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# Bridging the Credit Gap: The Influence of Regional Bank Structure on the Expansion of Peer-to-Peer Lending


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## Abstract

This paper investigates the extent to which the regional credit market structures, characterized by the presence and lending capacity of traditional banks, shape the growth of online lending marketplaces using peer-to-peer (P2P) lending data. Using an instrumental variables (IV) approach, our study suggests that areas underserved by traditional banks witness more significant growth in P2P lending. This impact is more pronounced in regions with a lower presence of small bank outreach. Furthermore, we find that an increase in P2P lending is associated with a reduced risk of borrower default. Our findings also show that the expansion of online lending marketplaces positively impacts borrowers' financial well-being by improving their credit scores.



*JEL Classification:* D40, G20, G21, G23

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## Introduction

Banks have historically used branch networks to foster customer relationships and leverage borrower-lender proximity to secure an informational edge (Boot and Thakor, 2000; Boot et al., 2021). Their physical presence facilitates trust, accessibility, and institutional knowledge, mitigating informational frictions. However, the spatial distribution of banks has not been uniform. Vast segments of the population have found themselves marginalized, with the World Bank's Global Findex Database 2017 revealing that 22% of unbanked adults cite the physical distance from banking institutions as a significant impediment to account ownership (Demirguc-Kunt et al., 2018). Such spatial market frictions and the consequent financial exclusion pose systemic challenges and are often detrimental to socio-economic development.

This spatial gap provides a niche for online lending marketplaces, more popularly known as peer-to-peer (P2P) lending, which capitalizes on virtual interactions.[1] These platforms, with their data-driven technology, facilitate swift transactions and offer a wide array of credit solutions, potentially tackling financial exclusion that has been left by traditional banks (US Department of Treasury, 2016) or credit rationing resulting from information asymmetries (Stiglitz and Weiss, 1981). By catering to the needs of underserved segments and fostering a diversified financial environment, online lending marketplaces could inadvertently promote financial inclusion, thereby potentially enhancing economic resilience (Boot, 2017). Yet, a lack of robust regulatory oversight might expose online lending marketplaces to risks such as predatory lending, inadequate risk management, and opaque operations.[2] Consequently, unchecked growth in this sector could amplify, rather than mitigate, market frictions.

While there exists research accentuating banking sector outreach (Beck and Demirgüç-Kunt, 2008; Beck et al., 2008; Butler and Cornaggia, 2011; Allen et al., 2016), its relationship with the uptake of online lending marketplaces remains scantily explored. The current literature primarily focused on the dynamics between P2P lending and bank lending (e.g., Butler et al., 2016; Cornaggia et al., 2018; Tang, 2019). However, a gap in understanding the implications of expanding online lending marketplaces exists. Pertinent questions arise: Do these online lending marketplaces alleviate or intensify market frictions stemming from the absence of

[1] Notably, in the US context, the proportion of unsecured personal loans facilitated by online lending platforms has surged from 5% in 2013 to 38% in 2019. Retrieved from <https://newsroom.transunion.com/fintechs-continue-to-drive-personal-loans-to-record-levels/> [Accessed 13 July 2023].

[2] For instance, after loan origination, borrowers might employ the loan for purposes other than those stated, potentially introducing increased risk.

traditional banks? How does the broader accessibility to finance through online lending marketplaces affect borrowers' financial well-being?

To empirically engage with these queries, we employ data from Lending Club, the largest online lending marketplace in the US. Specifically, we measure the outreach of online lending marketplaces based on both the quantity and total value of loans issued by Lending Club. We consider the number of bank branches and their associated deposits to assess the presence and lending capacity of traditional banks regionally. We match these two datasets at the three-digit ZIP code level. Our final dataset spans from 2012 to 2018, encompassing approximately 884 three-digit ZIP codes. The objective of the initial phase of our study is to investigate whether the local market dynamics of traditional banks influence the regional expansion of the online lending marketplace.

In our empirical analysis, we control for factors related to regional economic conditions, borrower characteristics, bank performance, and experience in the regressions. However, unobservable variables that simultaneously influence both the regional growth of online lending platforms and the presence of bank branches may still exist. Reverse causality also poses a potential issue. The rise of online lending platforms might lead banks to close their branches, especially if more individuals prefer digital over brick-and-mortar financial services. To mitigate potential endogeneity concerns, we use an instrumental variables (IV) approach to force the exogenous portion of bank outreach to explain the growth of peer-to-peer lending. Specifically, we use the distance to the nearest regional area and historical bank outreach as instruments for local bank outreach. These instrumental variables are highly correlated with regional bank outreach (relevance condition). They are unlikely to directly affect the current outreach of online lending marketplaces (exclusion restriction), given that peer-to-peer lending transpires exclusively in virtual environments.

The IV estimation results confirm a negative and statistically significant relationship between regional bank branch presence and online lending outreach. This result suggests that online lending marketplaces increase access to finance in areas underserved by traditional banks. For context, a 1% decrease in the regional presence of bank branches (regional lending capacity) leads to an estimated 0.11% (0.12%) increase in the regional outreach of online lending marketplaces (the amount of loans issued by online marketplaces). This impact is notably economically significant. We also find that the growth of online lending is more pronounced in areas with a lower presence of small banks than large banks, suggesting that small banks play a more critical role in the regional market. This finding can be attributed to small banks' expertise, knowledge, and specialization in consumer credit and serving local and small borrowers (Berger et al., 2001; Berger et al., 2004). Given that online lending marketplaces also specialize in facilitating personal and small business loans, they could potentially act as substitutes for the services offered by small banks.

While the expansion of online lending marketplaces undoubtedly fills a regional gap left by traditional banks, there is the question: what if low-quality borrowers disproportionately self-select into these platforms? This self-selection process could trigger moral hazard concerns, with borrowers exploiting the new financing avenue for riskier ventures (Akerlof, 1970; Miller, 2015; Karlan and Zinman, 2009). [3] To explore this, we further examine the correlation between the regional growth of online lending marketplaces and borrowers' subsequent payment behavior by measuring borrowers' risk of default *ex post*. Our results show that regional growth in online lending marketplaces is associated with a lower risk of borrower default *ex post*. In other words, areas witnessing an uptick in online lending marketplace presence have a decline in borrower default rates, suggesting that online lending marketplaces may identify creditworthy borrowers who are underserved by traditional banks. Quantitatively, the magnitude of the result suggests that a 1% increase in the regional outreach of online lending marketplaces is associated with an estimated 2% reduction in the borrower default hazard rate.

Building on the previously established context, we explore a deeper understanding of the transformative power of peer-to-peer lending and its potential impact on borrowers' financial well-being. Analyzing changes in borrowers' credit scores post-engagement with these platforms provides invaluable insights. There is a double-edged potential: borrowers might over-borrow due to easy access, or they might benefit from reduced interest rates as a result of the elimination of financial intermediaries, which in turn, enable individuals to consolidate high-interest debt and enhance their overall risk profile. Our findings lean towards the latter. An increase in the regional growth of online marketplaces is significantly associated with enhancements in borrowers' credit scores. Other things being equal, a 1% increase in the regional growth of online marketplaces results in a 0.15% rise in borrowers' credit scores at the end of the loan.

Our study is related to a rapidly growing literature on the dynamic between peer-to-peer lending and traditional banking. Cornaggia et al. (2018) investigate how P2P lending affects banks' loan volumes and quality, while Butler et al. (2016) explore the influence of local bank

[3] For instance, subsequent to loan origination, borrowers might employ the loan for purposes other than those stated, potentially introducing increased risk.

finance access on the interest rates that consumers pay for P2P loans. Tang (2019) identifies P2P lending as both a substitute for and a complement to bank lending, depending on the borrower/loan segments. Similarly, Maskara et al. (2021) find differing impacts of bank outreach on P2P loans across rural versus urban settings, and De Roure et al. (2022) document an increase in P2P lending following regulatory shocks to banks. Distinct from these studies, our study employs an instrumental variables (IV) approach to robustly address potential endogeneity issues, isolating the causal effect of traditional bank outreach on the expansion of online lending marketplaces. We demonstrate that this effect is more pronounced in regions with fewer small banks, suggesting that P2P lending platforms effectively substitute for these institutions. Our study enriches the understanding of how online marketplaces interact with traditional banking structures.

Furthermore, while most existing studies focus on assessing P2P borrower quality *ex ante* (Tang, 2019; De Roure et al., 2022), our work diverges by utilizing loan-level P2P data to evaluate borrower performance *ex post*. This longitudinal analysis, encompassing approximately 20 million monthly loan observations from 2012 to 2018, offers a perspective on the long-term effects of online lending in regions variably affected by banking structure changes. Unlike Di Maggio and Yao (2021) and Chava et al. (2021), who find that improvements in borrowers' credit profiles via FinTech are only transient, our findings suggest that P2P platforms not only bridge the gaps left by traditional banks but also potentially reshape local credit markets by surmounting geographical and market constraints. This extensive analysis underlines the potential for significant economic benefits and welfare improvements through the expansion of online lending marketplaces.

The remainder of this paper proceeds as follows. Section 2 reviews the relevant literature and derives the hypothesis. Section 3 discusses the methodology used in this paper. Section 4 describes the data and variables used in this study. Sections 5 and 6 present the empirical findings. Finally, section 7 concludes the study.

## 2. Institutional Background and Hypothesis Development

### 2.1. Institutional Background

Financial intermediaries, such as banks, exist to mitigate market frictions related to informational asymmetries and transaction costs (Leland and Pyle, 1977; Boyd and Prescott, 1986; Allen and Santomero, 1998). They primarily perform two fundamental roles in the financial market: 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). Banks also provide maturity transformation, transforming shorter maturity deposits to meet borrowers' demand for relatively medium- and long-term loans (Bhattacharya and Thakor, 1993). In addition, banks transfer risk by using riskless liquid deposits from risk-averse savers to fund risky and illiquid loans where borrowers have the risk of default (Diamond, 1984). To mitigate inherent risks, banks diversify their asset portfolios, pool various risks, and maintain strict oversight of borrowers (Berger et al., 1995; Demsetz and Strahan, 1997). Furthermore, banks hold capital and reserves as a buffer against unexpected losses (Cebenoyan and Strahan, 2004; Bikker and Metzemakers, 2005). Banks effectively manage and hedge the risks accompanying their services by performing these intermediary functions.

The financial landscape faces structural changes due to the entrance of technology-oriented players (Boot, 2016; Thakor, 2020; Boot et al., 2021). Technology-based businesses face low market entry barriers (Einav et al., 2016). Online lending marketplaces, for instance, operate without physical branches or local agents, significantly reducing overhead and operational costs (Thakor, 2020). Their exemption from capital mandates positions them advantageously against traditional banking institutions. In addition, with capabilities in big data analytics and pioneering solutions, online lending marketplaces disintermediate most conventional banking functions (Morse, 2015). For example, Peer-to-peer (P2P) lending platforms offer a digital conduit for borrowers and investors. They pre-screen applicants based on their credit criteria and present viable loans to potential investors, who can then select based on their risk preferences. Unlike traditional banks, these platforms do not amalgamate funds. Instead, they aggregate borrowers of varying creditworthiness to match the diverse risk appetites of investors. These P2P platforms also streamline transactional processes, including payment collections (Wang et al., 2009). However, it is important to note that they do not assume the same risk management undertaken by banks. By leaning heavily on data-driven analytics and innovative strategies, these platforms shift many banking functions and responsibilities onto platform users (Moenninghoff and Wieandt, 2013; Morse, 2015).

### 2.2. Hypothesis Development

The geographical proximity between borrowers and banks plays an important role in influencing the quality and supply of local credit. It does so by enhancing qualitative information and the bank-borrower relationship (De Young et al., 2008).

First, geographic proximity can bolster the exchange of qualitative information. A bank situated closer to its borrowers is more likely to have a better understanding of local market conditions, which includes potential risks and opportunities. Consequently, such a bank can customize loan terms to align more congruently with a borrower's unique circumstances. Moreover, such closeness augments the efficiency of information acquisition, underpinning effective credit screening and facilitating the allocation of funds to creditworthy borrowers (Alessandrini et al., 2009). Notably, Agarwal and Hauswald (2010) underscore the importance of local information in which banks possess a diminishing informational edge with the widening geographical distances. Thus, informed lenders, armed with this informational edge, exercise significant market power to attract borrowers, while uninformed lenders face challenges due to adverse selection (Dell'Ariccia and Marquez, 2004). However, increasing the distance between banks and borrowers intensifies information challenges, including poorer credit assessments, higher default rates, and error-prone lending decisions (De Young et al., 2008; Hauswald and Marquez, 2006). Such challenges could result in market failures (Boot and Thakor, 2015).

Second, geographic proximity does more than improve information quality; it also nurtures robust bank-borrower relationships (Agarwal et al., 2011). Such strong locational ties can engender trust, enabling banks to understand better and serve their borrowers (Beck and Demirgüç-Kunt, 2008; Beck et al., 2008; Butler and Cornaggia, 2011; Allen et al., 2016; Nguyen, 2019). This may manifest in more favorable loan terms, particularly when banks recognize the merits of proximity and adopt a relationship-based lending strategy for nearby borrowers (De Young et al., 2008). This strengthened relationship acts as a safeguard against the challenges posed by asymmetric information in lender-borrower interactions (Sufi, 2007; Hollander and Verriest, 2016; Kysucky and Norden, 2016). For example, holding face-to-face meetings or engaging in quick dialogues can expedite conflict resolutions, ensuring a streamlined credit process.

Therefore, decreased geographical proximity can adversely impact the quality of information that banks acquire and weaken bank-borrower relationships, diminishing the competitive advantage banks hold in their local markets (Agarwal and Hauswald, 2010). The regional absence of banks may lead to a market gap due to losing their localized informational and relationship strengths. This creates an opening for online lending marketplaces to cater to customer demands and bridge this market void. Unlike conventional banks, online lending platforms leverage digital capabilities to overcome geographic limitations and market frictions, offering a seamless and accessible financial service experience across various locations (Agrawal et al., 2015). These platforms employ standard and non-standard data in their lending processes to evaluate borrower creditworthiness (Iyer et al., 2015).[4] This approach provides online marketplaces with a distinct advantage in information gathering, especially when traditional banks struggle with limited regional data access. Iyer et al. (2015) highlight an improvement in the ability of online platforms to screen and accurately assess borrowers. They argue that the reduced hierarchical distance between lenders and borrowers in online settings enables more effective use of non-standard information. Based on this, we present the following testable hypothesis: Online lending marketplaces expand more in regions with lower bank presence.

## 3. Methodology

### 3.1. Main Specification

To assess how the regional presence of banks affects the outreach of online lending marketplaces, we estimate the following model:

$$\mathrm{Ln}(Online\ Outreach_{z,t}) = \alpha + \beta\ \mathrm{Ln}(Bank\ Branches\ Outreach_{z,t}) + \gamma Z_t + Year_t + State_s + \varepsilon_{z,t} \qquad (1)$$

$\mathrm{Ln}(Online\ Outreach_{z,t})$ 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 $t$. Our main independent variable $\mathrm{Ln}(Bank\ Branches\ Outreach_{z,t})$ 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. These measures have been widely used as indicators of banks' regional market structure (Becker, 2007; Butler and Cornaggia, 2011; Cornaggia, 2013). Furthermore, bank branches with closer physical proximity to borrowers tend to have better lending relationships (Berger et al., 2005; Agarwal and Hauswald, 2010; Nguyen, 2019). Hence, ZIP codes with more bank branches and deposits have higher competition between banks and better access to bank credit (Erel and Liebersohn, 2022). $Z$ is

[4] The non-standard data includes elements like endorsements from friends, the content of loan descriptions, and the aggregated assessments of multiple investors (Lin et al., 2013; Morse, 2015; Iyer et al., 2015; Dorfleitner et al., 2016).

a vector of control variables at the three-digit ZIP code level and the state level. Appendix A provides definitions of the variables used in the paper. One possible issue of our study is that some unobservable variables might affect the presence of online lending marketplaces and correlate with regional bank branch networks. Additionally, time-varying macroeconomic factors that influence the level of regional loans issued by online lending marketplaces could be unobserved. To mitigate these concerns, we include $Year_t$ and $State_s$ to capture year and state fixed effects, respectively.

### 3.2. Identification Strategy

A possible caveat facing empirical work in our paper is that unobservable economic conditions and borrower quality may be correlated with bank branch outreach. The growth of online lending marketplaces may also cause banks to close their branches as more people might use online facilities rather than physically going to banks. Therefore, online lending marketplaces and regional bank branch networks could be endogenously determined due to omitted variables and reverse causality.[5] To establish the causal effects of regional bank branch networks on online marketplace lending activities, we implement an instrumental variable (IV) approach as ordinary least squares (OLS) estimates could bias our results.

We employ two instrumental variables for regional bank outreach. For an instrument to be valid, it must be strongly correlated with regional bank outreach (relevance condition) and only affect online lending marketplaces through regional bank outreach (exclusion restriction). The first instrument is the average distance to the nearest three-digit ZIP code area.[6] This instrument measures the average travel distance to the nearest market. The greater the distance between the local market and alternative markets, the more critical the local market becomes since customers face higher transportation costs and are required to travel a long distance to find alternative markets. In other words, the greater distance, in turn, will lead to more regional bank branches due to the increased demand. However, peer-to-peer lending occurs entirely in a virtual environment; it arises independently of the physical distance to other markets. Therefore, it is unlikely that the instruments will correlate with the error term in the second-stage regression equation since it is doubtful that the growth of peer-to-peer lending can

[5] In unreported results, we conduct a panel vector autoregressive (PVAR) model to investigate the Granger causality between online marketplace outreach and bank branch outreach. We find that bank branch outreach Granger causes online marketplace outreach, suggesting there is a unidirectional relationship from bank branch outreach to online marketplace outreach.

[6] 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 the National Bureau of Economic Research.

directly affect the distance between the local market and alternative markets. The second instrument we use is the regional bank branch outreach in 2000 per 1,000 people. Bank branch presence in the past is strongly related to the current presence of bank branches. However, it is unlikely that past bank branch networks will directly impact the current outreach of online lending marketplaces. The year 2000, which we reference for bank outreach, predates the launch of online marketplaces in 2005. Together, these two instruments satisfy the criteria of suitable instruments. While they are relevant to explaining regional bank branch outreach, they have no systematic relation to online lending outreach.

## 4. Data

This study's primary two datasets contain information about banks' and online lending marketplaces' regional 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 bank branches' exact physical addresses and other branch-level data, such as the amount of deposits held by individual branches and the year of branch incorporation. We use loan application data from Lending Club for the online lending marketplace data. Lending Club is the largest online lending marketplace in the US, with a loan issuance value of greater than $47 billion at the end of 2019 (since inception). We match these two datasets at the three-digit ZIP code level. Our data are annually from 2012 until 2018,[7] covering around 884 three-digit ZIP codes.

Peer-to-peer lending is a rising phenomenon that emerged in 2005 in the UK and then transferred to the US in 2007. Online lending marketplaces mainly specialize in facilitating small-unsecured loans to borrowers online without the need for banks. According to different algorithms, Lending Club provides qualified borrowers with various loan offers that might entail different interest rates and maturity options after screening borrowers' applications and credit history. Borrowers can choose the loan offer that best suits their financial needs; afterward, different investors fund the loans online, and borrowers automatically receive their loans. Lending Club charges borrowers a one-time loan origination fee in addition to monthly payments. Additionally, Lending Club allows investors to build different investment portfolios according to their investment strategies and risk tolerance. Lending Club divides loans into

[7] Lending Club has discontinued the publication of new data beyond our current dataset's endpoint, which limits our ability to integrate more recent data while maintaining consistency and reliability in our sources.

small fractions known as notes, which investors can invest in amounts as low as $25. This permits investors to diversify their risk by investing in small fractions of loans corresponding to different borrowers with various risk levels.

### 4.1. Main Variables Measurement

In this research, we construct two key variables to evaluate the outreach of both traditional banking and online lending marketplaces. As in Butler and Cornaggia (2011), Cornaggia (2013), Beck et al. (2014), and Butler et al. (2016), we measure regional bank branch outreach using the number of bank branches per 1,000 people in the three-digit ZIP code. This measure reflects the regional presence of branch networks and the distance between traditional lenders and borrowers. Moreover, this measure indicates banks' ability to capture soft information about the areas they operate in, which could affect their regional lending decisions and informational advantage (Hauswald and Marquez, 2006; Ergungor, 2010). As the distance between borrowers and banks increases, banks might lose their local advantage, allowing other lenders to penetrate the regional credit market and compete for borrowers. For robustness, we use local deposits held by bank branches to measure access to finance and proxy for regional lending capacity. Bank deposits positively impact local loan supply, which affects regional access to finance (Becker, 2007; Butler and Cornaggia, 2011). Additionally, bank branch deposits could proxy the actual use of the bank's services (Beck et al., 2007).

We adopt similar measures for the outreach of online lending marketplaces. Specifically, 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 finance offered by online marketplaces. Furthermore, this allows us to assess the degree to which online lending marketplaces have penetrated local credit markets.

### 4.2. Control Variables

To isolate the effect of online marketplace outreach from unobserved economic conditions and borrower quality, we saturate our regression with vectors of control variables from several sources at the three-digit ZIP code and state level.

We control for regional market concentration to capture economic conditions by including the Herfindahl-Hirschman Index (HHI) based on branch deposits within the three-digit ZIP code. Guzman (2000) shows that credit rationing is more prevalent in monopolistic banking systems than in competitive ones. We control for the region's net worth by using the 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 regional areas (Dell'Ariccia et al., 2012; Ramcharan and Crowe, 2013). Moreover, we control for regional economic development by including the number of business establishments[8] per 1,000 people in the three-digit ZIP code. We obtain establishment data from ZIP Code Business Patterns issued by the US Census Bureau.

Borrower characteristics might also affect their decision to use online lending marketplaces. We control for several demographic characteristics at the three-digit ZIP code level to mitigate the possibility that could drive our results. First, we control for the percentage of the white population and the percentage of the male population. Second, to control the region's education level, we include the percentage of the population aged 25 years or older and the percentage of the population who at least holds a bachelor's degree. Lastly, we include the percentage of the unemployed labor force and the share of the population living below the poverty line. Measures about local demographics come from the American Community Survey's 5-year estimates.[9]

We also include several state-level control variables in our model. We control for real GDP per capita from the Bureau of Economic Analysis. In addition, we control for credit demand and quality by including states' auto debt balance per capita, credit card balance per capita, and mortgage debt balance per capita. Finally, we 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 A provides a detailed description of the variables used and their sources.

We add bank performance measures 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. These measures are associated with the likelihood of bank failure, which in turn could affect the bank's expansion (Wheelock and Wilson, 2000; Jin et al., 2017). Also, we control for the bank's local experience and branding by including the median age of bank branches in the local market. This measures how long banks have been operating in the local market. Intuitively, consumers are more loyal to local banks if they are long-established in the area.

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[8] The number of business establishments excludes institutions engaged in lending activities and any other activities related to finance and insurance.

[9] The American Community Survey is published by the US Census Bureau. The Census Bureau employs a ZIP code tabulation area (ZCTA) that closely approximates US ZIP codes.

### 4.3. Summary Statistics

Table 1 presents summary statistics of the variables used in this study. The number of bank branches varies from less than 0.0314 per 1,000 people to a maximum of around 2.79 branches per 1,000 people. The mean number of bank branches per 1,000 people is 0.33, which is consistent with Butler et al. (2016). For online lending marketplaces, the mean value is 0.9 loans issued per 1,000 people, with a maximum of 3.4 loans. These figures exceed those reported by Tang (2019), which finds a county-level mean of 0.05 and a maximum of 2 loans per 1,000 people in the P2P market. The disparity between these figures can be attributed to the different time spans of the datasets. Tang's data covers 2009 to 2012, while our study analyzes the period from 2012 to 2018. The intervening years likely witnessed considerable growth in the P2P lending sector, as suggested by our higher loan issuance rates. This trend indicates the sector's evolution and the growing mainstream acceptance of P2P platforms.

[Insert Table 1 here]

Furthermore, bank branches have an average deposit value of $38,438 per 1,000 people in the three-digit ZIP code.[10] Comparatively, individuals in the three-digit ZIP code borrow $13,354 per 1,000 people from online lending marketplaces. The value of online loans may appear small compared to bank deposits, suggesting a growth opportunity for online marketplaces to provide consumer loans.

The mean Herfindahl-Hirschman Index (HHI) is 0.0695 for bank deposits with a minimum value of 0.004. The average age of branches operating in the three-digit ZIP code is 33.6 years and varies between 8 and 116 years. The rest of the descriptive statistics of other control variables employed in this study at the three-digit ZIP code and state level are given in Table 1.

[10] Butler et al. (2016) document an average bank deposit value at the county level, amounting to $42.1 million, over the period from 2008 to 2010. They further standardize this variable to conform to a distribution with mean zero and unit variance. However, it is crucial to acknowledge that direct comparisons between their findings and ours are limited due to differences in the sample periods and the units of analysis (county-level data in their case).

## 5. Main Results

### 5.1. The Effect of Bank Branch Outreach on the Expansion of Online Lending

Table 2 presents the main instrumental variable estimates for the effect of bank branch outreach on online marketplace outreach.[11] Model 1 reports the instrumental variable estimates for regional bank branch outreach. Model 2 reports the instrumental variable estimates for regional bank branch deposits as a proxy of regional lending capacity.

[Insert Table 2 here]

Column (1) of Table 2 shows the first stage estimates that assess the relationship between the average distance to the nearest three-digit ZIP code and bank outreach in the year 2000 and the current bank outreach. Similarly, column (3) of Table 2 shows the first stage estimates that relate the average distance and bank branch deposit level in the year 2000 to the current bank branch deposits. The results confirm that the instruments used are significantly and positively correlated with the regional number of bank branches and deposits. The first-stage F-statistics are 1194 and 685, respectively. Based on Stock and Yogo's (2005) rule of thumb ($F > 10$), we can also verify the strength of our instruments.

Columns (2) and (4) of Table 2 present the second stage results for both models, which support our hypothesis that online lending marketplaces increase access to finance in areas with lower bank presence. As shown in column (2) of Table 2, the coefficient estimate of regional bank branch presence is negative and statistically significant at the 1% level. This finding indicates that the regional absence of traditional banks is positively associated with the expansion of online lending marketplaces. Considering the log form of the dependent and independent variables, a 1% decrease in bank branch regional presence leads to a 0.11% increase in the regional outreach of online lending marketplaces. In column (4), we find a similar relationship between bank branches' local deposits and the amount of online loans issued per 1,000 people. This suggests that the regional lending capacity of bank branches affects the local lending levels of online lending marketplaces. Online lending marketplaces tend to meet underserved customers' demand for loans in regional areas deprived of bank presence. Specifically, a 1% decrease in the regional lending capacity measured by bank deposits leads to a 0.12% increase in the amount of loans issued by online marketplaces. Interestingly, the coefficient on bank market concentration coefficient (HHI) exhibits

[11] We provide the OLS results in Appendix B. We find the negative impact of regional bank branch presence and regional bank deposits on online lending marketplace outreach, respectively.

significance only in the second model. This suggests that higher market concentration and a lower degree of competition among banks are associated with higher growth in online lending marketplaces. These findings collectively support our hypothesis that online lending platforms are more likely to flourish in markets that are inadequately served by traditional banking institutions.

Our findings are consistent with the argument that banks reduce their loan funding in markets with a less local informational advantage due to their regional absence (Cortés and Strahan, 2017). The absence of regional banks creates a market gap and allows competitors to start poaching customers, as seen with online lending marketplaces. Therefore, individuals turn to online lending marketplaces when there is lower access to regional bank financing. Our results are consistent with Butler et al. (2016), who find that traditional banking's regional lending capacity affects consumers' borrowing decisions on online marketplaces. They show that borrowers who reside in areas with more access to bank finance seek online loans at lower interest rates. Our findings also align with those of Tang (2019), based on the US market, and De Roure et al. (2022) in the German context. Both studies find that online lending marketplaces expand in regions impacted by negative shocks in bank credit supply and increased regulatory costs.

We include year and state dummies in all specifications to control for unobserved changes in economic conditions (e.g., business cycles, interest rate fluctuations, and regional development disparities). Furthermore, we provide additional tests to ensure 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 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 P-values for Hansen's J-tests for the first and second models are 0.35 and 0.15, respectively. This test implies that our instruments are adequate to identify the equations.

One of the potential concerns for our results is that our instruments (the average distance to the nearest alternative market and the bank outreach in the year 2000) are related to some local economic conditions or local demand for credit and consumer credit quality, which might impact peer-to-peer lending. To alleviate these concerns, in our regressions, we control for regional economic conditions and development by including GDP, poverty rate, unemployment rate, income per capita, 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 Cornaggia et al. (2018). While these vectors of control variables help mitigate the risk of omitted variable bias affecting our results, they do not entirely eliminate endogeneity concerns.

Another caveat is that regions with a high average distance to the nearest alternative market or a low historical bank outreach tend to be large and expanse land with relatively low economic growth. If so, our instruments would presumably be negatively associated with current bank branch outreach. However, we find that both the instruments of average distance and the bank outreach in the year 2000 are positively related to current bank branch outreach as they are likely to increase the demand for the regional bank branches (banking services). It is doubtful that the average distance to the nearest adjacent region and historical bank outreach could affect peer-to-peer lending through channels other than current bank branches, which satisfies the exclusion restriction that the instruments are not correlated with the error term in our models.

### 5.2. The Role of Small Banks in the Local Market

Our analysis focuses on how regional bank branch presence impacts online lending marketplaces. However, prior research has found that financial services and comparative advantages may differ among banks of varying sizes (Berger et al., 2004; Berger et al., 2017). Small banks often rely on soft information and emphasize personal relationships in their lending practices (Carter and McNulty, 2005). First, small banks decentralized structure enables them to use soft information more effectively than large banks (Berger and Udell, 2002; Stein, 2002; Berger et al., 2005; Kysucky and Norden, 2016). Second, with a better understanding of local conditions, small banks usually have more profound relationships with local borrowers (Berger et al., 2001). They invest in these relationships through geographically concentrated operations (Yeager, 2004). Therefore, small banks offer more retail-oriented financial services and have soft information-based relationship loans with small borrowers. (Berger et al., 2004). In contrast, large banks tend to offer wholesale-oriented financial services and make hard-information-based transition loans to larger borrowers (Berger et al., 2004; Berger et al., 2005; Canales and Nanda, 2012).

In Table 3, we examine whether the growth of peer-to-peer lending is more pronounced in areas with a lower presence of small banks. To differentiate between small and large banks, we follow two criteria. Column (1) categorizes banks with assets under $1 Billion as small, while those with assets exceeding this threshold are classified as large (DeYoung et al., 2004; Berger et al., 2017). For robustness, column (2) employs an asset threshold of $300 Million to distinguish between small and large banks (Strahan and Weston, 1998; Black and Strahan, 2002). Table 3 provides the second stage results of the instrumental variable regressions for small and large banks.[12] The two main independent variables are the total number of large and small banks per 1,000 people within the three-digit ZIP code. The dependent variable is the number of online loans per 1,000 people. Employing the same instruments used in Eq. (1) for small and large bank outreach, we find that the presence of small banks is negatively and significantly associated with the growth of online lending marketplaces. In contrast, the presence of large banks does not significantly impact the growth of online lending marketplaces.[13] More specifically, the results in columns (1) and (2) indicate that a 1% decrease in the regional presence of small bank branches is associated with an increase of 0.20% and 0.17% in the regional outreach of online lending, respectively. These findings imply that online lending platforms primarily compete with small banks. Unlike large banks, small banks and online lenders both specialize in small loans. The reduced presence of small banks in a region, resulting in a loss of local informational and relational advantages, could potentially leave a segment of small borrowers underserved. This gap may, in turn, drive substantial growth in online lending marketplaces.

[Insert Table 3 here]

Table 4 compares the average online outreach measured by the number of online loans per 1,000 people across the quintiles of the distribution of bank outreach measured by the number of branches per 1,000 people. As we move from the smallest quintile of bank outreach to the largest bank outreach, we observe a decreasing trend of online lending marketplace outreach for all banks. This decreasing trend is consistent with our hypothesis that online lending marketplace activities increase as bank branches' regional presence decreases. Additionally, we compare the differences between large and small banks. We find that the average online outreach decreases as the outreach of small bank branches increases. In contrast, regions dominated by larger banks see increased online lending outreach. A possible reason for these findings could be that borrowers in areas with a predominant large bank presence lean towards

[12] For brevity, we do not report the first stage estimates in Table 3, given that we have two endogenous variables (small and large bank outreach). We report the first stage results in Appendix C for small and large banks using $1 billion and $300 million as thresholds.

[13] We present the OLS regression results in Appendix D, which are consistent with our IV estimates.

peer-to-peer lending, as large banks do not invest in relationships with local borrowers as much as small banks do. The finding is consistent with Balyuk et al. (2022), who find that FinTech lenders are more likely to penetrate local markets with a greater presence of large/out-of-market banks. The results also align with the argument that local markets dominated by small banks are more affected by changes in the credit market structure, leading to a notable shift in the credit supply (Hakenes et al., 2015; Gilje, 2019). These findings suggest that the negative relation between the outreach of online lending marketplaces and regional bank branch networks could be driven mainly by small banks, which, compared to large banks, have greater regional knowledge and comparative advantage in relationships with local and small borrowers. This implies that local credit supply still matters and that the diminishing presence of small banks creates an opportunity for online lending marketplaces to expand. The p-values associated with the t-tests show significant differences in online outreach levels between the lowest quintile of the distribution of bank branch outreach and the highest quintile.

[Insert Table 4 here]

## 6. Additional Results

### 6.1. Does Online Outreach Affect Borrowers' Default?

Bank-borrower proximity can mitigate asymmetric information issues by enhancing qualitative information and reinforcing the bank-borrower relationship, as discussed in the hypothesis development section. However, an increased distance between these parties amplifies problems stemming from information asymmetry. For example, it may manifest in banks adopting spatial discrimination in 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 terms (Hollander and Verriest, 2016).

In contrast, online lending marketplaces transcend geographical constraints, devoid of traditional economic frictions (Agrawal et al., 2015). A notable observation from prior sections is the inverse relationship between regional bank outreach and the growth of online lending platforms. Yet, the rise of online lending platforms brings forth new considerations. On the one hand, these online platforms might alleviate market frictions by using sophisticated data analytics and non-standard information in their credit screening and allocation processes that traditional banks might not have access to (Morse, 2015; Iyer et al., 2015). Over time, they could also accrue more nuanced insights into local markets, especially in regions where the presence of small banks is dwindling (Di Maggio and Yao, 2021). On the other hand, online platforms may intensify market frictions due to their operation within a comparatively less regulated environment, in contrast to traditional banks. [14] The absence of robust regulatory oversight can heighten the possibility of predatory lending, insufficient risk management, and diminished transparency. For example, there's a potential for lower-quality borrowers to gravitate toward these platforms, possibly due to lax lending criteria. Such borrowers may subsequently face challenges in meeting interest obligations or repaying the loans. This might also result in a moral hazard problem as borrowers might have a greater incentive to engage in risky activities *ex-post*. To test these two competing hypotheses, we study the impact of the regional growth of online lending marketplaces on borrower default.

To do so, we use monthly loan-level data of 1,245,121 loans originated between 2012 and 2018 by Lending Club.[15] 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 defaults on their payment. Since our data is a monthly discrete-time panel, we estimate our empirical model using a Complementary log-log model (cloglog), equivalent to the Cox proportional hazard model. Allison (1982) defines a discrete-time hazard rate by:

$$P_{it} = \Pr[T_i = t \mid T_i \geq t, X_{it}] \tag{2a}$$

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 2012 and 2018 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 borrowers' monthly decision to pay back the loan or default should not directly affect the current regional outreach of online lending marketplaces. More specifically, we use the Complementary log-log function as:

$$\log(-\log(1 - P_{it})) = \alpha_j + \beta' X_{it} \tag{2b}$$

[14] Fintech companies have more flexibility to test their innovative products without immediately incurring restricted regulations based on a regulatory sandbox.
[15] The final regression analyses include approximately 20 million monthly loan data.
[16] The reason for dividing survival time at a particular point is to ensure that there is a failure event within each duration interval.

The primary variable of interest is the natural logarithm of the total number of loans issued by online marketplaces per 1,000 people in the three-digit ZIP code. We use another measure of online marketplace outreach for robustness, 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 borrowers' credit scores and the remaining loan balance at the beginning of each month. Monthly-invariant covariates include borrowers' debt-to-income ratio, annual income, the number of open credit accounts, loan interest rate, loan term, and homeownership status. Additionally, we include three-digit ZIP code and state control variables, as in Eq. (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 5.

Overall, our results suggest that the greater outreach of online lending marketplaces is significantly and negatively associated with borrower default. Regarding the economic significance of the findings, the results in column (1) of Table 5 show that a 1% increase in the regional outreach of online lending marketplaces is associated with around $[\exp(0.0162)-1] \times 100 = 2\%$ decrease in the hazard rate of borrower default. In column (3) of Table 5, we use the total amount of online loans per 1,000 people to measure the regional outreach of online marketplaces, and the results are quantitatively the same as in column (1). Our results suggest that online lending marketplaces can reduce market frictions arising from the limited presence of banks. This can be attributed to the ability of online lending platforms to identify creditworthy borrowers through the application of big data and the incorporation of non-traditional or soft information. This is further complemented by online lending platforms' improved ability to screen and discipline borrowers rigorously (Morse, 2015; Iyer et al., 2015; Dorfleitner et al., 2016). These findings align with Freedman and Jin's (2011) proposition that online lending marketplaces can act as a counterweight to market frictions. Additionally, our results align with the observations of Iyer et al. (2015), who find a marked improvement in the screening efficacy of online lending platforms and their accuracy in evaluating borrowers. They argue that the reduced hierarchical distance between lenders and borrowers in the online environment facilitates more effective utilization of non-standard information.

In addition, our monthly variant and invariant control variables exhibit consistent estimates across the various models employed. For instance, we observe a positive correlation between the remaining loan balance in each month and the risk of borrower default. Additionally, certain borrower characteristics appear to increase default risk. These include rental homeownership status, a higher debt-to-income ratio, a longer contract term (60 months), and a greater number of open credit accounts at the time of loan origination. Conversely, an improvement in the borrower's monthly credit score and higher reported income levels are associated with a reduced likelihood of default. These findings underscore the multifaceted nature of factors influencing the risk of P2P borrower default.

[Insert Table 5 here]

Our IV regressions in section 5 assume that local bank outreach impacts borrowers' propensity to use online lending marketplaces predominantly through local lending conditions. Nevertheless, there is a possibility that this relationship is also driven by unobserved borrower characteristics. If regional bank branch outreach is correlated with unobserved borrower quality, we should expect that regional bank branch outreach has a strong predictability power of borrowers' probability of default (Butler et al., 2016). To test this possibility, we modify our borrower default models to include bank branch outreach in column (2). We find no significant relationship between bank branch outreach and online borrower default. Similarly, we include bank branch deposits in column (4) and find that bank branch deposits display a significant and positive association with borrower default. These findings imply that bank branch outreach is less likely to be endogenously related to the expansion of online lending marketplaces compared to bank branch deposits. It is also worth noting that while bank branches might, over the long term, relocate to areas with certain borrower profiles, in the short term, borrower characteristics in a locality are unlikely to significantly influence changes in the number of local bank branches.

In Table 6, we measure the default rate of peer-to-peer lending at the three-digit ZIP code level rather than at the individual borrower level. Specifically, we define the regional default rate as the share of defaulted borrowers at the three-digit ZIP code level. Additionally, we include a number of online borrower characteristics at the three-digit ZIP code level, including the mean of debt-to-income ratio, credit score, number of open accounts, annual income, loan amount, and interest rate. The aggregated results in columns (1) and (3) show that the growth of online marketplaces is significantly associated with a lower online default rate in the local credit market. Columns (2) and (4) of Table 6 repeat the analyses in Table 5 by adding bank branch outreach and bank branch deposits in the regression models. Interestingly, the results show that neither bank branch outreach nor bank branch deposits have a significant impact on the regional default rate. This suggests that unobserved borrower quality variables do not drive the estimates in our main regressions.

[Insert Table 6 here]

Overall, the findings of this section suggest that the increased outreach of online lending marketplaces does not lead to lower borrower quality. Instead, peer-to-peer lending's local growth is associated with a lower risk of borrower default, suggesting that online lending marketplaces meet the needs of safer borrowers whom banks underserve due to their regional absence. Online lending marketplaces utilize non-standard or soft information and big data models to identify creditworthy borrowers, giving them a comparative advantage in markets where banks lose their local advantage due to their absence.

### 6.2. Does the Local Growth of Online Marketplaces Affect Borrowers' Financial Welfare?

In this section, we further examine the potential financial welfare implications of increased access to financing through online lending marketplaces. This heightened access can lead to divergent outcomes. On the one hand, online lending platforms increase credit access, especially in areas constricted by the absence of banks. Such enhanced accessibility may empower individuals to consolidate debts and improve their financial position, hereby elevating their welfare (Bhutta, 2014). Additionally, enhanced liquidity from online lending platforms can assist individuals in managing income inconsistencies and unexpected expenses (Morse, 2011; Morgan et al., 2012; Bhutta, 2014). Notably, debt consolidation is often cited as a primary motivation for borrowers to obtain loans from these platforms. Furthermore, studies by Cornaggia et al. (2018) and De Roure et al. (2022) indicate that peer-to-peer (P2P) loans typically offer lower risk-adjusted interest rates relative to those from traditional banks. On the other hand, there's a risk that this expanded access to credit might inadvertently incentivize individuals toward over-borrowing, such as an increase in credit card limits (Chava et al., 2021; Wang and Overby, 2022). There is also a concern that peer-to-peer (P2P) borrowers might underestimate the costs associated with credit (Stango and Zinman, 2009; Stango and Zinman, 2011). In addition, borrowers may not use the loan proceeds from online lending platforms for their declared intentions, like debt consolidation. As a result, individuals may mismanage their debt and have more significant debt problems, which in turn compromises their overall financial welfare (Bhutta, 2014).

To differentiate between these divergent outcomes, we examine the extent to which the expansion of online lending marketplaces in the local market affects borrowers' financial welfare by looking at future changes in the borrowers' credit scores. Specifically, we use 1,245,121 completed online loans to test whether the increased expansion of online lending marketplaces is associated with an improvement or deterioration in borrowers' financial position by estimating the following equation:

$$FICO\ Change_{\ i,t}\ \% = \alpha + \beta\ \mathrm{Ln}(Online\ Outreach_{z,t}) + \gamma Z_t + Year_t + State_s + \varepsilon_{i,t} \quad (3)$$

We track changes in borrowers' credit qualities by measuring the percentage change in the borrowers' credit scores (FICO) at the end of the loan (i.e., the borrower paid off his loan or defaulted). 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 future changes in borrowers' credit scores should not directly affect the current regional online outreach.

The main independent variable $\mathrm{Ln}(Online\ Outreach_{z,t})$ is the natural logarithm of the outreach of online lending marketplaces in three-digit ZIP code $z$ measured by the aggregated number and amount of online loans issued per 1,000 people. Furthermore, we control for borrower characteristics: debt-to-income ratio, annual income, homeownership status, and the number of open accounts. We also add the credit grade assigned by Lending Club to control for borrowers' quality at the time of loan origination. We include control variables at the three-digit ZIP code and at the state levels. Origination year and state dummies are also included. We present the OLS and logit results in Table 7.

[Insert Table 7 here]

In the first two columns of Table 7, we provide the OLS results using the total number of online loans per 1,000 people in the three-digit ZIP code to measure regional online lending marketplaces' outreach. The results suggest that an increase in the outreach of online marketplaces is positively correlated with improvements in borrowers' financial position. More specifically, column (1) shows that a 1% increase in the regional lending activities of online marketplaces is associated with a 0.15% increase in the borrowers' credit scores at the end of the loan. For robustness, we use a logit model where the dependent variable is defined as a binary outcome—assigned a value of 1 for borrowers who exhibit a positive change in their credit scores by the end of their loan period, and 0 otherwise. We present the marginal effects of the logit model in the last two columns of Table 7. This approach yields results consistent with those from the OLS model. We observe that a greater regional outreach of online lending marketplaces increases the likelihood of borrowers experiencing positive changes in their credit scores at the end of their loans, thereby indicating improved 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 lending marketplaces' outreach (See details in Appendix E).

In Table 8, we aggregate the data at the three-digit ZIP code level to assess the overall impact of the growth of online lending marketplaces on local credit improvement. We use the mean percentage of change in credit scores at the three-digit ZIP code level as our dependent variable. The findings from this aggregated analysis align with those observed at the individual borrower level in Table 7. This consistency underscores the conclusion that an increased use of online lending marketplaces is associated with overall enhancement in regional credit conditions.

[Insert Table 8 here]

Echoing our analysis of borrower defaults, we also include bank branch outreach and deposits into the models shown in columns (2) and (4) of Tables 7 and 8 and in the appendix table in Appendix E. These variables mostly show no significant correlation with future shifts in borrowers' credit scores, with an exception in column (4) of Table 7. These findings reinforce the notion that regional bank outreach is largely independent of unobserved borrower quality. Consequently, our assessment of the link between regional bank branch outreach and the growth of online lending platforms remains unaffected by latent borrower quality factors.

Our results are in line with Balyuk (2021), who finds a positive information spillover for P2P borrowers. Enhanced screening and discipline by P2P lenders signal a more favorable outlook for borrowers. This may lead traditional banks to expand credit to these P2P borrowers, thereby bolstering their prospective borrowing capacities. Our results also share some congruence with Chava et al. (2021), who observe a transitory increase in borrowers' credit scores—ranging between 13 and 38 points—after securing loans from online lending platforms, compared to non-P2P borrowers. Notably, this ascent is temporary, with the credit score declining between 2 and 7 points below the benchmark groups two years after obtaining the online loan. However, it is important to note that the reference group in Chava et al. (2021) is non-P2P borrowers, including those denied credit by traditional banks and those who successfully obtained bank loans. We focus on the implications of the growth of online lending marketplaces on the financial welfare of P2P borrowers in local markets.

## 7. Conclusions

This paper presents evidence on online financial inclusion in underserved areas and its implications for borrowers. The regional absence of bank branches affects borrower-lender proximity, which in turn could result in market frictions related to the loss of banks' local informational and relational advantage. Can online marketplaces fill in the credit market gaps left by banks' regional absence? To answer this question, our study investigates the relationship between the regional growth of online marketplaces and regional bank branch networks. Using an instrumental variables (IV) approach, we find an inverse causal relationship between bank branches' presence and lending capacity and the growth of online lending marketplaces. This suggests that online marketplaces facilitate access to finance for underserved areas by offering low-cost and convenient lending options. It may reduce credit rationing, making it easier for credit-constrained borrowers to obtain credit (Balyuk, 2021).

Our study also sheds light on the potential implications of the growing presence of online lending marketplaces in local markets. One might speculate that low-quality borrowers could flock to these online platforms in the absence of regional banks, leading to moral hazard concerns. Challenging this perspective, our findings suggest that online lending platforms help alleviate market frictions. Specifically, the regional growth of online lending marketplaces is associated with lower borrower default risk *ex post*. Furthermore, the growth of these platforms appears to impact borrowers' credit welfare positively. These results suggest the capacity of innovative online lending platforms to counteract information asymmetries, potentially through financial disintermediation and the leveraging of non-traditional data sources (Dorfleitner et al., 2016; Freedman and Jin, 2017).

Financial market imperfections arising from the absence of banks in regional markets can impede individuals' access to finance, thereby limiting economic growth and financial inclusion. Our findings suggest that FinTech lenders, such as online lending marketplaces, effectively bridge this gap by catering to areas overlooked by traditional banks. To bolster its impact, regulators should recognize and support FinTech lending as an essential tool for financial inclusion. They could consider implementing regulatory incentives or support mechanisms, ensuring these FinTech lenders can continue to serve underserved areas.

However, these FinTech lenders, while promising, are not without their pitfalls. Challenges such as predatory lending, inadequate risk management, and opaque operations require a more tailored regulatory framework emphasizing stringent transparency standards, rigorous auditing, consistent risk evaluations, and promoting ethical lending practices. Furthermore, regulators must ensure a balanced competitive environment due to the apparent competitive landscape between traditional banks (particularly smaller ones) and P2P platforms. This means implementing equal regulatory oversight and robust consumer protection and promoting collaboration between traditional banks and FinTech lenders, allowing them to leverage each other's strengths. In summary, as FinTech lenders are structurally transforming the financial market by promoting greater diversity, regulatory frameworks must be supportive and vigilant, ensuring that the broader goals of financial inclusion, stability, and consumer financial well-being are achieved.

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**Table 1: Summary Statistics**

| VARIABLES | (1) Mean | (2) SD | (3) Min | (4) Max | (5) N |
|---|---|---|---|---|---|
| Bank Branch Outreach (per 1,000) | 0.3326 | 0.1615 | 0.0314 | 2.7972 | 6,184 |
| Bank Branch Deposits (per 1,000) | 38,438 | 351,696.1 | 551.03 | 14,627,406 | 6,184 |
| Online Outreach (per 1,000) | 0.9046 | 0.5553 | 0.0017 | 3.3980 | 5,915 |
| Online Amount (per 1,000) | 13,454.5 | 8,851.6 | 5.8412 | 66,961.9 | 5,915 |
| HHI | 0.0695 | 0.1007 | 0.0044 | 1 | 6,184 |
| Median Branch Age | 33.6013 | 16.5462 | 8.0000 | 116 | 6,184 |
| Median Return on Assets | 0.0073 | 0.0033 | 0.0010 | 0.0191 | 6,184 |
| Median ALLL | 0.0087 | 0.0019 | 0.0036 | 0.0171 | 6,184 |
| *Three-digit ZIP code level controls:* | | | | | |
| House price index | 434.03 | 269.72 | 100.96 | 2,820.79 | 6,146 |
| Percentage of white population | 0.7935 | 0.1606 | 0.0245 | 0.9866 | 6,202 |
| Percentage of male population | 0.4951 | 0.0181 | 0.42 | 0.8905 | 6,202 |
| Poverty rate | 0.1557 | 0.0557 | 0.0350 | 0.4285 | 6,202 |
| Business establishments (per 1,000) | 23.9418 | 31.5014 | 1.6532 | 1,161.28 | 6,202 |
| Unemployment rate | 0.0770 | 0.0279 | 0 | 0.2508 | 6,209 |
| Percentage of over 25 population With bachelor degree | 0.1662 | 0.0581 | 0.0305 | 0.4838 | 6,202 |
| Income per capita | 26,792.6 | 9,029.1 | 9,328 | 121,914 | 6,202 |
| *State Level controls:* | | | | | |
| Credit Card delinquency rate | 7.6909 | 1.8152 | 3.5 | 17 | 6,184 |
| Auto delinquency rate | 3.4903 | 1.1858 | 1 | 8.5 | 6,184 |
| Mortgage delinquency rate | 2.3799 | 1.9819 | 0.5 | 16 | 6,184 |
| Credit card per capita | 2,823.24 | 491.96 | 1,650 | 4,350 | 6,184 |
| Auto loans per capita | 3,985.62 | 803.86 | 2,280 | 6,720 | 6,184 |
| Mortgage per capita | 30,248.3 | 10,526.6 | 14,340 | 63,430 | 6,184 |
| GDP | 52,430.5 | 11,200.9 | 33,247 | 177,615 | 6,184 |

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), the number of observations (N). All the variables are defined in Appendix A.

**Table 2: Online Outreach and Bank Branch Outreach**

| | Model (1) | | Model (2) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| VARIABLES | First stage | Online Outreach | First stage | Online Amount |
| Average Distance | 0.0019*** | | 0.0018*** | |
| | (0.0002) | | (0.0004) | |
| Bank Branch Outreach in 2000 (ln) | 0.5786*** | | | |
| | (0.0139) | | | |
| Bank Branch Deposits in 2000 (ln) | | | 0.5513*** | |
| | | | (0.0153) | |
| Bank Branch Outreach (ln) | | -0.1112*** | | |
| | | (0.0295) | | |
| Bank Branch Deposits (ln) | | | | -0.1190*** |
| | | | | (0.0261) |
| HHI | -0.1088*** | -0.0192 | 2.9012*** | 0.3387*** |
| | (0.0285) | (0.0441) | (0.1218) | (0.0923) |
| Median Branch Age (ln) | 0.0516*** | -0.0577*** | -0.0201 | -0.0794*** |
| | (0.0105) | (0.0214) | (0.0228) | (0.0248) |
| Median Return on Assets (ln) | -0.0653*** | -0.1267*** | 0.0382 | -0.1044** |
| | (0.0220) | (0.0384) | (0.0466) | (0.0442) |
| Median ALLL (ln) | 0.1027*** | 0.1176** | -0.0651 | 0.0969* |
| | (0.0249) | (0.0499) | (0.0474) | (0.0575) |
| Observations | 5,840 | 5,840 | 5,840 | 5,840 |
| 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 | 1,194.07 | | 684.86 | |
| Under-identifcation test (Kleibergen-Paap rk LM statistic P-value) | | 0.0000 | | 0.0000 |
| Hansen's Over-identification test (P-value) | | 0.3534 | | 0.1458 |

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

**Table 3: Online Outreach and Bank Branch Outreach by Bank Size (Small and large Banks)**

| VARIABLES | (1)<br>Online Outreach | (2)<br>Online Outreach |
|---|---|---|
| Small Bank Branch Outreach $1B (ln) | -0.2018** | |
| | (0.0939) | |
| Large Bank Branch Outreach $1B (ln) | 0.2409 | |
| | (0.2319) | |
| Small Bank Branch Outreach 300 M (ln) | | -0.1682*** |
| | | (0.0554) |
| Large Bank Branch Outreach 300 M (ln) | | 0.1802 |
| | | (0.1417) |
| HHI | 0.0189 | 0.0085 |
| | (0.0494) | (0.0469) |
| Median Branch Age (ln) | -0.0425 | -0.0253 |
| | (0.0431) | (0.0368) |
| Median Return on Assets (ln) | -0.1580*** | -0.1849*** |
| | (0.0485) | (0.0483) |
| Median ALLL (ln) | 0.0918 | 0.0926* |
| | (0.0594) | (0.0534) |
| Observations | 4,692 | 5,137 |
| 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 asset thresholds of $1B and $300M, respectively. Robust standard errors are in parentheses.
*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

**Table 4: Distribution of Average Online Outreach by Bank Branch Outreach Quintiles**

| | | (1) = Lowest Bank Branch Outreach | (2) | (3) | (4) | (5) = Highest Bank Branch Outreach | T-test |
|---|---|---|---|---|---|---|---|
| All Banks (Obs.: 6,184) | Online Outreach (Mean) | 1.0497 | 0.9864 | 0.8996 | 0.8018 | 0.7520 | 0.000*** |
| Small Banks (Obs.: 6,184) | Online Outreach (Mean) | 1.0878 | 1.0034 | 0.8916 | 0.7901 | 0.7110 | 0.000*** |
| Large Banks (Obs.: 6,184) | Online Outreach (Mean) | 0.7311 | 0.8171 | 0.8880 | 0.9566 | 1.1093 | 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 branch 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 branch outreach. Small and large banks are defined using asset thresholds of $1B. The table also includes p-values from a t-test, which assesses the equality of means in the average proportion of online outreach between the lowest and highest quintile of bank outreach.
*** indicates significance at the 1% level

**Table 5: Online Outreach and Borrower Risk**

| VARIABLES | (1)<br>Clog-log | (2)<br>Clog-log | (3)<br>Clog-log | (4)<br>Clog-log |
|---|---|---|---|---|
| Online Outreach (ln) | -0.0162*** | -0.0156*** | | |
| | (0.0040) | (0.0041) | | |
| Bank Branch Outreach (ln) | | 0.0018 | | |
| | | (0.0033) | | |
| Online Amount (ln) | | | -0.0071* | -0.0091** |
| | | | (0.0038) | (0.0039) |
| Bank Branch Deposits (ln) | | | | 0.0059*** |
| | | | | (0.0014) |
| Loan Beginning Balance (ln) | 0.5726*** | 0.5726*** | 0.5705*** | 0.5727*** |
| | (0.0012) | (0.0012) | (0.0012) | (0.0012) |
| Last FICO | -0.0161*** | -0.0161*** | -0.0161*** | -0.0161*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Debt-to-income Ratio | 0.0102*** | 0.0102*** | 0.0099*** | 0.0102*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Annual Income (ln) | -0.4450*** | -0.4450*** | -0.4572*** | -0.4451*** |
| | (0.0016) | (0.0016) | (0.0016) | (0.0016) |
| Open Accounts | 0.0179*** | 0.0179*** | 0.0176*** | 0.0179*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Interest Rate | 0.0304*** | 0.0304*** | 0.0312*** | 0.0304*** |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| Loan Term (60 months) | 0.6346*** | 0.6346*** | 0.6331*** | 0.6346*** |
| | (0.0017) | (0.0017) | (0.0017) | (0.0017) |
| Homeownership Status (Rent) | 0.2175*** | 0.2175*** | 0.2280*** | 0.2175*** |
| | (0.0014) | (0.0014) | (0.0014) | (0.0014) |
| Observations | 20,011,205 | 20,011,205 | 20,011,205 | 20,011,205 |
| Three-digit ZIP code level controls | Yes | Yes | Yes | Yes |
| State Level controls | Yes | Yes | Yes | Yes |
| State Dummies | Yes | Yes | Yes | Yes |
| Origination Year Dummies | Yes | Yes | Yes | Yes |

This table provides the results of the complementary log-log model. In columns (1&2), the main independent variable is the natural logarithm of the total number of online loans per 1,000 people. In columns (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 defaults on a loan in a given month, zero otherwise. The reference category for Loan Term is '36 months', and for Homeownership Status, the base category is 'owner'. Debt-to-income ratio, annual income, and open accounts are winsorized at the 1st percentile. Robust standard errors are in parentheses.
*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

**Table 6: Regional Online Default Rate and Online Outreach**

| VARIABLES | (1)<br>Default Rate | (2)<br>Default Rate | (3)<br>Default Rate | (4)<br>Default Rate |
|---|---|---|---|---|
| Online Outreach (ln) | -0.0189** | -0.0192** | | |
| | (0.0091) | (0.0091) | | |
| Bank Branch Outreach (ln) | | -0.0054 | | |
| | | (0.0048) | | |
| Online Amount (ln) | | | -0.0177** | -0.0177** |
| | | | (0.0086) | (0.0087) |
| Bank Branch Deposits (ln) | | | | -0.0005 |
| | | | | (0.0018) |
| Mean Debt-to-income Ratio (ln) | 0.0470* | 0.0477* | 0.0472* | 0.0472* |
| | (0.0271) | (0.0271) | (0.0271) | (0.0271) |
| Mean FICO (ln) | 0.0213 | 0.0243 | 0.0127 | 0.0123 |
| | (0.2748) | (0.2747) | (0.2764) | (0.2764) |
| Mean number of Open Accounts (ln) | 0.0516* | 0.0502* | 0.0517* | 0.0517* |
| | (0.0273) | (0.0273) | (0.0273) | (0.0273) |
| Mean Income (ln) | -0.0287 | -0.0297 | -0.0272 | -0.0272 |
| | (0.0236) | (0.0238) | (0.0235) | (0.0236) |
| Mean Loan Amount (ln) | 0.0636*** | 0.0642*** | 0.0744*** | 0.0745*** |
| | (0.0200) | (0.0200) | (0.0219) | (0.0219) |
| Mean Int Rate (ln) | 0.2180*** | 0.2172*** | 0.2171*** | 0.2170*** |
| | (0.0449) | (0.0447) | (0.0447) | (0.0447) |
| Observations | 5,824 | 5,824 | 5,824 | 5,824 |
| 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. This table shows 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 regional 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 columns (1&2), the main independent variable is the natural logarithm of the total number of online loans per 1,000 people. In columns (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 percentile. Robust standard errors are in parentheses.
*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

**Table 7: Online Outreach and Borrowers' 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) | 0.1505*** | 0.1469*** | 0.0142*** | 0.0156*** |
| | (0.0519) | (0.0536) | (0.0029) | (0.0030) |
| Bank Branch Outreach (ln) | | -0.0118 | | 0.0045* |
| | | (0.0442) | | (0.0024) |
| Debt-to-Income ratio | -0.0467*** | -0.0467*** | -0.0021*** | -0.0021*** |
| | (0.0011) | (0.0011) | (0.0001) | (0.0001) |
| Annual Income (ln) | 0.2310*** | 0.2310*** | -0.0009 | -0.0009 |
| | (0.0173) | (0.0173) | (0.0010) | (0.0010) |
| Open Accounts | -0.0544*** | -0.0544*** | -0.0025*** | -0.0025*** |
| | (0.0017) | (0.0017) | (0.0001) | (0.0001) |
| Homeownership status (Rent) | -0.3485*** | -0.3485*** | -0.0004 | -0.0004 |
| | (0.0186) | (0.0186) | (0.0010) | (0.0010) |
| *Credit Grade:* | | | | |
| Grade B | -0.6679*** | -0.6679*** | -0.0021 | -0.0021 |
| | (0.0211) | (0.0211) | (0.0013) | (0.0013) |
| Grade C | -2.2927*** | -2.2927*** | -0.0625*** | -0.0625*** |
| | (0.0227) | (0.0227) | (0.0014) | (0.0014) |
| Grade D | -3.6744*** | -3.6744*** | -0.1124*** | -0.1123*** |
| | (0.0293) | (0.0293) | (0.0016) | (0.0016) |
| Grade E | -4.9635*** | -4.9636*** | -0.1545*** | -0.1545*** |
| | (0.0421) | (0.0421) | (0.0021) | (0.0021) |
| Grade F | -6.1485*** | -6.1486*** | -0.1916*** | -0.1916*** |
| | (0.0726) | (0.0726) | (0.0034) | (0.0034) |
| Grade G | -6.8638*** | -6.8639*** | -0.2156*** | -0.2156*** |
| | (0.1412) | (0.1412) | (0.0063) | (0.0063) |
| Observations | 1,245,121 | 1,245,121 | 1,245,121 | 1,245,121 |
| Three-digit ZIP code level controls | Yes | Yes | Yes | Yes |
| State Level controls | Yes | Yes | Yes | Yes |
| State Dummies | Yes | Yes | Yes | Yes |
| Origination Year Dummies | Yes | Yes | Yes | Yes |

This table reports the results of Eq. (3). In Model 1, we provide the OLS regression results 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 borrowers' 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. Within this model, 'grade A' serves as the base category for credit grade, and 'owner' is the base category for homeownership status. Debt-to-income ratio, annual income, and open accounts are winsorized at the 1st percentile. Robust standard errors are in parentheses.
** and *** indicate significance at the 5% and 1% levels, respectively.

**Table 8: Average Regional Change in FICO and Regional Online Outreach**

| VARIABLES | (1)<br>Change in<br>FICO % | (2)<br>Change in<br>FICO % | (3)<br>Change in<br>FICO % | (4)<br>Change in<br>FICO % |
|---|---|---|---|---|
| Online Outreach (ln) | 0.4140* | 0.4226* | | |
| | (0.2272) | (0.2288) | | |
| Bank Branch Outreach (ln) | | 0.2016 | | |
| | | (0.1293) | | |
| Online Amount (ln) | | | 0.4474** | 0.4489** |
| | | | (0.2131) | (0.2135) |
| Bank Branch Deposits (ln) | | | | 0.0463 |
| | | | | (0.0489) |
| Mean Debt-to-income Ratio (ln) | -2.4183*** | -2.4434*** | -2.4845*** | -2.4840*** |
| | (0.9355) | (0.9307) | (0.9131) | (0.9123) |
| Mean FICO (ln) | -15.1791* | -15.4022* | -14.5899* | -14.5936* |
| | (8.0219) | (8.0253) | (7.8914) | (7.8906) |
| Mean number of Open Accounts (ln) | -1.2663 | -1.2101 | -1.2855 | -1.2820 |
| | (0.8725) | (0.8749) | (0.8723) | (0.8724) |
| Mean Income (ln) | 0.0898 | 0.1135 | -0.1252 | -0.1240 |
| | (0.6985) | (0.7013) | (0.6724) | (0.6727) |
| Observations | 5,824 | 5,824 | 5,824 | 5,824 |
| 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 shows 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 mean percentage change for borrowers in a three-digit ZIP code. In columns (1&2), the main independent variable is the natural logarithm of the total number of online loans per 1,000 people. In columns (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 percentile. Robust standard errors are in parentheses.

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

## Appendix A: Variables Definitions

***Panel A: Key Variables***

| Variable | Description | Source |
|---|---|---|
| Bank Branch Outreach | The total number of bank branches in a three-digit ZIP code area per 1,000 people. | FDIC |
| Bank Branch Deposits | The sum of bank branch deposits in a three-digit ZIP code area per 1,000 people. | FDIC |
| Online Outreach | The total number of online loan applications in a three-digit ZIP code area per 1,000 people. | Lending Club |
| Online Amount | Sum of the total amount of online loan applications 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 B: 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 the 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 US Census Bureau |
| Income per capita | The median income per capita within a three-digit ZIP code | 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 |
| ***Panel D: 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 bank branches in a three-digit ZIP code area per 1,000 people in the year 2000. | FDIC |
| Branch Deposits in 2000 | Sum of bank branch deposits in a three-digit ZIP code area per 1,000 people in the year 2000. | FDIC |
| ***Panel E: 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 |
| Interest rate | Interest Rate on the loan | Lending Club |

| | | |
|---|---|---|
| Homeownership | The homeownership status provided by the borrower during registration or obtained from the credit report. | Lending Club |
| Loan Term | The number of payments on the loan. Values are in months and can be either 36 or 60. | Lending Club |
| Credit Grade | Credit grade assigned by Lending Club. | Lending Club |

**Appendix B: Online Outreach and Bank Branch Outreach (OLS Results)**

| | (1) | (2) |
|---|---|---|
| VARIABLES | Online Outreach | Online Amount |
| Bank Branch outreach (ln) | -0.1026*** | |
| | (0.0223) | |
| Bank Branch Deposits (ln) | | -0.0365*** |
| | | (0.0127) |
| HHI | -0.0159 | 0.0907 |
| | (0.0440) | (0.0606) |
| Median Branch Age (ln) | -0.0612*** | -0.0826*** |
| | (0.0209) | (0.0244) |
| Median Return on Assets (ln) | -0.1246*** | -0.1066** |
| | (0.0386) | (0.0439) |
| Median ALLL (ln) | 0.1132** | 0.0863 |
| | (0.0499) | (0.0570) |
| Observations | 5,854 | 5,854 |
| 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. 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. The main independent variable is the natural logarithm of the sum of bank branch deposits per 1,000 people. Robust standard errors are in parentheses.
** and *** indicate significance at the 5% and 1% levels, respectively.

**Appendix C: Online Outreach and Bank Branch Outreach by Bank Size (First Stage IV Results)**

| | First Stage: $1B | | First Stage: $300M | |
|---|---|---|---|---|
| | (1) | (2) | (1) | (2) |
| VARIABLES | Small Banks | Large Banks | Small Banks | Large Banks |
| Average Distance | 0.0034*** | -0.0007 | 0.0038*** | -0.0015*** |
| | (0.0003) | (0.0006) | (0.0003) | (0.0006) |
| Bank Branch Outreach in 2000 (ln) | 0.6922*** | 0.3042*** | 0.7301*** | 0.3084*** |
| | (0.0216) | (0.0283) | (0.0216) | (0.0258) |
| HHI | -0.1700*** | -0.0530 | -0.1507*** | 0.0144 |
| | (0.0366) | (0.0859) | (0.0414) | (0.0699) |
| Median Branch Age (ln) | -0.0028 | -0.1677*** | 0.0322** | -0.2088*** |
| | (0.0148) | (0.0324) | (0.0146) | (0.0257) |
| Median Return on Assets (ln) | -0.1135*** | 0.0038 | -0.1493*** | 0.1108* |
| | (0.0325) | (0.0657) | (0.0324) | (0.0608) |
| Median ALLL (ln) | 0.1267*** | 0.0643 | 0.1636*** | 0.0337 |
| | (0.0362) | (0.0784) | (0.0351) | (0.0728) |
| Observations | 4,692 | 4,692 | 5,137 | 5,137 |
| 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 first stage of instrumental variable regression. 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 small and large bank branches using asset thresholds of $1B and $300M, reported, respectively. Robust standard errors are in parentheses.

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

**Appendix D: Online Outreach and Bank Branch Outreach by Bank Size (OLS results)**

| VARIABLES | (1)<br>Online Outreach | (2)<br>Online Outreach |
|---|---|---|
| Small Bank Branch Outreach $1B (ln) | -0.0946***<br>(0.0178) | |
| Large Bank Branch Outreach $1B (ln) | 0.0024<br>(0.0130) | |
| Small Bank Branch Outreach 300 M (ln) | | -0.1037***<br>(0.0163) |
| Large Bank Branch Outreach 300 M (ln) | | 0.0058<br>(0.0109) |
| HHI | 0.0318<br>(0.0430) | 0.0251<br>(0.0417) |
| Median Branch Age (ln) | -0.0878***<br>(0.0256) | -0.0659***<br>(0.0238) |
| Median Return on Assets (ln) | -0.1459***<br>(0.0447) | -0.1572***<br>(0.0420) |
| Median ALLL (ln) | 0.0974*<br>(0.0557) | 0.0892*<br>(0.0515) |
| Observations | 4,699 | 5,144 |
| State Level controls | yes | yes |
| Three-digit ZIP code level controls | Yes | Yes |
| State Dummies | Yes | Yes |
| Year Dummies | Yes | Yes |

This table provides the OLS results. 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 asset thresholds of $1B and $300M, reported, respectively. Robust standard errors are in parentheses.
*, and *** indicate significance at the 10%, and 1% levels, respectively.

**Appendix E: Online Amount and Borrower's Financial Welfare**

| VARIABLES | Model (1) Change FICO % | Change FICO % | Model (2) Positive FICO change | Positive FICO change |
|---|---|---|---|---|
| Online Amount (ln) | 0.0937* | 0.1004** | 0.0120*** | 0.0126*** |
| | (0.0498) | (0.0503) | (0.0028) | (0.0028) |
| Bank Branch Deposits (ln) | | 0.0169 | | 0.0016 |
| | | (0.0191) | | (0.0011) |
| Debt-to-Income ratio | -0.0467*** | -0.0467*** | -0.0021*** | -0.0021*** |
| | (0.0011) | (0.0011) | (0.0001) | (0.0001) |
| Annual Income (ln) | 0.2305*** | 0.2304*** | -0.0010 | -0.0010 |
| | (0.0173) | (0.0173) | (0.0010) | (0.0010) |
| Open Accounts | -0.0544*** | -0.0544*** | -0.0025*** | -0.0025*** |
| | (0.0017) | (0.0017) | (0.0001) | (0.0001) |
| Homeownership status (Rent) | -0.3483*** | -0.3484*** | -0.0004 | -0.0004 |
| | (0.0186) | (0.0186) | (0.0010) | (0.0010) |
| *Credit Grade:* | | | | |
| Grade B | -0.6678*** | -0.6678*** | -0.0021 | -0.0021 |
| | (0.0211) | (0.0211) | (0.0013) | (0.0013) |
| Grade C | -2.2925*** | -2.2924*** | -0.0625*** | -0.0625*** |
| | (0.0227) | (0.0227) | (0.0014) | (0.0014) |
| Grade D | -3.6742*** | -3.6741*** | -0.1124*** | -0.1124*** |
| | (0.0293) | (0.0293) | (0.0016) | (0.0016) |
| Grade E | -4.9634*** | -4.9632*** | -0.1545*** | -0.1545*** |
| | (0.0421) | (0.0421) | (0.0021) | (0.0021) |
| Grade F | -6.1484*** | -6.1481*** | -0.1916*** | -0.1916*** |
| | (0.0726) | (0.0726) | (0.0034) | (0.0034) |
| Grade G | -6.8639*** | -6.8638*** | -0.2157*** | -0.2157*** |
| | (0.1412) | (0.1412) | (0.0063) | (0.0063) |
| Observations | 1,245,121 | 1,245,121 | 1,245,121 | 1,245,121 |
| Three-digit ZIP code level controls | Yes | Yes | Yes | Yes |
| State Level controls | Yes | Yes | Yes | Yes |
| State Dummies | Yes | Yes | Yes | Yes |
| Origination Year Dummies | Yes | Yes | Yes | Yes |

This table reports the results of Eq. (3). In the first model, we provide the OLS regression results 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 the borrower's FICO at the end of the loan. In Model 2, we present the results of the logit regressions. The dependent variable is whether a borrower experienced a positive change in credit score at the end of the loan. Within this model, 'grade A' serves as the base category for credit grade, and 'owner' is the base category for homeownership status. Debt-to-income ratio, annual income, and open accounts are winsorized at the 1st percentile. Robust standard errors are in parentheses.
*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.