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The Impact of Peer-to-Peer Lending on Small Business Loans

Abstract

We investigate the impact of peer-to-peer lending on the small business loans originated by US depository institutions that are subject to the Community Reinvestment Act. We present a model where a borrower can choose between a traditional bank and a crowdlending platform and show that the entry of crowdlending can induce a switching effect as well as a credit expansion effect. Using the staggered entry of LendingClub across states between 2009 and 2017, we find that the platform entry reduced the small business loans originated by banks, in particular, in the low- or moderate-income tracts as well as in the distressed middle-income tracts with a high poverty rate. A conservative estimate suggests that the crowdlending entry may have reduced the aggregate lending volume to small businesses.

JEL-Codes: D260, G210, G280.

Keywords: crowdfunding, marketplace lending, fintech, Community Reinvestment Act.

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1 Introduction

Peer-to-Peer (P2P) lending, also known as marketplace lending or crowdlending, is a type of crowdfunding investment where individual as well as institutional lenders collectively finance loan applications.[1] Loans are originated utilizing an online platform, wherein borrowers from eligible geographies apply for a loan and similarly lenders from eligible geographies lend money after reviewing (or based on) the creditworthiness and other information about the borrower and loan to be funded. According to various reports (e.g., annual survey distributed by the Cambridge Centre for Alternative Finance), the global crowdlending market has been rapidly growing in the past decade. In the US, the crowdlending volume was about \$40 billion in 2017, which amounts to 0.2% of gross domestic product or \$200 per capita (Dietrich et al., 2019).

There are two main categories of crowdlending: consumer lending and business lending. While the literature has focused on the former, there is a growing evidence that crowdlending is important for small and mid-size enterprises. For instance, Zhang et al. (2018) find that in the UK 68% of the total market volume raised via P2P lending platforms was channelled to businesses with an annual turnover of less than £2 million, and they estimate that as much as 29% of all new loans issued to small businesses in 2017 was from P2P lending. In the US, the bulk of the P2P loans are unsecured personal loans with the reported intent of refinancing loans or credit cards. These stated purposes are indeed vague, because they "may not reflect actual usage" as the platforms' disclaimers say. Hence, it is possible that at least some of these personal loans were used for businesses.

The goal of this paper is to investigate the impact of P2P lending on small business loans originated by traditional banks. As is well know, some argue that alternative finance helps close the small business funding gap, while others argue that traditional banks will be hit hard by the fintech disruption. Both arguments have some validity: On the one hand, "According to the Federal Reserve's Survey of Terms of Business Lending, in 2007 roughly 84 percent of the value of loans under \$100,000 was secured by collateral, and by 2013 that figure had

[1] Other types of crowdfunding include donation-, reward-, and equity-based crowdfunding, where investors receive nothing, a token or product, and an equity stake in return, respectively. In debt-based crowdlending, investors are promised an interest payment as a reward proportional to the amount they invest.

increased to 90 percent. As a result, bank lending to small businesses has yet to recover and is currently at 2002 levels" (Williams, 2014). Therefore, as Li (2016) found in a dataset of Swedish firms, crowdlending may provide for the firms that lack both internal funds and sufficient assets pledgeable as collateral to receive external credit.

At the same time, some industries (e.g., music) have been hit hard by the digital disruption, and there are plenty of discussions in newspapers and magazines on fintech as a new form of digital disruption. Interestingly, we find that the entry of LendingClub, the largest P2P lending platform in the US, is causally associated with a significant decrease in the number and volume of small business loans originated by US depository institutions.[2] This effect is significant for the smallest loan-size category (under \$100,000) reported under the Community Reinvestment Act (CRA) and not for the larger loan-size categories (above \$100,000 and up to \$1,000,000). This is suggestive of some displacement effect crowdlending may have on the traditional banking sector, because most business loans issued by LendingClub have been indeed under \$100,000.

We also find that the LendingClub entry is causally associated with a statistically significant decrease in the number and volume of loans extended to firms with an annual revenue less than \$1,000,000, implying that crowdlending may have an impact on the small businesses as well as the banks. Further, somewhat surprisingly, the entry of LendingClub has a disproportionately negative effect on the so-called 'CRA-eligible' assessment areas. These areas include low- and moderate-income tracts as well as distressed and underserved middle-income tracts annually designated by the financial regulators. While the number and volume of small business loans in the CRA-eligible areas may tend to be larger than those in more affluent areas, the entry of LendingClub in those areas more than offset the increase in the loan number and volume, resulting in dispersed displacement effects.

Therefore, our difference-in-difference-in-differences style estimates suggest that the banks may have a harder time in meeting the CRA performance target by providing enough capital to CRA-eligible communities. This may then force traditional banks to consider adopting online

[2]The association may be causal if the state permission of LendingClub borrowing was plausibly exogenous to the unobserved heterogeneity with regard to business loans. As we will elaborate below, the state securities regulators seem to be mainly concerned with investor protection rather than the credit market.

lending facilities (for instance, in 2018, U.S. Bank launched an all digital platform for small business loans up to $250,000). While our data do not allow us to pin down the exact mechanism behind our finding of the displacement effect (e.g., whether the banks are receiving less applications for small business loans or they are turning down more of those applications), we provide a theoretical analysis in which we show that traditional banks will get the lower risk types while the platforms attract the higher risk types, and the aggregate lending volume may decline following the entry of crowdlending platforms.

The emergent literature on crowdfunding is diverse and rapidly growing. Yet, it mostly confines itself to the workings of the crowdfunding (especially reward-based) platforms themselves, which we do not attempt to survey here in great details (see, e.g., Schwienbacher and Larralde (2012), Agrawal et al. (2014), and Belleflamme et al. (2015) for earlier surveys on investment- as well as reward-based crowdfunding). For instance, Ahlers et al. (2015), Vulkan et al. (2016), and Mohammadi and Shafi (2018) investigate the success factors of crowdfunding projects and the investor behavior on an equity crowdfunding platform; and Cumming and Hornuf (2020) do so for a peer-to-business lending platform, showing that traditional adverse selection might not be so applicable in the context of crowdlending.[3] The key difference in our paper is that we do not directly focus on the fundraising outcomes or investor behavior on a platform per se.

Instead, we focus on the effect of crowdlending on small business loans issued by traditional lenders. Such an effect, external to the platforms, may be viewed as spillovers; however, from an industry standpoint, this subject is one of the central issues in fintech innovation and may have policy implications for financial markets and institutions. Thus, we build on a stream of the literature that lies at the intersection of P2P lending and small business lending. For instance, Mach et al. (2014) examine small business loans issued by LendingClub, finding that relative to small business loans from traditional lenders P2P borrowers paid an interest rate that was about two times higher. Li (2016) finds that small firms borrowing from the crowd tend to have higher sales growth rates but lower cash holdings and lack tangible assets to pledge as collateral.

[3] There is a larger set of prior works on peer-to-peer consumer lending (e.g., Duarte et al. (2012), Zhang and Liu (2012), Lin et al. (2013), and Ravina (2019) to name a few); however, as Cumming and Hornuf (2020) find, the decision to crowdfund businesses might be different from funding private individuals.

These findings imply that P2P lenders may serve more vulnerable firms that have a difficulty in obtaining conventional loans.

Although these studies compare P2P loans and traditional business loans, they do not directly examine the effect of P2P lending on the overall volume of small business loans issued by traditional lenders. While we are not aware of previous studies that investigated the link between crowdlending and small business loans reported under CRA, there are several studies that examine whether P2P lending in general is a complement or substitute to traditional loans. For instance, Padhi (2017) shows, using LendingClub data aggregated to the three-digit zip code level, that the demand for P2P loans is greater in areas where the banking sector is more concentrated and/or a minority population is large. Jagtiani and Lemieux (2018) also find that LendingClub's lending activities could expand credit access to those areas that may be underserved by traditional banks and where the local economy is not well. These studies imply that P2P lending may allow access to credit for those who were previously credit-rationed.[4]

Our finding is different, but not necessarily contradictory to the above findings, because P2P lending may expand credit access to some borrowers while at the same time substitute traditional lending activities. In this regard, Cornaggia et al. (2018), Cole et al. (2019), and Tang (2019) are the most closely related studies. Cornaggia et al. (2018) show that, using the Call Reports, total consumer credit volume and personal loan volume are negatively correlated with the volume of P2P loans originated in the lender's (deposit-weighted) market. Using the size of investor population in the P2P lending market as an instrument, they find that a substantial portion of P2P lending volume is a substitution away from banks for those with poor credit scores, and the loss is concentrated among small commercial banks. Our finding is complementary to theirs because our data source (CRA) reports small business loans originated by large financial institutions, and our identification depends on more discrete changes in platform entries.

Cole et al. (2019) show that bank failures in a county might negatively affect the amount of crowdfunded capital for rewards-based projects as well as crowdlending projects. They argue

[4]Similarly, Jagtiani et al. (2019) examine whether fintech mortgage lenders serve borrowers and communities with similar characteristics as those served by traditional mortgage lenders, and find that fintech lenders have greater market shares in areas with lower credit scores and higher mortgage denial rates.

that bank finance may be a complement to, and not a substitute for, crowdfunding because, for instance, if bank failures were caused by crowdfunding, then we should see a positive correlation between crowdfunding volume and bank closures. Ours is a flip side of this finding because we investigate the relation between traditional loan volume and entry of a P2P platform. On the other hand, Tang (2019) shows that, using a regulatory shock to accounting standards (i.e., the implementation of FAS 166/167 in 2011), P2P lending volume is a substitute for bank lending, and the P2P borrowers belong to the left tail of the quality distribution. Therefore, the literature has found mixed evidence, and thus we contribute to the debate on this topic by providing a theoretical and empirical analysis.

Finally, the role of depository institutions in serving the local community's capital needs is a subject of great interest to the financial regulators. Small business lending (as reported by the CRA and the Call Reports) has declined significantly following the Great Recession while there exists a substantial heterogeneity across neighborhoods (Dore and Mach, 2018). Ding et al. (2019), using a sample of neighborhoods that changed CRA eligibility status, show that the CRA indeed promotes small business lending in low-income areas. Our results are consistent with the literature in that the standalone effect of CRA-eligible tracts is positive, and the novel finding is that the entry of the crowdlending platform can sometimes offset this positive effect of CRA in the low-income areas as well as some distressed and underserved middle-income areas. Therefore, P2P lending may have important implications not only on the demand for but also the supply of small business loans by traditional sources.

The remainder of this paper is organized as follows. Section 2 briefly discusses small business lending by traditional banks and crowdlending. Section 3 presents a simple theoretical framework to discuss the effects of crowdlending entry. Section 4 describes our dataset, and Section 5 contains empirical evidence on the effects of crowdlending on small business loans. Section 6 concludes.

2 Background

According to Mills and McCarthy (2014), most small businesses in the US are 'mom and pop' businesses rather than high-growth firms or those belonging to large commercial or government supply chains. This means that traditional term loans rather than, say, venture capital plays an important role in allowing everyday small business owners and entrepreneurs to hire employees, stock inventories, and grow their businesses. US small business lending has been gradually improving since the 2008 financial crisis; however, it still remains below the pre-crisis level, creating a potential credit gap (e.g., Williams, 2018). Indeed, "Most banks say they are lending to small businesses, but major surveys of small business owners point to constrained credit markets" (Mills and McCarthy, 2014).

"In addition, bankers note the dampening effect of increased regulatory oversight on the availability of small business credit. Not only is there more regulation and higher compliance costs, there is uncertainty about how regulators view the credit characteristics of loans in their portfolios, making them less likely to make a loan based on "softer" underwriting criteria such as knowledge of the borrower from a long term relationship" (Mills and McCarthy, 2014). This means that banks make traditional loan offers to small businesses based on mostly objective criteria such as the owner's business and personal credit scores, annual revenues and years in business. This is also true for Small Business Administration (SBA) loans provided by banks and other lenders who receive a guaranty from the SBA.[5]

In either case (traditional or SBA loans), banks must screen applicants (and apply for SBA loans, if applicable). Hence, applicants must meet the banks' (as well as the SBA's) criteria to be issued a loan offer. Importantly, this includes collateral—assets, such as equipment, property or inventory, that will be seized and sold by the lender if the borrower defaults. (Similarly, SBA loans require "adequate" collateral on all loans, plus a personal guarantee from every owner of 20 percent or more of the business.) This means that if the assets being financed by the loan are not sufficient to secure the loan, then banks typically require the borrowers to pledge their

[5] "Under the 7(a) guaranteed loan program SBA typically guarantees from 50% to 85% of an eligible bank loan up to a maximum guaranty amount of $3,750,000. The exact percentage of the guaranty depends on a variety of factors such as size of loan and which SBA program is to be used" (SBA, 2011).

personal assets as additional collateral. Some lenders might be more flexible weighing multiple criteria, but in all likelihood, some form of collateral will be required by traditional lenders.

The terms of small business loans may be negotiable but in most cases are determined by the lender's operating policies. (SBA loans generally have rates and fees that are similar to traditional bank loans.) For instance, banks base their rates on local market factors, such as level of competition, as well as macroeconomic factors, such as inflation rate environment. In addition, banks offer their prime rates to their most valuable and creditworthy customers (e.g., through relationship banking) while they may offer higher rates and fees if the customer is deemed to be a higher risk. In all cases, it can take several months to close a deal with traditional lenders, and the personal assets such as residential properties tied up as collateral come at a significant opportunity cost of capital, because it could limit the owner's future financial plans and opportunities.

At the same time, in the backdrop of the Great Recession, the peer-to-peer (marketplace) lending has seen a remarkable growth. P2P lending has some attractive features. For instance, P2P lenders (or platforms) developed proprietary algorithms to quickly rate online loan applications using not only the traditional sources but also nontraditional inputs (e.g., card transactions and social networks), which reduces the lender's screening costs. Further, P2P lenders can be more flexible in terms of meeting the traditional loan criteria; in fact, they often require little to no collateral even for explicit business loans.[6] Thus, even if a business is (or is not) qualified for traditional small business loans, the owner might be able to get funded through P2P lending platforms in a matter of days.

The downside of obtaining a business loan from crowdlending is that it comes with a higher interest rate given the unsecured nature of the loan. For instance, while most SBA 7(a) business loans have an annual rate of six to eight percent, LendingClub currently has interest rates ranging from 6.95% to 35.89% for personal loans (and 5.99% to 29.99% for business loans) with an average rate of about 13%. Another issue is that P2P loans are limited at $40,000, although

[6]Since small business owners often co-mingle their personal and business finances and the intended purpose of P2P loans is not to be replied upon (as the platforms warn themselves), it might be fair to say that P2P loans put more emphasis on the borrower's personal credit records than any business criteria.

LendingClub offers up to $500,000 for explicit business loans. In either case, the ceiling is less than the $1 million threshold financial regulators use to define small business loans. However, both our data and other surveys indicate that the majority of small businesses are seeking loans of less than $100,000 (Mills and McCarthy, 2014).

The US P2P lending market has been dominated by LendingClub and Prosper with their combined market share of 98% in 2014 (Kambayashi, 2014). While they launched their services in 2007 and 2006, respectively, in a regulatory vacuum, it was not until they finished their registration process with the Securities and Exchange Commission (SEC) in 2008 and 2009 that their lending volume started to grow rapidly.[7] In terms of their relative sizes, LendingClub has originated a much larger volume of new loans than Prosper has (e.g., The Economist, 2016). Thus, some of the literature above tends to focus exclusively on LendingClub when it examines the effect on the banking sector. Further, while LendingClub has offered explicit business loans with a higher limit, Prosper only offered general-purpose personal loans up to $40,000.

On the other hand, P2P lenders are also subject to state regulations, and some states have been slower than others in allowing their residents to invest in or borrow from the platforms. The exact timing and holdup at each state since the SEC registration has been something of a mystery as well as a cause for complaints by many in the P2P communities. Supposedly, state regulators were concerned about the perceived (high) risk of these types of loans and wanted to protect their citizens; and given the uncertainty surrounding how the existing state laws may be applied to P2P lenders, this created the staggered entry of the P2P platforms into states. Some states allowed borrowing but not investing because borrowing may involve much less risk. We will focus on borrowing for our purpose because loans can be funded by investors in other eligible states.

[7]The SEC registration means that the individual as well as institutional investors are not in fact directly lending money to the borrowers but they are buying a promissory note (a securities agreement) from the P2P platform which obliges the platform to pay the investors as long as the borrower pays back.

3 Theoretical Analysis

The previous section tells us that both banks and crowdfunding platforms base their decisions on a set of criteria or an algorithm using traditional and/or nontraditional sources of information, which are essentially characteristics of the business and/or the borrower. Although there may be room for negotiation or bidding on the loan terms, it is reasonable for our modelling purpose to assume that the loan parameters are given by the lenders vis-à-vis entrepreneurs.[8] Relatedly, we do not explicitly consider competition among lenders of the same type, but we assume that each borrower has chosen a bank, which may represent the bank that he has relationship banking ties with, and also a platform (given our focus on LendingClub). However, as long as the platform charges a higher interest rate than banks do, the qualitative implications of our model would remain unchanged even in the presence of competition among banks and platforms. Further, we assume that adverse selection is not a significant factor in the small business loan markets (Cumming and Hornuf, 2020).[9]

Specifically, we assume that risk-neutral entrepreneurs, denoted by i, plan to carry out a risky project in location j that must be financed by external debt.[10] The size of the project (or the loan) is denoted by x_i and endogenous, and if the project is successful, it will create a gross profit of size $\alpha_j \pi_i(x_i)$ where α_j measures the market potential of location j with $\pi_i(0) = 0$, $\pi_i'(0) > 0$ and $\pi_i''(\cdot) < 0$. Since small businesses rely on local markets, we expect that α_j is large (small) in areas with a large (small) market potential in terms of income and population. The success probability is denoted by $p_i(e_i)$, $0 \leq p_i(e_i) < 1$, which depends on the efforts of the entrepreneur, e_i, after the project has received funding. The entrepreneur can increase the success probability by putting more efforts, which are non-contractible. Thus, we will employ

[8] One might note that Prosper started with a business model where investors bid on loan rates; however, it abandoned the reverse auction process in 2010 and started using pre-set rates. Some speculate that the change was because Prosper's loan volume was much smaller than that of its competitior, LendingClub.

[9] In the so-called credit rationing (adverse selection) models (e.g., Stiglitz and Weiss, 1981; Bester, 1985), collateral can be used as a screening but not incentive device; and collateral can be only used for screening under perfect competition among banks (see, e.g., Besanko and Thakor, 1987; Bester, 1987).

[10] Without much loss, we assume penniless entrepreneurs. Nothing relevant would change, however, in our analysis below if we assumed instead that the business owner had a positive wealth to invest into the project, as long as the desired level of investment exceeds the fund already available to the entrepreneur.

a moral hazard model in which bank's collateral requirement incentivizes entrepreneurs.[11] In particular, we assume that $p_i(0) = 0$, $p_i'(\cdot) > 0$, and $p_i''(\cdot) < 0$; and efforts come with a cost $C_i(e_i)$, where $C_i(0) = 0$, $C_i'(\cdot) > 0$, and $C_i''(\cdot) > 0$ hold true.

3.1 Bank

When dealing with a bank, the entrepreneur faces a repayment of $R_i x_i$, which is the sum of principal and accrued interest, in the case of success and a requirement to put up collateral against default. The collateral is some combination of paper and hard assets which the lender will seize and sell if a borrower defaults. However, because the economic worth of the defaulting firm's collateral tends to be lower, the lender's recovery rate based on the value of the collateral is on average only around 40 percent of the full amount due with a large variation (e.g., Mora, 2012). Thus, we let Ψ_i denote the (expected) market value of collateralized assets, and assume that $\Psi_i < R_i x_i$, meaning that the size of the collateral that will be lost in the case of failure would be smaller than the full repayment due.

In addition, putting up collateral has a cost for the entrepreneur, because he cannot dispose or use the collateral for other growth opportunities. Thus, the entrepreneur incurs an opportunity cost of putting up collateral, $\gamma_i \Psi_i$ (just like banks do as they are unable to convert their loans to cash frictionlessly). If the collateral the entrepreneur posts is purely cash and has no opportunity cost, then the entrepreneur would be better off by using the cash to finance the project; however, commercial and residential real estate, often used as collateral for small business loans, represent two-thirds of the assets of small business owners (Mills and McCarthy, 2014). Therefore, the expected payoff of an entrepreneur applying for a traditional bank loan is given by

$$U_i(e_i, x_i) = p_i(e_i)\left[\alpha_j \pi_i(x_i) - R_i x_i\right] - \left[1 - p_i(e_i)\right]\Psi_i - \gamma_i \Psi_i - C_i(e_i). \tag{1}$$

The entrepreneur takes all parameters of the model (α_j, R_i, Ψ_i, γ_i) as given and maximizes

[11] While the entrepreneurial moral hazard problem sometimes entails that the entrepreneurs receive private benefits when they shirk (e.g., Holmström and Tirole, 1997), we abstract from the private benefit in order to focus on the incentive problem created under the collateral posting requirement.

the utility function in (1) with respect to the project size x_i when applying for a bank loan; and after receiving the loan, he will maximize the same function with respect to effort level e_i, where the only difference is that the collateral cost, $\gamma_i \Psi_i$, will be sunk after closing.

The respective first-order condition yields

$$\begin{aligned} \frac{\partial U_i(e_i^*, x_i^*)}{\partial e_i} &= p_i'(e_i^*) \left[\alpha_j \pi_i(x_i^*) - R_i x_i^* + \Psi_i\right] - C_i'(e_i^*) = 0, \\ \frac{\partial U_i(e_i^*, x_i^*)}{\partial x_i} &= p_i(e_i^*) \left[\alpha_j \pi_i'(x_i^*) - R_i\right] = 0, \end{aligned} \tag{2}$$

if $\alpha_j \pi_i'(0) > R_i$; otherwise, the project will never be profitable through bank lending. Notice that since $\partial^2 U_i(e_i^*, x_i^*)/\partial e_i^2 < 0$, $\partial^2 U_i(e_i^*, x_i^*)/\partial x_i^2 < 0$ and $\partial^2 U_i(e_i^*, x_i^*)/\partial e_i \partial x_i = 0$, the first-order conditions in (2) are also sufficient. If $U_i(e_i, x_i)$ is strictly concave for any e_i and x_i, then the first-order conditions in (2) give a unique global maximum. In what follows, we assume that this condition is fulfilled.[12]

We also find that

$$\begin{aligned} \frac{\partial^2 U_i(e_i^*, x_i^*)}{\partial e_i \partial \Psi_i} &= p_i'(e_i^*) > 0, \frac{\partial^2 U_i(e_i^*, x_i^*)}{\partial e_i \partial \alpha_j} = p_i'(e_i^*) \pi_i(x_i^*) > 0, \\ \frac{\partial^2 U_i(e_i^*, x_i^*)}{\partial x_i \partial \Psi_i} &= 0, \frac{\partial^2 U_i(e_i^*, x_i^*)}{\partial x_i \partial \alpha_j} = p_i(e_i^*) \pi_i'(x_i^*) > 0. \end{aligned} \tag{3}$$

Expressions in (3) imply that an increase in collateral requirement, Ψ_i, incentivizes the entrepreneur to put more efforts to increase the success probability. Thus, collateral helps the bank to overcome the moral hazard problem to some extent, but it imposes an opportunity cost for the entrepreneur. Further, an increase in market potential, α_j, increases both the entrepreneur's efforts and the project size. On the other hand, it is straightforward that collateral cost, γ_i, has no effect on efforts or project size. However, this does not mean that the collateral cost plays no role here because the entrepreneur has to be able to cover the collateral cost $\gamma_i \Psi_i$ to be profitable.

[12] In the Appendix, we show that $-p''(e_i) \geq p'(e_i)^2/p(e_i)$ and $-V_i''(x_i) \geq V_i'(x_i)^2/V_i(x_i)$ are sufficient conditions for global concavity where $V_i(x_i) = \alpha_j \pi_i(x_i) - R_i x_i$ denotes the profit conditional on success. These conditions are fulfilled if the degree of concavity is larger or equal to the square root functions.

How do the size of collateral, the cost of collateral and the market potential affect the maximized payoff? Let $U_i^B(\alpha_j, \Psi_i, \gamma_i) \equiv U_i(e_i^*, x_i^*)$ denote the maximized payoff of the entrepreneur. Using the Envelope Theorem,

$$\begin{aligned} \frac{\partial U_i^B(\alpha_j, \Psi_i, \gamma_i)}{\partial \Psi_i} &= -\left[1 - p_i(e_i^*)\right] - \gamma_i < 0, \frac{\partial U_i^B(\alpha_j, \Psi_i, \gamma_i)}{\partial \gamma_i} = -\Psi_i < 0, \\ \frac{\partial U_i^B(\alpha_j, \Psi_i, \gamma_i)}{\partial \alpha_j} &= p_i(e_i^*)\pi(x_i^*) > 0. \end{aligned} \tag{4}$$

While an increase in collateral incentivizes the entrepreneur to increase efforts, it reduces his expected payoff; and the cost of putting up collateral also clearly reduces the payoff. This has an effect on the extensive margin: For those entrepreneurs with high collateral requirements and/or costs, $U_i^B(\cdot) < 0$, so the project will not be realized if only bank lending is available. Entrepreneurs facing a larger market potential, however, are more likely to seek project financing, other things being equal.

3.2 Platform

We now turn to the crowdfunding platform. As mentioned above, the platform sets the interest rate based on the information provided by the borrower, and their interest rates are most often higher than those of traditional small business loans. Further, there is no collateral requirement. For instance, LendingClub does not require any collateral on loans of $100,000 or less; and for business loans above $100,000, they only require a blanket lien on business assets and not any personal assets as collateral. On the other hand, P2P lending is a two-sided market, so there is a chance that a loan might not get funded. That is, a loan request can only stay on the platform's website for a limited time, and the loan might not attract enough funding from the investors (especially during an economic downturn).

This is the same for personal and small business loans facilitated by LendingClub. That is, even for the explicit business loans, initially ranging from $15,000 to $100,000, LendingClub decides on whether to approve the application based on its proprietary (small business) scoring algorithm, and then the approved loans are posted on its website. The only difference was that the business loan applicants were given an option to purchase the loan in a private transaction with LendingClub's partner investors. While it is unknown what fraction of business loan applicants chose private transactions, the oversized small business loans only accounted for 7% of the LendingClub loans, while personal loans accounted for 93% as of 2018.[13] Hence, we focus on the platform market which involves some uncertainty.

We formalize this by assuming that there is an exogenous probability $q_i \in (0, 1)$ that the project proposed by entrepreneur i will receive sufficient funding.[14] The expected payoff of an entrepreneur applying for crowdfunding is then given by

$$\tilde{U}_i(e_i, x_i) = q_i p_i(e_i) \left[\alpha_j \pi_i(x_i) - \tilde{R}_i x_i\right] - C_i(e_i), \tag{5}$$

where $\tilde{R}_i x_i$ denotes the combined principal and interest payment due to the platform. As mentioned above, we assume $\tilde{R}_i > R_i$. Similarly to before, there are two stages of decision-making processes for the entrepreneur. The first is the application stage in which the entrepreneur chooses the size of the desired funding, x_i, and the second is the post-financing stage in which he decides on the level of efforts, e_i, to increase the success probability that will be relevant only if the project has been successfully funded (i.e., conditional on $q_i = 1$).[15]

The respective first-order condition yields

$$\begin{aligned} \frac{\partial \tilde{U}_i(e_i^{**}, x_i^{**})}{\partial e_i} &= p_i'(e_i^{**}) \left[\alpha_j \pi_i(x_i^{**}) - \tilde{R}_i x_i^{**}\right] - C_i'(e_i^{**}) = 0, \\ \frac{\partial \tilde{U}_i(e_i^{**}, x_i^{**})}{\partial x_i} &= q_i p_i(e_i^{**}) \left[\alpha_j \pi_i'(x_i^{**}) - \tilde{R}_i\right] = 0, \end{aligned} \tag{6}$$

if $\alpha_j \pi_i'(0) > \tilde{R}_i$; otherwise, the project will never be profitable through crowdfunding. Again,

[13] Failing to achieve the scaling-up objective, LendingClub stopped offering explicit small business loans in 2019. Instead, it encourages small business owners to apply for personal loans by saying "If you are looking for start-up capital, we recommend using a personal loan for business purposes through LendingClub."

[14] Alternatively, q_i may decrease with x_i, meaning that a larger scale project have a higher risk of not attracting enough investors. However, this alternative assumption will lend even more support to our results, because the entrepreneur has an incentive to choose a smaller scale project. We thus hold q_i fixed for simplicity.

[15] Strausz (2017) analyzes reward-based crowdfunding under moral hazard ('take the money and run'), with a focus on showing how crowdfunding schemes can implement optimal allocations. One difference is that in our model, both the project budget and the entrepreneur's efforts are modelled as continuous choices.

since $\partial^2\tilde{U}_i(e_i^{**}, x_i^{**})/\partial e_i^2 < 0$, $\partial^2\tilde{U}_i(e_i^{**}, x_i^{**})/\partial x_i^2 < 0$ and $\partial^2\tilde{U}_i(e_i^{**}, x_i^{**})/\partial e_i \partial x_i = 0$, the first-order conditions in (6) are sufficient for an interior solution, which is the unique global maximum if $\tilde{U}_i(e_i, x_i)$ is concave for any e_i and x_i. As before, we assume that this condition is satisfied (see Appendix).

We also find that for the crowdlending a larger market potential implies larger efforts as well as a larger project size as

$$\frac{\partial^2\tilde{U}_i(e_i^{**}, x_i^{**})}{\partial e_i \partial \alpha_j} = p_i'(e_i^{**})\pi_i(x_i^{**}) > 0, \frac{\partial^2\tilde{U}_i(e_i^{**}, x_i^{**})}{\partial x_i \partial \alpha_j} = q_i p_i(e_i^{**})\pi_i'(x_i^{**}) > 0. \tag{7}$$

How do effort level and project size compare between bank lending and crowdlending? Comparing the interior solutions characterized by (2) and (6), respectively, we find the following result conditional on participating in the loan market.

Lemma 1. *An entrepreneur receiving a bank loan will make a larger effort ($e_i^* > e_i^{**}$) and also run a larger project ($x_i^* > x_i^{**}$) compared to those receiving crowdfunding.*

Proof. We compare the first-order conditions in (2) and (6). Since $\tilde{R}_i > R_i$, $\pi'(x_i^*) < \pi'(x_i^{**})$ due to the strict concavity of the profit function which implies $x_i^* > x_i^{**}$. By the Envelope Theorem, the maximized value of $\alpha_j\pi_i(x_i) - R_i x_i$ is decreasing in R_i. Thus, $x_i^* > x_i^{**}$ implies $\alpha_j\pi_i(x_i^*) - R_i x_i^* + \Psi_i > \alpha_j\pi_i(x_i^{**}) - \tilde{R}_i x_i^{**}$. Due to the convexity of $C_i(e_i)$, it follows that $e_i^* > e_i^{**}$. $\square$

The lemma shows that the bank's collateral requirement leads to larger efforts and thus a higher success probability. Further, due to the lower interest rate, the project size is larger with bank lending than with crowdlending. Letting $U_i^C(\alpha_j) \equiv \tilde{U}_i(e_i^{**}, x_i^{**})$ denote the maximized payoff of the entrepreneur under crowdlending, we find that an increase in the market potential increases the payoff:

$$0 < \frac{dU_i^C(\alpha_j)}{d\alpha_j} = q_i p_i(e_i^{**})\pi_i(x_i^{**}) < p_i(e_i^*)\pi(x_i^*) = \frac{\partial U_i^B(\alpha_j, \Psi_i, \gamma_i)}{\partial \alpha_j}. \tag{8}$$

However, expression (8) shows that the rate of increase is smaller than that of bank lending.

This has three reasons. First, the entrepreneur may not get sufficient funding on the platform ($q_i < 1$). Second, lower efforts imply a lower success probability. Third, a lower project size implies that an increase in market potential does not increase the payoff as much as in the case of bank lending.

3.3 Competition

So far, we have scrutinized how entrepreneurs choose the project size (i.e., loan size) and their efforts to increase the success probability under bank lending and crowdlending, respectively. If crowdfunding is not available, the first-order conditions in (2) determine the entrepreneur's choices at the intensive margin. The extensive margin (or participation) is determined by $U_i^B(\alpha_j, \Psi_i, \gamma_i) = 0$, which is a function of the market potential α_j, the collateral requirement Ψ_i and the collateral cost γ_i, such that all entrepreneurs for whom $U_i^B(\cdot) \geq 0$ will go for bank lending while others will not run the project. In what follows, we discuss what happens when a crowdlending platform enters the small business lending market. In so doing, we assume that the bank does not change its lending policy, such as interest rates, in response to the entry of a crowdfunding platform. The reason is that the competitive pressure from crowdlending does not seem to have a major impact on bank's lending policies. Traditional, large banks keep focused on making lower-risk loans, and smaller community banks are forming partnerships and alliances with crowdlending platforms rather than competing against them (Jagtiani and Lemieux, 2016).[16]

The existence (or entry) of a crowdlending platform changes the entrepreneurs' behavior because they can choose between the two types of lending based on the comparison of $U_i^B(\cdot)$ and $U_i^C(\cdot)$. If $U_i^B(\cdot) > U_i^C(\cdot)$, then the entrepreneur will go for bank lending (and crowdfunding if otherwise). This has two effects. First, projects for which $U_i^B(\cdot) \geq 0$ and $U_i^B(\cdot) < U_i^C(\cdot)$ will switch from bank lending to crowdfunding. Which projects may switch? We know that collateral cost is a fixed cost for entrepreneurs; thus, if this fixed cost is large, then entrepreneurs

[16]For instance, as also mentioned by Jagtiani and Lemieux (2016), LendingClub partnered with BancAlliance in 2015, a nationwide network of some 200 community banks, whereby the banks would direct their small business customers to LendingClub and have an opportunity to purchase loans from LendingClub.

would want to avoid the fixed cost even if they will have a smaller project size and face the risk of not receiving crowdfunding. Further, we know from (8) that a larger market potential favors bank lending over crowdlending. Hence, crowdlending becomes relatively more attractive for entrepreneurs facing a small market potential. The consequence is that the platform will receive projects where effort levels are low and thus success probabilities are small, and project sizes are smaller than bank lending. Because these entrepreneurs run the risk that crowd investors will not fund their projects, this effect will lead to an unambiguous decrease in bank and aggregate lending volume. We label this the *switching effect*.

Second, entrepreneurs for whom $U_i^B(\cdot) < 0$ due to a small market potential and/or high collateral requirement and cost are now able to get funding from the platform, unless $\tilde{R}_i > \alpha_j \pi_i'(0)$. Since the probability of funding is non-zero, this effect will increase aggregate lending volume, and we call this effect the (credit) *expansion effect*. Let us now consider all entrepreneurs $i \in \mathcal{I}_j$ where $\mathcal{I}_j \equiv \{i | \alpha_j \pi_i'(0) > \tilde{R}_i\}$ is the set of entrepreneurs located in region j facing the market potential α_j and for whom crowdlending is profitable. We can then divide this set into three disjoint subsets, $\mathcal{A}_j$, $\mathcal{B}_j$ and $\mathcal{C}_j$, whereby (i) $\mathcal{A}_j = \{i \in \mathcal{I}_j | U_i^B(\alpha_j, \Psi_i, \gamma_i) \geq U_i^C(\alpha_j)\}$ is the subset that will stay with the bank lending as their payoffs are lower with crowdlending, so the aggregate lending volume within this group will not change; (ii) $\mathcal{B}_j = \{i \in \mathcal{I}_j | U_i^C(\alpha_j) > U_i^B(\alpha_j, \Psi_i, \gamma_i) > 0\}$ is the subset that will switch from bank lending to crowdlending; and (iii) $\mathcal{C}_j = \{i \in \mathcal{I}_j | U_i^C(\alpha_j) > 0 > U_i^B(\alpha_j, \Psi_i, \gamma_i)\}$ is the subset for whom bank lending is not profitable but crowdfunding is. We can summarize the change in the aggregate lending as follows.

Proposition 1. *Crowdlending decreases the aggregate lending volume in region j if the switching effect is stronger than the expansion effect, that is, if $\sum_{i \in \mathcal{B}_j} (x_i^* - q_i x_i^{**}) > \sum_{i \in \mathcal{C}_j} q_i x_i^{**}$.*

Our analysis also allows us to predict how small business lending by banks will be affected by crowdlending across different areas:

Proposition 2. *Other things being equal, the switching effect will be stronger in areas with large collateral requirement and/or cost, and smaller in areas with large market potential.*

Proof. The first part follows from $\partial U_i^B(\alpha_j, \Psi_i, \gamma_i)/\partial \Psi_i < 0$ and $\partial U_i^B(\alpha_j, \Psi_i, \gamma_i)/\partial \gamma_i < 0$ (see

(4)), which increases the number of entrepreneurs who want to switch from bank lending to crowdlending because the latter does not have collateral requirement. The second part follows from $\partial U_i^B(\alpha_j, \Psi_i, \gamma_i)/\partial \alpha_j > dU_i^C(\alpha_j)/d\alpha_j > 0$ (see (8)); that is, a larger market potential increases payoffs for both lending regimes given any collateral requirement/cost, but more so for the bank lending. $\square$

Proposition 2 gives us some guidance as to what we might expect to find in our empirical analysis. That is, we expect to see a larger decrease in the bank small business loan volume in areas where collateral requirement and cost are higher because bank lending is more costly to the entrepreneur. In areas where market potential is high, however, the switching effect will be less strong because project sizes matter more and banks are better at funding larger projects. In terms of the total small business lending volume, the prediction is ambiguous given the general functional forms, because the expansion effect may or may not offset the switching effect. Nonetheless, the switching effect entails that the entrepreneurs take out smaller-sized loans from the platform than what they would have from banks. Hence, for most plausible distributions of entrepreneurs in the parameter space, it can be cautiously interpreted that the overall small business lending volume might decrease with the entry of crowdlending.[17]

While Proposition 1 suggests that the aggregate lending volume may go down due to the entry of crowdfunding platforms, it does not tell us whether the entry is socially desirable or not. To see this, suppose that the social cost of public funds is given by $\rho \equiv 1 + r$, where r may be proxied by the interbank borrowing rate. Since lenders are for-profit firms, $R_i > \rho$ would hold true due to a positive interest spread. To find the first-best outcome, a social planner would maximize the expected social surplus $\mathcal{S}_i = p_i(e_i)\alpha_j\pi_i(x_i) - \rho x_i - C_i(e_i)$ with respect to e_i and x_i. Collateral is not included in this expression because it only imposes an additional cost and thus does not play a role for the first best. Similarly, the planner takes into account the social cost of public funds as the true opportunity cost, but these costs arise irrespective of the sucess

[17]This is assuming that the bank will not change its interest rate in response to platform entry. If banks do lower the rate and/or collateral, then it will reduce the switching effect as well as the expansion effect; however, these effects are not likely to disappear altogether unless banks respond in some dramatic fashion.

probability. Thus, the first-order conditions are given by

$$\begin{aligned}
\frac{\partial \mathcal{S}_i(\hat{e}_i, \hat{x}_i)}{\partial e_i} &= p_i'(\hat{e}_i)\alpha_j \pi_i(\hat{x}_i) - C_i'(\hat{e}_i) = 0, \\
\frac{\partial \mathcal{S}_i(\hat{e}_i, \hat{x}_i)}{\partial x_i} &= p_i(\hat{e}_i)\alpha_j \pi_i'(\hat{x}_i) - \rho = 0,
\end{aligned} \tag{9}$$

assuming an interior optimum for $\hat{e}_i$ and $\hat{x}_i$.

Comparing (9) with (2), we see that the efforts under bank lending (with collateral requirement) are smaller than the first-best level. That is, $\Psi_i < R_i x_i^*$ implies $p_i'(e_i^*)[\Psi_i - R_i x_i^*] < 0$ and thus $e_i^* < \hat{e}_i$. However, the entrepreneur only has to make the repayment if the project succeeds while the planner has to consider the social opportunity cost both in the cases of success and failure. Since it is ambiguous how $p_i(e^*)R_i$ and ρ compare in general, we do not know whether the size of bank loans (x_i^*) is too large or too small relative to the first best ($\hat{x}_i$). If it were too small, then the entry of crowdfunding platforms would lead to more distortions in the loan size, while the overall welfare effect would still be ambiguous due to the expansion effect (especially, given the lower cost of public fund, ρ). If the loan size were too large, then the entry of crowdfunding platforms would lead to less distortions through the switching effect and an improvement in overall social welfare.

4 Dataset

Our primary data source is the Federal Financial Institutions Examination Council (FFIEC). FFIEC was given statutory responsibilities to facilitate public access to the data that certain financial institutions must disclose under the Home Mortgage Disclosure Act of 1975 (HMDA) as well as the Community Reinvestment Act of 1977 (CRA) by, among others, aggregating such data annually at the census tract level.[18] FFIEC is empowered to prescribe uniform principles, standards, and forms for the examinations of financial institutions by the Federal

[18] We do not use data from HDMA because HDMA is concerned with mortgage loans, which do not necessarily fit our theoretical framework above. Further, LendingClub has not yet expanded into the secured loan market. Given its size of personal loans, LendingClub loans are unlikely to substitute for mortgage loans.

Reserve Board of Governors (FRB), the Federal Deposit Insurance Corporation (FDIC), the Office of the Comptroller of the Currency (OCC), the National Credit Union Administration (NCUA), and the Consumer Financial Protection Bureau (CFPB).

The CRA was enacted to encourage depository institutions to meet the credit needs of the communities in which they are doing business, including those with low and moderate income. That is, reversing the 'redlining'—a practice whereby banks avoid making loans to low-income families—was the main goal. Hence, the CRA requires federal regulators to assess each bank in terms of providing loans and other services for 'CRA-qualified' community development, and use the examination result in evaluating applications for such activities as bank mergers, charters, and branch openings.[19] While the CRA regulation does not require banks to make loans or provide services in any specific manner, some critics/media argued that it was a contributing factor in the risky lending that led to the financial crisis of 2007-08.

Although the evaluation process does not specify any quota that banks have to satisfy, examiners consider the level of the institution's lending activity in the different assessment areas, such as *low- and moderate-income* (LMI) areas, *distressed middle-income* areas designated by the regulators based on poverty rate, unemployment and population loss, and *underserved middle-income* areas based population size, density and dispersion.[20] While the bank's investments and services count (if they relate to community development), lending activity is typically most important. For instance, distribution of home mortgage loans across the income spectrum matters. However, the distribution of small business loans are most often scrutinized in terms of loan sizes and annual revenues of the business as well as the income category of the geography.

To be precise, small business loans are loans that are $1 million or less and secured by nonfarm nonresidential properties (i.e., commercial real estate loans) or commercial and industrial loans which may be secured by anything other than real estate, or unsecured. We use the Aggregate

[19]FRB regulates state chartered member banks; OCC regulates banks with a national charter; and FDIC regulates non-FRB member banks. Credit unions backed by NCUA are exempt from the CRA. Note that the Office of Thrift Supervision was merged with OCC, FDIC, and CFPB by the Dodd-Frank Act.

[20]Specifically, if the median family income is less than 50 percent of the Metropolitan Statistical Areas (MSA/MD) median income, then the census tract's income level is low; if it is at least 50 percent and less than 80 percent, then it is moderate; and if it is at least 80 percent and less than 120 percent, then it is middle.

Flat Files to extract the small business loan originations and the associated data at the census tract level for calendar years 2009 to 2017. These represent all of the CRA report data, but only 'large institutions' are required to collect CRA loan data. A large institution is defined by an asset threshold of \$1.109 billion in 2009 (and \$1.226 billion in 2017), and the regulators say "CRA reporters account for about 71 percent of small business loans outstanding (by dollars) at bank and thrift institutions" (FDIC, 2017). Hence, the CRA data may not capture small banks' loans.[21]

Table 1 shows the list of US states that prohibited borrowing from LendingClub and Prosper, respectively. These were extracted from LendingClub's and Prosper's annual reports (10-K) and cross-checked with actual LendingClub and Prosper loan data (available on the respective website). In a few cases, we found discrepancies in which there is little to no loan record in a state while the proxy statement no longer lists the state as being an ineligible state. Our assumption here is that the state permission came too late into the year, so the platform did not enter the market in that year.[22] As one can see, the number of initially held-up states is larger for LendingClub than for Prosper. Further, while the state permissions for LendingClub borrowing exhibit staggered entries, there is a much less useful variation for Prosper borrowing.

For Prosper, three states (Iowa, Maine, North Dakota) persistently prohibited borrowing throughout the sample period. Although Pennsylvania disallowed Prosper borrowing from 2015 to 2016 and West Virginia did so in 2017, these status changes are swept by the fact that LendingClub borrowing was available in Pennsylvania and West Virginia through the period. This would only leave the variation among Iowa, Maine, and North Dakota to exploit if we were to code that borrowing was enabled by either platform. However, focusing on a small number of states would increase the risk of our results being confounded and it also ignores the fact that LendingClub's market share was at least four times as large as Prosper's during the sample

[21]We do not examine the effect on small farm loans, because farming is only applicable to a limited scope of areas. Further, "CRA reporters account for about 29 percent of small farm loans outstanding (by dollars) at bank and thrift institutions" (FDIC, 2017), so the data coverage does not seem to be adequate.

[22]Specifically, in the case of LendingClub, we changed the status for Tennessee in 2012, Mississippi in 2013, and Idaho in 2015 as being ineligible because there was little to no loan record. Similarly, in the case of Prosper, we changed the status for Pennsylvania in 2014 and 2016 and West Virginia in 2016.

period. Thus, our strategy here is to ignore Prosper entry and focus on LendingClub entry to properly identify the entry effect on bank loans.

Table 2 describes our panel dataset, where the unit of observation is a census tract in a calendar year. The first variable at the top is an indicator for whether residents in a state could borrow from LendingClub. For those states listed in Table 1, the indicator is 0 until LendingClub borrowing was permitted, and 1 thereafter. For all other states, it is always 1. Because the majority of states allowed borrowing on LendingClub following its SEC registration in 2008, only a small number of states initially held up their residents from borrowing on LendingClub. Although they represent a relatively small fraction (at most one fifth) of all the US states, it is preferable to make use of all the US states in our regression analysis because they are the sample universe. Our main results are robust, though, if we only used the subset of states that initially held up LendingClub borrowing.

The next two lines in Table 2 show the two primary continuous control variables. Tract median family income is the estimated MSA/MD median family income (adjusted annually by FFIEC), multiplied by the tract median family income as a percentage (carried to two decimal places) of the MSA/MD median family income in which the tract is located. Tract house price index is the annual index provided by the Federal Housing Finance Agency, which tracts average price changes in repeat sales or refinancings on the same properties. As mentioned above, there is a significant exposure to the housing market by small businesses, so housing market can serve as a proxy for collateral value. For all types of loans, we expect that income and collateral would significantly correlate with the lending activities.

Table 2 then shows the indicators for the geographies in which bank lending would be well received by the bank regulators: Namely, an indicator for the low- and moderate-income tracts (i.e., median family income less than 80 percent of MSA/MD level); three indicators for distressed middle-income tracts; and an indicator for underserved middle-income tracts. These are relatively small fractions of all tracts, except for the low- and moderate-income tracts which comprise about 28 percent. Note that the regulators review these designations and update annually, so they can be in principle time-varying; however, they tend to be stable over time, so in our analysis we examine how the low-income and distressed and underserved tracts were differentially affected by LendingClub from the other tracts within state.

Finally, Table 2 shows the total average number and volume of the loans originated by CRA-reporting banks to the small businesses located in the tract. Although small business loans are defined by the SBA as loans of $1 million or less, regardless of annual revenue, the CRA data additionally show the subset of loans made to businesses with less than $1 million in gross revenues. A large fraction of loans is in fact under $100,000, where as much as 90 percent of these loans are secured by collateral according to the SBA reports. On average, less than the majority of these loans are made to businesses with less than $1 million sales, which implies that there is also a large number of businesses with greater than $1 million sales that seek loans under $100,000. Hence, the smallest loan category is relevant for larger businesses as well.

5 Empirical Evidence

Section 3's analysis yields a couple of testable implications. Specifically, Proposition 1 tells us that only if the switching effect is strong enough, the aggregate loan volume would shrink. That is, only if the displacement of traditional loans by the entry of crowdlending is small enough (or nonexistent), will crowdlending increase the overall credit market by allowing previously discouraged or excluded borrowers to access credit. We thus provide empirical evidence on the effect of the LendingClub entry on the CRA-reported small business loan volumes. In particular, since most of LendingClub borrowings were loans less than $100,000 (in which case collateral was not required at all), we expect that the switching effect would be most significant (if at all) in the smallest loan size category (i.e., less than $100,000).

Proposition 2 adds that the switching effect would be stronger in the areas where either collateral requirement/cost is large or market potential is small. Such areas may correspond to the CRA-designated areas, namely, low- and moderate-income areas and middle-income areas that are either distressed or underserved. It seems to be reasonable to expect that in such areas traditional lenders would perceive of higher risks associated with small business loans due to the lower income or credit score, etc, and thus require more collateral from the borrowers. Given the economic disadvantage, borrowers may find it more costly to post collateral, too. Further, the business's profit may be also smaller in those areas for the same reason. Hence, we may expect to find the heterogeneous effect of the platform entry across CRA designations.

Our empirical strategy is to take the LendingClub entry (i.e., borrowing eligibility) across states as a quasi-natural experiment. As alluded to earlier, the exact reason why some state regulators held up LendingClub are not known to the researchers. There is anecdotal evidence by those who have talked with some state regulators, suggesting frauds and other procedural difficulties as the reason for the state's hold-up (e.g., Renton, 2011); however, most of these discussions pertain to the investor's side, so any comment on the regulator's concerns over the borrower's side is scarce to find. One possibility might be that LendingClub would not want to operate in a state that does not allow them to "export" the interest rate permitted in the state of business, regardless of the limitations imposed by the usury laws of the borrower's state of residence.

However, LendingClub can still operate in such states that have opted out of federal interest rate authority, as long as they have the state's license and the loans made therein conform to the maximum interest rate limit set by the state usury laws. Further, there are states that did not allow LendingClub borrowing, even though the state has not opted out of federal preemption. Thus, the state regulator's decision to not allow LendingClub borrowing does not seem to be driven by the state's opt out decision. On the other hand, we have not come across any other discussion such as that the banking sector lobbied the state regulators to delay LendingClub entry by promising to lend more to small businesses, so we think that the state's hold-up as well as the timing of state resolution (hence entry) is reasonably exogenous.

Nonetheless, it is prudent to compare the trends of loan volume between the states that did and did not hold up the entry. Figure 1 shows the average (tract level) loan volume for the two groups of states. The solid line represents the total volume of small business loans (i.e., less than \$1 million), and the dashed line shows that of loans extended to businesses with less than \$1 million in annual revenues. In both cases, the pattern of the average loan volumes does not differ significantly across the two groups. That is, although it is difficult to make an ‘apple to apple’ comparison of the trends because the timing of the entry varies and each state’s lending volume differs as well, the figure does not suggest a strong reason to suspect that the common trend assumption is misguided. Rather, the average trends seem to move surprisingly in tandem.

We thus employ a difference-in-differences style estimation which compares the small business loan volumes before LendingClub entry to those after the entry across the two groups of states. The baseline specification is as follows:

$$Loan_{it} = \alpha LC_{it} + X'_{it}\beta + s_i + \tau_t + \varepsilon_{it},$$

where $Loan_{it}$ is either the number or the volume of loans in tract i and year t, LC_{it} is 1 if residents in tract i were eligible to borrow from LendingClub; 0 otherwise. The control variables in X_{it} include the log of median family income, the log of house price index, and a series of CRA-designated area flags introduced above. Tract fixed effects, s_i, absorb unobserved heterogeneities; and year fixed effects, τ_t, absorb common shocks that vary over time. As is standard, we cluster the error term, ε_{it}, at the tract level to account for autocorrelation within tract over time.

Table 3 shows the estimation results. Column (1) indicates that on average the entry of LendingClub reduced the number of small business loans of size less than \$100,000 by around 6.5, and column (2) shows that in terms of loan volume, this amounts to a reduction of \$127,000 credit originated by banks. Hence, the evidence suggests that the small business loans offered by traditional banks (especially those with assets above \$1 billion) contracted in the smallest loan size category (i.e., less than \$100,000) that are most sought after by the small businesses. Interestingly, the effects of LendingClub entry are all insignificant in the larger loan size categories as shown by the results in columns (3) to (6). Given the fact that LendingClub did not originate much of loans in these size categories, the evidence renders support for the switching effect.

We next examine the effect of LendingClub entry on the subset of bank loans made to businesses with less than \$1 million in gross revenues. Although the loans that are less than \$1 million are likely to be made to small businesses, the three loan-size categories do not pertain to the size of the businesses themselves. Here, in columns (7) and (8), the complementary result is that, regardless of the loan size, the number of loans made to businesses with less than $1 million in revenues decreased by similar magnitudes; that is, a reduction of 6.4 loans, which amounts to a reduction of $107,000 in terms of loan volume. Given that there are about 74,000 tracts in the 2010 Census, the magnitudes of these effects imply that a potentially large number of businesses switched away from banks to crowdlending platforms, and the overall credit market would likely have shrunk.

In particular, a back-of-the-envelope calculation suggests that the total reduction in loan volume in the smallest loan size category could be $127,000 times, say, 40,000 economically viable tracts, which is about $5 billion per year. Since LendingClub and other crowdlending platforms have operated since 2009 or so, the cumulative effects up to 2019 could be (very roughly) a reduction of small business loans of about $55 billion. On the other hand, LendingClub has generated a total of $56 billion by the end of 2019. Note that it is unlikely that all of LendingClub loans were used for business purposes. Hence, the total amount of loans facilitated by LendingClub (and other smaller platforms) may not have compensated for the loss of small business loans originated by traditional banks. At a minimum, our results show that the switching effect may be as important or even more important as the expansion effect.

At the same time, the coefficient estimates on the CRA-designated areas suggest that banks are not significantly more likely to lend to businesses located in low- or moderate-income (LMI) tracts, as their coefficients are not significant in columns (1) to (6) at the conventional level. In fact, column (7) indicates that banks are less likely to make loans to small businesses located in these areas, holding other factors constant. This is because, even though CRA examination results are potentially important for the banks, they are not in any way obliged to make loans to anyone. Since small business loans in low-income areas are generally of greater risk, the banks can be too reluctant to lend.

The other coefficient estimates suggest that banks are in fact more likely to lend to businesses in distressed middle-income tracts due to high unemployment or population loss for the smallest loan size category or for those with less than $1 million in revenues. At the same time, however, banks are less likely to lend in distressed middle-income tracts where the reason for the designation is persistent poverty. This implies that banks may give some special considerations to businesses located in areas with high unemployment or population loss, but they are still reluctant to lend to businesses when it comes to low income or higher poverty even in the middle-income tracts.

Hence, it would be of some policy interest to inquire whether the LendingClub entry differentially affected CRA-designated areas and other more affluent areas. We examine this issue by using a triple differencing strategy, which employs a within-state comparison across tracts that experience the same state-specific trends to net out the differences in loans. The results are presented in Table 4. The coefficients of interest are those on the interactions between LendingClub entry and the CRA-designation flags. Here, we find that the LendingClub entry caused a further reduction of bank loans in the smallest loan size category for businesses located in distressed middle-income tracts (due to poverty rate) and underserved (remote/rural) middle-income tracts. We also find that the entry negatively affected loans made to low- or moderate-income tracts in the middle size category (between $100,000 and $250,000). These findings are consistent with our theoretical prediction.

Similarly, column (7) shows that the LendingClub entry caused a further reduction in the number of loans made to businesses less than $1 million in revenues in low- and moderate-income tracts as well as all distressed and underserved middle-income tracts except for the reason due to population loss. On the other hand, column (8) suggests that in terms of the loan volume, the LendingClub entry caused a further reduction of loans only in the low- and moderate-income tracts, but it did not significantly affect the volume in the CRA-designated middle-income tracts. These findings suggest that the switching effect is stronger for these loans in the economically vulnerable (low-income) areas. The fact that the number of loans decreased while the volume of loans were not significantly affected in the distressed or underserved middle-income tracts implies an increase in the bank loan concentration to a smaller number of (presumably safer) businesses located in the CRA-qualified areas.

6 Conclusion

We studied the likely impact of crowdlending entry into the traditional small business loan market in a theoretical framework as well as in an empirical context. Theoretically, the entry of crowdlending platforms can induce some entrepreneurs to switch from traditional loans while encourage those who were previously excluded from the credit market to access credit, so the overall effect is ambiguous and it boils down to the relative size of the switching and expansion effects. However, our model suggests that in the case of switching from traditional banks to crowdlending, the entrepreneur-borrower would choose a lower level of effort as well as a small project (loan) size. Hence, unless the expansion effect is sufficiently large, there may be a peril of shrinking the total volume of credit offered to small business owners.

Indeed, in our analysis of CRA-reported small business loans, we found plausible evidence that the LendingClub entry is causally associated with a statistically and economically significant decrease in the number and volume of small business loans originated by traditional (large) banks. We also found some evidence suggesting that this reduction in traditional loans following the LendingClub entry is larger in low-income areas as well as middle-income areas distressed with persistent poverty. The contraction of traditional loan market is likely to be an unintended consequence for the securities regulators as far as the small business lending post the 2008 financial crisis is viewed as being suboptimal. While crowdlending platforms have tended to emphasize the expansion effect, our study shows that we need to consider the switching effect.

To be clear, crowdlending platforms have the potential to fill the credit gap for small businesses, especially during a recession or even in a pandemic. They are more flexible in terms of lending criteria and much faster than traditional or government-guaranteed loans. Further, some small businesses are clearly unable to access traditional credit market because of a lack of collateral, or a high collateral cost. As our social welfare analysis shows, it is also possible that the entry of crowdlending may bring the market outcome closer to the social optimum, when the traditional loan size would have been too large from the efficiency standpoint. Given that the debate on this subject in the literature has only just begun, our theory model and empirical analysis could offer some guidance about the effects of crowdlending.

Appendix

Let $V_i(x_i) = \alpha_j \pi_i(x_i) - R_i x_i$ denote the profit conditional on project success. The second derivatives of $U_i(e_i, x_i)$ are then given by

$$\begin{aligned}
\frac{\partial^2 U_i(e_i,x_i)}{\partial e_i^2} &= p_i''(e_i)\left[V_i(x_i)+\Psi_i\right] - C_i''(e_i) < 0,\\
\frac{\partial^2 U_i(e_i,x_i)}{\partial x_i^2} &= p_i(e_i)V_i''(x_i) < 0,\\
\frac{\partial^2 U_i(e_i,x_i)}{\partial e_i \partial x_i} &= p_i'(e_i)V_i'(x_i).
\end{aligned}$$

Thus, global concavity is given if the Hessian determinant is positive, that is, if

$$\det(H) = \frac{\partial^2 U_i(e_i,x_i)}{\partial e_i^2}\frac{\partial^2 U_i(e_i,x_i)}{\partial x_i^2} - \left[\frac{\partial^2 U_i(e_i,x_i)}{\partial e_i \partial x_i}\right]^2 > 0.$$

Due to $\Psi_i > 0$ and $C_i''(e_i) > 0$, we observe that

$$\frac{\partial^2 U_i(e_i,x_i)}{\partial e_i^2} < p_i''(e_i)V_i(x_i),$$

implying

$$\det(H) > p_i''(e_i)V_i(x_i)p_i(e_i)V_i''(x_i) - \left[p_i'(e_i)V_i'(x_i)\right]^2.$$

Thus, a sufficient condition for concavity is

$$p_i(e_i)V_i(x_i)p_i''V_i''(x_i) \geq \left[p_i'(e_i)V_i'(x_i)\right]^2,$$

and this condition is fulfilled if $-p_i''(e_i) \geq p_i'(e_i)^2/p_i(e_i)$ and $-V_i''(x_i) \geq V_i'(x_i)^2/V_i(x_i)$. Note that $f(y) = A\sqrt{y}$ implies $-f''(y) = f'(y)^2/f(y)$, and thus if the degree of concavity for $p_i(e_i)$ and $V_i(x_i)$ is not less than for the respective square root function, $U_i(e_i, x_i)$ is globally concave.

For crowdlending, replace $V_i(x_i)$ by $\tilde{V}_i(x_i) = \alpha_j \pi_i(x_i) - \tilde{R}_i x_i$. We then also observe that

$$\frac{\partial^2 \tilde{U}_i(e_i, x_i)}{\partial e_i^2} < p_i''(e_i)\tilde{V}_i(x_i),$$

due to $C_i''(e_i) > 0$, and consequently it leads to similar sufficient conditions.

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Table 1: Borrowing Prohibited States

Year	No LendingClub borrowing	No Prosper borrowing
2009	Idaho, Indiana, Iowa, Kansas, Maine, Mississippi Nebraska, North Carolina, North Dakota, Tennessee	Iowa, Maine, North Dakota
2010	Idaho, Indiana, Iowa, Maine, Mississippi, Nebraska North Dakota, Tennessee	Iowa, Maine, North Dakota
2011	Idaho, Indiana, Iowa, Maine, Mississippi, Nebraska North Dakota, Tennessee	Iowa, Maine, North Dakota
2012	Idaho, Indiana, Iowa, Maine, Mississippi, Nebraska North Dakota, Tennessee	Iowa, Maine, North Dakota
2013	Idaho, Iowa, Maine, Mississippi, Nebraska North Dakota	Iowa, Maine, North Dakota
2014	Idaho, Iowa, Maine, Nebraska, North Dakota	Iowa, Maine, North Dakota
2015	Idaho, Iowa	Iowa, Maine, North Dakota Pennsylvania
2016	Iowa	Iowa, Maine, North Dakota Pennsylvania
2017	Iowa	Iowa, Maine, North Dakota West Virginia

These are the state-years in which the residents were not eligible to borrow from LendingClub and Prosper, respectively, based on their (10-K) proxy statements cross-checked with the platform's loan data disclosures.

Table 2: Summary Statistics

Variable	Mean	Std. dev.	N
LendingClub borrowing available	.946327	.225372	646148
Tract median family income (MFI)	67.7211	32.3403	642277
Tract house price index (HPI)	223.553	130.537	427261
Low- or moderate-income tract (LMI)	.283785	.450834	646148
Distressed middle-income tract (due to Poverty)	.029874	.170240	646148
Distressed middle-income tract (due to Unemployment)	.009968	.099343	646148
Distressed middle-income tract (due to Population loss)	.009032	.094607	646148
Underserved middle-income tract (due to Remote rural)	.019913	.139703	646148
Number of small business loans (Loan size $\leq$ \$100,000)	68.2590	78.2914	625298
Volume of small business loans (Loan size $\leq$ \$100,000)	959.663	1295.78	625298
Number of small business loans (>\$100,000 & $\leq$ \$250,000)	2.58253	4.68195	625298
Volume of small business loans (>\$100,000 & $\leq$ \$250,000)	453.218	823.590	625298
Number of small business loans (>\$250,000 & $\leq$ \$1,000,000)	2.73199	5.35378	625298
Volume of small business loans (>\$250,000 & $\leq$ \$1,000,000)	1478.27	3017.33	625298
Number of small business loans (Ann. revenue $\leq$ \$1,000,000)	34.0637	38.1024	625298
Volume of small business loans (Ann. revenue $\leq$ \$1,000,000)	1055.30	1443.70	625298

The data source except for LendingClub borrowing and HPI is FFIEC from 2009 to 2017, which aggregates CRA-reported small business loan data at the census tract level by year. The volume of small business loan originations in all size categories and the median family income are in thousand dollars. LendingClub borrowing eligibility is based on the company's proxy statements; and HPI is from the Federal Housing Finance Agency. All data can be time-varying at the tract level, although CRA designations (i.e., low/modrate-income and distressed or underserved middle-income tracts) are relatively stable over time.

Table 3: Average Effect on Small Business Loans

	Loan Size≤$100K		$100K<Loan Size≤$250K		$250K<Loan Size≤$1M		Loan to Firm Rev.<$1M	
	(1) No.	(2) Amt.	(3) No.	(4) Amt.	(5) No.	(6) Amt.	(7) No.	(8) Amt.
LC available	-6.49	-127	-.043	-6.54	-.019	-6.36	-6.38	-107
	(.245)***	(5.36)***	(.032)	(5.57)	(.030)	(16.9)	(.178)***	(11.1)***
LMI	.239	.081	.038	5.09	-.002	-2.31	-.538	2.39
	(.292)	(4.75)	(.022)*	(3.83)	(.023)	(13.1)	(.211)**	(7.26)
Poverty	-.490	-11.6	.072	10.4	.064	31.0	-1.03	-7.80
	(.283)*	(5.64)**	(.040)*	(6.67)	(.034)*	(18.5)*	(.223)***	(12.8)
Unemployment	1.33	18.2	.035	5.81	-.059	-35.8	1.59	-5.33
	(.383)***	(7.47)**	(.045)	(7.94)	(.040)	(21.3)*	(.307)***	(15.6)
Pop. loss	5.08	83.4	.024	1.58	.067	53.8	6.34	98.2
	(.689)***	(15.6)***	(.089)	(15.3)	(.070)	(39.1)	(.563)***	(29.7)***
Remote rural	.477	8.30	-.065	-10.5	-.017	9.89	.918	-.290
	(.730)	(16.5)	(.085)	(14.4)	(.072)	(38.8)	(.612)	(34.0)
Log(MFI)	-.115	57.1	.185	35.0	.200	118	1.17	100
	(.643)	(10.9)***	(.049)***	(8.56)***	(.048)***	(27.3)***	(.468)**	(16.7)***
Log(HPI)	27.6	361	.699	124	.977	539	21.8	514
	(.576)***	(10.1)***	(.041)***	(7.11)***	(.041)***	(23.4)***	(.423)***	(13.7)***
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	427242	427242	427242	427242	427242	427242	427242	427242

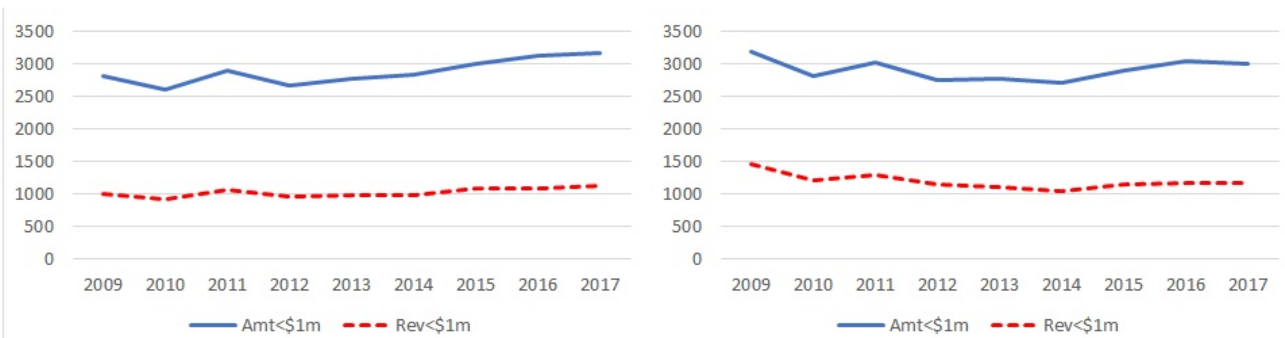
In odd-numbered columns, the dependent variable is the number of loans in each size category; and in even-numbered columns, the dependent variable is the volume of loans (in thousand dollars) in each size category. LC available is 1 if residents in a state in a year were allowed to borrow from LendingClub, and 0 otherwise. LMI is an indicator for low- and moderate-income tracts, and similarly for the distressed (Poverty, Unemployment, Population loss) and underserved (Remote rural) tracts. Coefficient estimates with tract fixed effects and year dummies are presented, together with standard errors clustered at the tract level in parentheses. Statistical significance is denoted as *** 1%, ** 5%, * 10%.

Table 4: Heterogeneous Effect on Small Business Loans

	Loan Size≤\$100K		\$100K<Loan Size≤\$250K		\$250K<Loan Size≤\$1M		Loan to Firm Rev.<\$1M	
	(1) No.	(2) Amt.	(3) No.	(4) Amt.	(5) No.	(6) Amt.	(7) No.	(8) Amt.
LC available	-6.31	-119	-.012	-1.58	-.006	5.23	-5.93	-93.4
	(.273)***	(5.95)***	(.035)	(6.15)	(.033)	(18.5)	(.195)***	(12.0)***
LC × LMI	.777	-15.8	-.152	-24.9	-.066	-56.8	-.952	-68.6
	(.453)*	(9.73)	(.067)**	(11.6)**	(.066)	(36.4)	(.331)***	(24.5)***
LMI	-.505	15.1	.182	28.7	.060	51.6	.361	67.6
	(.474)	(10.0)	(.067)***	(11.6)**	(.066)	(36.5)	(.347)	(24.4)***
LC × Poverty	-4.65	-96.9	-.157	-26.6	.041	2.64	-4.50	-53.5
	(.948)***	(21.0)***	(.132)	(22.1)	(.102)	(53.3)	(.839)***	(42.4)
Poverty	3.80	77.9	.217	35.1	.026	28.8	3.13	41.6
	(.940)***	(20.5)***	(.132)	(22.0)	(.102)	(53.0)	(.831)***	(41.7)
LC × Unemp	-.469	-28.7	-.163	-30.5	-.094	-46.3	-3.94	-23.5
	(1.23)	(22.8)	(.158)	(27.2)	(.125)	(67.9)	(.926)***	(54.9)
Unemployment	1.78	45.1	.185	33.8	.025	5.79	5.20	16.3
	(1.13)	(21.0)**	(.151)	(26.0)	(.120)	(64.9)	(.844)***	(52.7)
LC × Pop loss	.530	-10.6	.077	23.3	.054	7.35	-.321	53.6
	(1.52)	(34.6)	(.186)	(31.5)	(.143)	(78.4)	(1.13)	(59.5)
Population loss	4.53	89.9	-.036	-16.5	.023	46.1	6.49	55.4
	(1.49)***	(34.8)***	(.177)	(29.7)	(.132)	(72.3)	(1.10)***	(57.0)
LC × Remote	-4.37	-45.9	-.019	-.994	-.164	-112	-2.59	-75.7
	(1.12)***	(25.9)*	(.143)	(24.5)	(.137)	(75.8)	(1.06)**	(66.2)
Remote rural	4.25	47.4	-.049	-9.60	.126	107	3.13	65.5
	(1.20)***	(29.0)	(.159)	(27.4)	(.150)	(83.4)	(1.13)***	(71.0)
Log(MFI)	-.056	57.2	.181	34.4	.198	116	1.18	98.5
	(.642)	(10.9)***	(.049)***	(8.56)***	(.048)***	(27.3)***	(.468)**	(16.7)***
Log(HPI)	27.6	361	.699	124	.977	539	21.8	514
	(.575)***	(10.1)***	(.041)***	(7.11)***	(.041)***	(23.4)***	(.423)***	(13.7)***
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	427242	427242	427242	427242	427242	427242	427242	427242

In odd-numbered columns, the dependent variable is the number of loans in each size category; and in even-numbered columns, the dependent variable is the volume of loans (in thousand dollars) in each size category. LC available is 1 if residents in a state in a year were allowed to borrow from LendingClub, and 0 otherwise. LMI is an indicator for low- and moderate-income tracts, and similarly for the distressed (Poverty, Unemployment, Population loss) and underserved (Remote rural) tracts. Coefficient estimates with tract fixed effects and year dummies are presented, together with standard errors clustered at the tract level in parentheses. Statistical significance is denoted as *** 1%, ** 5%, * 10%.

Figure 1: Mean Tract Loan Volume



On the left is the tract average small business loan volume (in thousand dollars) for the control states that permitted LendingClub borrowing since the SEC registration; and on the right is the same figure for the treatment states that initially held up LendingClub borrowing as shown by Table 1. Solid line includes all CRA-reported small business loans (i.e., loan amount less than $1 million), and the dashed line represents the subset of the loans made to businesses with less than $1 million in gross annual revenues.