose of the loan applied for. The possible categories are debt consolidation, home improvement, credit card, car, house, major purchase, medical, moving, small business, vacation, and other.	Lending Club
Panel A: Three-digit ZIP code Controls		

Male population %	The percentage of the male population.	American Community Survey 5-year estimates (census bureau)
White population %	The percentage of the white population.	American Community Survey 5-year estimates (census bureau)
Percentage of over 25 population who hold at least a bachelor's degree	Percentage of the population aged 25 years and over with at least a bachelor's degree.	American Community Survey 5-year estimates (census bureau)
Unemployment rate	The number of unemployed individuals as a percentage of the labor force.	American Community Survey 5-year estimates (census bureau)
Panel C: State-level controls		
Real GDP per capita	Real per capita GDP.	Bureau of Economic Analysis
Credit card delinquency rate	Percent of Credit Card Debt Balance 90+ Days Delinquent.	New York Fed/Equifax Consumer Credit panel
Auto delinquency rate	Percent of Auto Debt Balance 90+ Days Delinquent.	New York Fed/Equifax Consumer Credit panel
Mortgage delinquency rate	Percent of Mortgage Debt Balance 90+ Days Delinquent.	New York Fed/Equifax Consumer Credit panel
Credit card per capita	Credit Card Debt Balance per Capita.	New York Fed/Equifax Consumer Credit panel
Auto loans per capita	Auto Debt Balance per Capita.	New York Fed/Equifax Consumer Credit panel
Mortgage per capita	Mortgage Debt Balance per Capita (excluding HELOC).	New York Fed/Equifax Consumer Credit panel

Appendix 4.2: Rounding and Loan Performance (Rounding Level: $10,000)

	Model (1)		Model (2)		Model (3)	
	(1)	(2)	(1)	(2)	(1)	(2)
VARIABLES	Delinquency	Default	SD(FICO)	SD(FICO)	Negative change	Negative change
Round ($10,000)	0.0064***	0.0119***	0.3775***	0.5624***	0.0080***	0.0136***
	(0.0008)	(0.0013)	(0.0370)	(0.0559)	(0.0013)	(0.0017)
Borrower Characteristics:						
FICO	-0.0011***	-0.0017***	0.0018**	-0.0062***	0.0019***	0.0017***
	(0.0000)	(0.0000)	(0.0007)	(0.0010)	(0.0000)	(0.0000)
DTI	0.0028***	0.0054***	0.0835***	0.1886***	0.0043***	0.0057***
	(0.0001)	(0.0001)	(0.0026)	(0.0044)	(0.0001)	(0.0001)
Credit age	-0.0000***	-0.0000	-0.0163***	-0.0146***	-0.0003***	-0.0002***
	(0.0000)	(0.0000)	(0.0002)	(0.0003)	(0.0000)	(0.0000)
Open accounts	0.0013***	0.0020***	0.0080**	0.0174***	0.0028***	0.0018***
	(0.0001)	(0.0001)	(0.0037)	(0.0063)	(0.0001)	(0.0002)
Ln(Income)	-0.0068***	-0.0166***	-0.4838***	-0.6496***	-0.0090***	-0.0190***
	(0.0011)	(0.0019)	(0.0468)	(0.0689)	(0.0018)	(0.0024)
Loan age	-0.0034***	-0.0003***	0.1276***	0.2187***	0.0031***	0.0040***
	(0.0001)	(0.0001)	(0.0028)	(0.0032)	(0.0001)	(0.0001)
Homeownership (rent)	0.0156***	0.0290***	0.5265***	0.9526***	0.0170***	0.0153***
	(0.0011)	(0.0021)	(0.0483)	(0.0735)	(0.0018)	(0.0023)
Observations	757,623	400,598	757,623	400,598	757,623	400,598
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Three-digit ZIP code level controls	Yes	Yes	Yes	Yes	Yes	Yes

State level controls	Yes	Yes	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Completed	Full	Completed	Full	Completed

This table presents the results of the baseline specification using multiplies of $10,000 as the rounding threshold. Across all the models, the main independent variable is an indicator of rounding behavior. The first model shows the results of the average marginal effects of the logit regression. In the first column, the dependent variable is one if the loan experience delinquency or default for the first time at any point of their cycle and the base category is loans that did not encounter delinquency or default throughout their credit cycle. In the second column, we present the results for only completed loans. The dependent variable is one if the loan is terminated through default rather than paying back. The second model contains OLS estimates for the full and completed loans sample where the dependent variable is the standard deviation of monthly changes in borrower's credit score. In the last model, the dependent variable is an indicator if the borrower has experienced a negative change in their credit score at the last observed month. Model (3) shows the results of the average marginal effects of logit regression for the full and completed loan sample. DTI, annual income, and open accounts are winsorized at the 1st and 99th percentile. Standard errors are clustered at the three-digit ZIP code level in parentheses.
** and *** indicate significance at the 5%, and 1% levels, respectively.

Appendix 4.3: Rounding and Loan Size: Evidence from Subsamples

	Dependent variable: Loan size					
	Model (1)		Model (2)		Model (3)	
VARIABLES	Rent	Own	Low credit	High credit	Low Inc	High Inc
Round	0.0025	-0.0029*	0.0021	-0.0034**	0.0010	0.0003
	(0.0019)	(0.0016)	(0.0016)	(0.0017)	(0.0017)	(0.0018)
<u>*Borrower Characteristics:*</u>						
FICO	0.0015***	0.0016***	0.0023***	-0.0002***	0.0012***	0.0019***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
DTI	0.0085***	0.0055***	0.0061***	0.0064***	0.0054***	0.0081***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Credit age	0.0001***	0.0001***	0.0001***	0.0003***	0.0002***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Open accounts	0.0015***	0.0020***	0.0029***	0.0004**	0.0024***	0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Ln(Income)	0.5811***	0.5445***	0.5273***	0.5834***	0.6082***	0.4832***
	(0.0033)	(0.0023)	(0.0023)	(0.0025)	(0.0036)	(0.0034)
Loan Term	0.4962***	0.4712***	0.5237***	0.4284***	0.5227***	0.4379***
	(0.0026)	(0.0021)	(0.0023)	(0.0021)	(0.0020)	(0.0025)
Homeownership (rent)			-0.0279***	-0.0277***	-0.0284***	-0.0257***
			(0.0021)	(0.0023)	(0.0022)	(0.0023)

Observations	298,913	458,710	403,854	353,769	386,590	371,033
R-squared	0.4153	0.4932	0.4180	0.4220	0.3737	0.2891
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Three-digit ZIP code level controls	Yes	Yes	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Full	Full	Full	Full	Full

This table reports the OLS estimates of the relation between rounding and loan size for the subsamples. Across all models, the dependent variable is the loan's amount and the main independent variable is an indicator of rounding. We divide the subsamples in Model (1) based on homeownership. Model (2) presents the results of the subsample based on credit score; we classify borrowers as having low fico if their credit score is below or equals the median credit score for a three-digit ZIP code in a given year. Model (3) is based on annual income; borrowers are classified as low income if their income is below or equals the median income for a three-digit ZIP code in a given year. The list of covariates is the same as discussed in Eq. (4.1). DTI, annual income, and open accounts are winsorized at the 1st and 99th percentile. Standard errors are clustered at the three-digit ZIP code level in parentheses.
*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Chapter 5

Conclusions

Technology is an important part of our daily lives. Almost everything is affected by innovative technology; the financial market is no exception. One of the consequences of technology advancement is the emergence of online lending marketplaces that provide different types of financial products. Online lending marketplaces are becoming an important player in the credit market as an alternative source of finance. These marketplaces provide consumers with a better lending experience that is convenient and easily accessible. Online lending marketplaces reduce transaction costs by eliminating the need for branch networks or local agents. In peer-to-peer lending, borrowers are directly matched with investors without the need for financial intermediaries. Therefore, borrowers do not depend on one investor and thus increases their funding opportunities. This will ultimately benefit borrowers who are credit rationed. Moreover, it provides investors with diversification benefits as online marketplaces pool borrowers with different credit risk to accommodate investors' various risk needs. The innovative technology used by online marketplaces could help in transforming the financial structure and revolutionize the financial process in a way that meets the different needs of market participants. This thesis investigates the credit dynamics of online lending marketplaces and its impact on the financial environment and borrower's economic outcomes. Throughout the analysis of this thesis, we use data from Lending Club. Lending Club is considered the largest online lending marketplace in the U.S. This chapter provides a brief summary of the main findings of this thesis. Furthermore, it highlights policy implications and prospective areas for future research.

5.1. Summary of Findings

This thesis first examines whether online lending marketplaces can satisfy the needs of underserved segments. The findings of Chapter 2 show that regions that are underserved by the traditional banking system experience higher growth of peer-to-peer lending. This confirms that online lending marketplaces offer an alternative source of finance and hence increase access to credit for underserved segments. Moreover, we find that the absence of small banks has a more significant effect on the growth of peer-to-peer lending than large banks. This could be explained by the different roles that small and large banks have in the local market. Furthermore, this suggests that online lending marketplaces compete more with small banks since both specialize in small personal loans. We also find that this growth of peer-to-peer lending is not associated with worse borrower quality. Such results indicate that the growth of peer-to-peer lending in the local market does not exacerbate market frictions. Lastly, the findings of Chapter 2 show that increased access to finance by online lending marketplaces enhance borrowers' credit position by improving their credit score.

This thesis then proceeds to examine the individual benefits of social capital in online lending marketplaces. Chapter 3 shows that borrowers benefit from social capital by having a lower interest rate in peer-to-peer lending. The findings of this chapter suggest a consistent negative relationship between social capital and the pricing of loans in peer-to-peer lending. Moreover, Chapter 3 shows that this negative effect is more significant for borrowers that are more susceptible to moral hazard. This indicates that social capital is effective at mitigating market frictions. Furthermore, Chapter 3 provides evidence that social capital constrains opportunistic behavior and promotes altruistic behavior. Borrowers in high social capital communities are significantly less likely to default than borrowers in low social capital communities. Moreover, we find that the negative association between social capital and borrower default is stronger for higher risk borrowers.

Chapter 4 investigates the extent to which the presence of income rounding affects loan performance in peer-to-peer lending. The results in Chapter 4 suggest that the prevalence of income rounding in peer-to-peer lending is associated with adverse loan outcomes. Borrowers with a rounding tendency are more likely to experience delinquency or default. Furthermore, they are more likely to default than prepay the loan. In addition, taking into account the volatility of changes in credit score, we find that borrowers who exhibit rounding behavior experience higher fluctuations in their monthly credit score. Borrowers who provide round income figures are more likely to experience negative changes in their credit score than borrowers who provide income figures that are more accurate. In addition, the findings suggest that investors are not compensated for the extra risk associated with rounding. Borrowers who exhibit rounding behavior obtain lower interest rates.

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