COVID-19 Bust, Policy Response, and Rebound: P2P vs. Banks

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Abstract

Traditional intermediaries have the ability and the incentive to intertemporarily smooth outcomes. Fintechs, such as P2P platforms, enable riskier borrowers without regard to intertemporal smoothing. U.S. data from January 2019 to June 2020 show that COVID-19 had an adverse impact on P2P lending. However, P2P is much more stable, timely, and resilient in a crisis compared to bank consumer lending. Moreover, the data indicate that P2P lending is a leading indicator for bank consumer lending. Worth noting, the policy response – (CARES) Act – caused a substantial rebound to bank consumer lending and, at best, neutralized an already-stabilized level of P2P lending.

Keywords: P2P Lending, Fintech, COVID-19, Bank Consumer Lending

JEL Codes: G21, G28, G51

Crises disrupt lending markets (Andersen, Bollerslev, Diebold, & Vega, 2007; Cull & Martínez Pería, 2013; Puri, Rocholl, & Steffen, 2011); however, it is well established that larger banks fare much better in crisis periods (Berger & Bouwman, 2013). Indeed, banks are able to smooth sources of capital and the uses of capital. Relationship banking brings out incentives to intertemporally smooth loans (Berger & Udel, 2002; Boot & Thakor, 2012). Banks build up capital in favorable periods and smooth out down periods by extending lines of credit to mitigate negative swings (Petersen & Rajan, 1995). The smoothing of capital over time is even encouraged by virtue of bank regulatory restrictions through reserve requirements and risk-taking constraints (de Roure, Pelizzon, & Thakor, 2019). By contrast, fintech startups have grown in recent years to take advantage of market segments that are underserved by traditional intermediaries. Peer-to-peer (P2P) lending platforms are one such example, as they enable lenders to directly link to borrowers through an online platform with no regards to intertemporal smoothing. P2P loans are typically smaller and riskier and have higher interest rates than loans normally available from traditional intermediaries with stronger requirements for collateral and other restrictions (de Roure, Pelizzon, & Thakor, 2019).

In this paper, we examine two interrelated questions that build on prior work but have not been directly examined in prior work. First, we examine the relationship between aggregate P2P lending and consumer bank loans as well as the comparative impact of COVID-19 on both lending channels. Prior work has not compared fintech to non-fintech intermediaries in a crisis period, and, more generally, which intermediary is a leading versus a lagged indicator. Second, we proceed to investigate the impact of COVID-19 on individual loan applications using P2P loan data since it provides rich data not available otherwise (Butler, Cornaggia, & Gurun, 2017). Specifically, we examine the impact of the COVID-19 crisis on the probability of credit allocation, funds raised relative to funds sought, and time-to-funding success and failure. We also highlight how the COVID-19's effects differ given the loan applicant's profile. We consider the impact of COVID-19, in general; the specific number of COVID-19 cases in the loan applicant's county; and the role of the U.S. Coronavirus Aid, Relief, and Economic Security (CARES) Act policy response in mitigating the negative impact of COVID-19 on the economy.

Our paper builds on the expectation that banks with sophisticated managers anticipate in advance the negative impact of COVID-19 and, as a result, decrease loan amounts prior to the crisis to better smooth loans intertemporally. And, moreover, we expect that smaller, riskier P2P loans would be much more sensitive to an economic shock, like the one caused by the COVID-19 crisis. The U.S. data that we examined for the period January 1st, 2015 to June 30th, 2020 shows the exact opposite. The data indicate that P2P lending dropped much earlier than consumer bank loans and NASDAQ. Specifically, COVID-19 caused P2P loans to drop a full two months earlier relative to bank consumer lending and one month earlier relative to NASDAQ. Furthermore, contrary to the expectations, the (normalized) declines in bank lending and NASDAQ were twice as large as that of P2P lending. Overall, the data show P2P fintech lending was only half as susceptible to the COVID-19 crisis compared to both bank consumer lending and NASDAQ.

Turning to individual loan applications, we note that COVID-19 has had a massive impact on P2P lending. The U.S. data, examined here from January 1st, 2019 to June 30th, 2020, show that COVID-19 lowered the probability of P2P funding success by 9.5%, reduced funding percentages obtained by 40%, decreased the likelihood of funding success by 21% with the passage of time, and increased the likelihood of funding failure by 810% with the passage of time. Moreover, our findings suggest that borrowers from states with higher levels of COVID-19 infections were more severely affected. Although COVID-19 caused an overall negative shock to credit allocation on P2P lending platforms, this adverse effect was amplified for riskier borrowers, while less risky borrowers who have built relationships on the platform through prior borrowing activity were less able to capitalize on their reputation. The data indicate that the policy response – the Coronavirus Aid, Relief, and Economic Security (CARES) Act – caused a substantial rebound to bank consumer lending and NASDAQ. But the CARES Act did little or nothing to stabilize P2P lending. P2P lending had already stabilized prior to the CARES act. At most, the CARES Act merely stabilized an already-stabilized level of P2P lending. Overall, we may infer that the CARES Act benefited banks and corporations (which, in turn, indirectly benefitted investors and borrowers from traditional intermediaries), but the CARES Act had little direct benefit to borrowers and lenders themselves if they did not use a traditional bank intermediary.

A possible explanation for our finding that the magnitude of the negative swing in P2P is less than that of bank consumer lending could be attributed to credit rationing in traditional credit markets (Tedeschi et al. 2012). Indeed, it is well documented that credit rationing increases in economic downturns and this specially affects riskier and smaller borrowers who are often not able to get credit from traditional intermediaries. Thus, these consumers would, in turn, switch to P2P lending resulting in a less pronounced drop in P2P loan levels. This explanation is in line with Tang's (2019) study, which states that although P2P loan markets generally complement bank consumer lending, they could serve as a substitute for borrowers with no access to traditional financing. All this highlights the relevant role of P2P markets in mitigating the adverse effects of economic shocks. However, this new lending model is severely prone to adverse selection problems. Loan default rates on P2P lending platforms are higher than that of conventional credit markets where collateral is required (Freedman & Jin, 2014). In an attempt to alleviate these issues, platforms have been relying on increasing prescreening intensity (Vallée & Zeng 2019) as well as adapting their mechanisms. For instance, Du et al. (2019) found that text message reminders that convey lenders' positive expectations regarding repayment increase substantially the likelihood of borrowers timely repayment. In general, developments in P2P lending platforms mechanisms are required to ensure its smooth functioning and existence as a reliable lending channel.

Our paper contributes to two main strands in the literature. First, it contributes to current work on the impact of COVID-19 on capital markets (Ari, Chen, and Ratnovski, 2021; Borri and Giorgio, 2021; Hasan, Politsidis, and Sharma, 2021; Li, Strahan, and Zhang, 2020; Nozawa and Qiu, 2021). Our paper shows a negative impact of the COVID-19 crisis on bank consumer loans and the importance of the CARES Act in alleviating this stress. However, comparing bank consumer lending to the fintech P2P sector, we show that the impact of COVID-19 on the fintech P2P sector has been in complete contrast to the bank consumer loan market. Second, this paper contributes to the literature on the relationship between P2P and bank consumer lending markets (Balyuk, Berger, & Hackney, 2020; Butler et al., 2017; Tang, 2019). Our findings highlight the complementarity amongst these two lending channels, at the aggregate level, during normal periods. However, it suggests a substitution effect during periods of crisis which is driven by credit rationing in traditional lending mediums (Tedeschi et al. 2012). This substitute role that P2P lending channels play during the crisis aid in dampening the adverse effects of the crisis.

This paper is organized as follows. Section 1 discusses the institutional context of the P2P market. Section 2 provides macro-level insight into the activity of P2P and bank consumer lending markets and highlights graphically and empirically the relationship between P2P and bank consumer lending markets. Section 3 describes the data and methods used to investigate the effects of COVID-19 at the loan application level. The results are presented in Section 4. Section 5 summarizes our findings, discusses the limitations and extensions for further work, and offers concluding remarks.

1. Institutional Context of P2P Lending

Peer-to-peer (P2P) lending has arisen as a mechanism that efficiently brings together lenders and borrowers. It has experienced dramatic growth across the world since its inception. In the United States, Prosper.com (hereinafter Prosper) was the first established online P2P lending platform. It was launched by the end of 2005 and opened to the general public on February 5th, 2006 (Herzenstein, Sonenshein, and Dholakia, 2011; Lin, Prabhala, and Viswanathan, 2013; Balyuk, 2016). As with all forms of two-sided markets, to ensure success, platforms should be able to attract both sides of the market (Rochet and Tirole, 2003). Indeed, Prosper was able to quickly gain traction and attract a large number of investors and borrowers, making it one of the leading P2P lending platforms in the United States (Balyuk, 2016).

Usually, P2P deals imply that lenders and loan applicants have no previous relationship. Investment decisions are, thus, almost exclusively based on the applicant's profile and the loan characteristics (Larrimore et al., 2011). Therefore, to engage in any transaction, Prosper's applicants and investors go through a verification process. This process entails the validation of the individual's identity, social security number, and bank account information. In addition, more personal information is requested from loan applicants (income level, employment status, length of employment, and occupation), and a comprehensive credit report is extracted through credit reporting agencies, such as Experian and Transunion (Herzenstein et al., 2008; Herzenstein et al., 2011; Michels, 2012; Lin et al., 2013). With this information, Prosper screens out loan applicants with credit scores below 640 and assigns a credit grade to the remaining applicants. The credit grades range from AA (extremely low risk) to HR (highest risk of default), with A, B, C, D, and E falling between (Herzenstein et al., 2008; Herzenstein et al., 2011; Lin et al., 2013).

Prosper's borrowing and lending process has been subject to changes over time. In regards to the credit allocation process, it was initially based on an auction-mechanism. In this business model, borrowers made an online listing that stated the requested loan amount (maximum of $25,000), its purpose, the duration of the auction (3-10 days), and the maximum interest rate they were willing to pay (from 5% to 35%). The loan request was accompanied by the applicant's location, credit grade, and other employment and traditional financial information. In this auction-type model, once the listing became active, investors could bid through Prosper's website on loans, stating the amount they were willing to fund and the minimum interest rate they were willing to receive (Iyer et al, 2009; Herzenstein et al., 2011; Lin et al., 2013). All listings were fixed-interest, fully amortizing 3-year unsecured loans. They could be funded through two types of auctions: *closed* auctions, which ended at the borrower's asking rate once the amount bid reached the amount requested; and *open* auctions, which remained open for a fixed time length, allowing investors to bid down the loan's interest rate, even when the bid amount and the asking rate were already met (Lin et al., 2013). Therefore, in the *closed* auction format, the ongoing interest rate was the borrower's asking rate, even if the minimum rate investors were willing to accept was lower. When the total amount of money bid by lenders met or exceeded the requested amount, the auction closed, and the listing became a loan. However, in the *open* format, the auction remained open until the specified auction duration had elapsed. The loan was then priced at the lowest market-clearing interest rate among all investors who were outbid (Herzenstein et al., 2008; Michels, 2012; Lin, et al., 2013). In this auction-based model, Prosper did not allow the partial funding of loans. Therefore, if a loan was not completely funded, the request failed, and the loan was not originated.

In December 20th, 2010, Prosper's credit allocation process was changed from an auction mechanism to a posted-price mechanism with a preset rate. Prosper's proprietary algorithm would evaluate the loan applicant's risk profile and assign a risk grade and a corresponding interest rate. Given the preset interest rate, loan grade, and the other financial and non-financial information, potential investors would evaluate the investment opportunity and make their investment decision. This investment decision would involve deciding whether or not to invest and how much to invest. Contrary, to the auction-model that required full funding, the preset rate model came with the possibility of partial funding (70% of the loan amount). By opting for the partial funding, if the loan applicant failed to secure 70% of their requested loan amount during the updated listing period of 14 days, the listing would expire with no credit being allocated to the applicant. Loan applicants opting for partial funding accounted for 93.21% of all loan listings for the period commencing in January1st, 2015 up to June 30th, 2020. Regardless of the credit allocation mechanism in place, auction-type or posted-price, the P2P loan did not originate if the listing failed to fund in time. If the loan were fully funded, Prosper would conduct a further verification of the documents as part of its screening endeavors to decide whether the loan originated. If the verification failed due to inaccurate information or the applicant did not provide the required documents, the listing was cancelled by the platform and the loan did not originate. Today, this posted-price mechanism is still in effect with Prosper offering fixed-interest, fully amortizing 3- and 5-year loans repaid monthly (Balyuk, 2016; Wei, and Lin, 2017).

The credit allocation mechanism was not the only change implemented by Prosper over the years; the information shared with potential investors also had its fair share of changes. Initially, only the debt to income ratio (DTI) computed by Prosper and the credit grade was supplied to potential investors as ‘hard’ information, while loan applicants were permitted to include some ‘soft’ information. This soft information included information which was not verified by the website, such as pictures and free-format textual descriptions which usually included the purpose of the loan, explanations for low credit scores, and interest rates currently paid on other loans (Lin et al., 2013; Larrimore et al., 2011; Michels, 2012; Freedman, and Jin, 2014). Later, information on whether the borrower owns a verified bank account and a home was included. More detailed hard information about credit lines and utilization, credit inquiries, delinquencies, and public records started being reported in May, 2006. Some months later, information about employment, occupation, and income was included (Freedman, and Jin, 2008). After the switch to a posted-price mechanism, Prosper stopped collecting the soft information previously provided by loan applicants. This made investors rely predominantly on hard information. All the information pertaining to the loan request was anonymously presented to potential investors (Michels, 2012).

In a nutshell, Prosper, as a lending platform, plays two major roles. First, it serves as a matching marketplace, where loan applicants and investors are matched. Second, Prosper maintains the loan and is responsible for managing the monthly loan repayments. In return for the matching process, Prosper charges loan applicants a loan origination fee of 5%, which is deducted upfront from the loan amount. This fee might be reduced to 2.4%, if the loan applicant has excellent credit. While maintaining the loan, Prosper charges investors an annual service fee of 1%. If payments are late for two or more months, Prosper pursues collection efforts through a collection agency. Furthermore, the platform reports delinquencies to credit reporting agencies. Defaulted borrowers are not allowed to borrow again on Prosper, while borrowers who have successfully paid back previous loans are rewarded with an improved credit grades, even if there was no improvement in their FICO credit score (Herzenstein, 2008; Michels, 2012; Lin et al., 2013).

We expect that the COVID-19 crisis would have a significant impact on the P2P market, just as it would for consumer bank lending and the stock market. What is less clear is the timing of the drops, the lead-lag relationship between these markets, and the comparative magnitude of the impact of COVID-19. We examine those data below.

2. Macro-level Insights: The Relationship between P2P and Bank Consumer Lending

Recently, growing numbers of institutional investors tap P2P lending platforms for the opportunity to diversify their portfolios by investing in an asset class not available to them before (Cummins, Mac an Bhaird, Rosati, and Lynn, 2020). Surprisingly, commercial banks that are able to extend credit through their own channels jumped on the bandwagon and started investing alongside other institutional (non-bank financial institutions, asset management firms) and retail investors. The benefit that P2P lending platforms brought to these commercial banks is the ability to syndicate consumer loans and diversify risk exposure. As institutional investors joined P2P lending platforms, the liquidity available on these platforms increased tremendously. This helped P2P lending platforms evolve into a significant source of liquidity in consumer lending markets. But, it is still unclear how P2P and bank consumer loan markets relate, are they complements or substitutes?

Butler, Cornaggia, and Gurun (2017) investigate the relationship between local banking conditions and P2P lending markets, and find that borrowers in areas with good access to financing request loans for lower interest rates on P2P lending platforms. Their findings suggest a substitution effect in the demand for funds. However, on the supply side of funds, lenders on P2P lending platforms do not factor local capital markets condition in their decision to extend credit to loan applicants. Tang (2019) further analyzes this relationship and highlights that P2P loan markets substitute bank lending for smaller loan applications while complement bank lending for larger loan applications. However, at the aggregate level it is still not clear how these two lending markets relate. In general, we expect that P2P loan markets would complement bank consumer loan markets in regular periods. However, during periods of crisis, such as COVID-19, there is a greater likelihood that marginal borrowers substitute bank loans for P2P loans. Given the disproportionate impact of larger loans at the aggregate level, we expect the effect of COVID-19 to be similar for both lending channels; however, due to different mechanisms the timing and the magnitude of the effects could vary.

There are at least four reasons from the prior literature as to why we expect the P2P market to respond to an economic shock quicker than consumer bank loans. First, banks build up capital over time in good periods, and they extend better lines of credit in bad periods. That is, banks have the ability to create intertemporal surpluses and smooth down periods. While increased credit market competition imposes constraints on the ability of borrowers and lenders to do this intemporal substitution, it is nevertheless still feasible (Petersen and Rajan, 1995). Second, de Roure, Pelizzon, and Thakor (2019) explain that banks have exogenously higher regulatory costs, while P2P lending can grow (or shrink) without the comparative regulatory burden. Regulatory oversight facilitates a smoother level of loans over time, due to bank reserve requirements and constraints on risk taking. Third, de Roure, Pelizzon, and Thakor (2019) also show that P2P loans are riskier and have higher risk-adjusted interest rates compared to bank loans. P2P platforms serve smaller, riskier borrowers who are underserved consumers (Beck, 2020). As such, there are higher adverse selection costs with P2P loans, and these expected costs are more pronounced in large negative market swings with more desperate borrowers using the P2P market in times of crisis. Fourth, Boot and Thakor (2012) explain that relationship banking facilitates an intertemporal smoothing of bank loans and even contract terms (Allen and Gale, 1995, 1997). Banks can absorb losses in one period and recoup those losses later on and in ways that mitigate information asymmetries and adverse selection costs through the banks' capacity to learn more about their borrowers over time (Petersen and Rajan, 1995).

Taken together, these smoothing considerations all point to the expectation that markets will swing more quickly in P2P markets than in traditional bank consumer lending markets. Moreover, the riskiness of P2P loans leads us to expect that the magnitude of swings will be more pronounced in the P2P lending market than the bank loan market.

2.1 Macro-level Data: P2P and Bank Consumer Lending

To investigate the association between P2P and bank consumer lending, we collect contemporaneous data on P2P loan market activity and bank consumer lending. Given that bank consumer lending data is reported weekly by FRED, we aggregate key P2P loan data weekly. The key variables of interest to us to gauge P2P loan market performance using Prosper loan-level data are *Credit Allocation*, *Prosper Loans*, *Funding Percent*, and *Campaign Duration. Credit Allocation* is the weekly percentage of loans approved on Prosper. *Prosper loans* is the total weekly amount allocated by investors to loans on the platform. *Funding Percent* is the weekly average funding rate of loans. *Campaign Duration* is the weekly average time it took for loan applicants to raise their requested funds. Turning to bank consumer lending, we capture consumer lending activity using *Net Consumer Loans*. *Net Consumer Loans* is the difference between current weekly outstanding consumer loans and previous week's outstanding consumer loans as reported by FRED. We also collect data on weekly *NASDAQ Returns* to use as an indicator of capital market condition. The weekly data collected covers the period January 1st, 2019 up to June 30th, 2020.

To gauge the general effect of COVID-19 on the variables of interest mentioned above, we conduct a two-tailed t-test means comparisons to see if there are significant differences pre- and post-COVID-19. We also test for significant differences in the volatility of each variable; for example, *Credit allocation SD* in Table 1 refers to the standard deviation of the % of loan applications approved on Prosper. The results are presented in Table 1.

[Table 1 About Here]

The data indicate that, relative to their pre COVID-19 values, post COVID-19 Credit Allocation on Prosper fell by 13.07%, Credit Allocation SD increased by 1397.67%, Prosper Loans dollar amounts fell by 57.93%, Prosper Loans SD fell by 38.37%, Funding Percent fell by 4.60%, Funding Percent SD increased by 80.91%, Campaign Duration increased by 163.79%, Campaign Duration SD increased by 346.13%, Net Consumer Loans fell by 278.96%, Net Consumer Loans SD increased by 264.40%, NASDAQ Returns fell by 29.51%, and NASDAQ Returns SD increased by 154.07%. Each of these differences is significant at the 1% level, with the exception of Prosper Loans (dollar amounts) SD and NASDAQ Returns, which are statistically insignificant. Although the direction of change in the means due to COVID-19 is the same, we note that the percentage drop in Net Consumer Loans dollar amounts was over 4.8 times that of Prosper Loans dollar amounts. Thus, the data, surprisingly, indicate a somewhat different pattern than what we predicted.

A possible explanation for our findings can be extended from the arguments made by Butler et al. (2017) and Tang (2019). Although P2P loan markets generally complement bank consumer lending at times when borrowers have access to credit from banks, it could have served as a substitute during the crisis when borrowers were not able to get credit from banks. Hence, the drop in the P2P loans is not as pronounced as that of bank consumer lending since consumers who would have normally sought bank loans switch to P2P markets. Thus, the fintech innovation of P2P mitigated the adverse effects of the crisis.

2.2 Macro-level Graphical Analysis: P2P and Bank Consumer Lending

A time series of P2P loan data, consumer bank loans, and the NASDAQ index are depicted graphically in Figures 1 and 2. Figure 1 shows the normalized levels of P2P loans versus bank consumer loans. The data indicate that the P2P loan market in the U.S. dropped starting on December 25, 2019 and fell continuously to January 29, 2020, with the initial Christmas break drop being less pronounced than the subsequent drop in January. We may infer that this drop is related to international news about COVID-19, at least in the absence of another compelling explanation. Thereafter, as COVID-19 was more widely recognized in the U.S., there was an increase in P2P loans, followed by a modest decline. By contrast, consumer bank loans peaked on March 4, 2020 and fell until April 15, 2020, just after the introduction of the CARES Act a few days before. Normalized P2P levels went from 0.3 to -2 in January, while normalized consumer bank loans went from 1.8 to -3.9, or approximately 2.5 times the size of the drop of the normalized P2P amounts. Over the contemporaneous period, when normalized bank loans dropped, P2P loans dropped by 1/5th. In short, the data are consistent with the view that there was a marked delay in the decline in the consumer bank loans market by 2-3 months relative to P2P loans, as expected. But counter to expectations, there was a much more pronounced decline in consumer bank loans relative to P2P loans. Finally, note that the CARES Act caused a strong rebound in the consumer bank loan market; but, in striking contrast, after the CARES Act, the subsequent performance of the P2P levels was slightly negative.

[Figures 1 and 2 About Here]

Figure 2 presents the same type of information as in Figure 1, except consumer bank loans are substituted for the NASDAQ index. The data indicate that NASDAQ responded about a month faster than consumer bank loans in response to the COVID-19 crisis, but still much later than P2P loans.

2.3 Macro-level Empirical Analysis: P2P and Bank Consumer Lending

Building on the data presented in Figures 1 and 2, Tables 2-5 present data and tests that address the question of whether Prosper loans are indeed a lead indicator of consumer loans as depicted in Figure 1. We examine weekly Propser loan amounts, consumer loans, as well as weekly NASDAQ returns, over the years 2015 to 2020. In Table 2, we use a vector auto regression model (VAR). The data indicate that lags of Prosper loans are significantly associated with net consumer loans. However, lagged consumer loans are not associated with Prosper loans. We further validate these inferences in Table 3 using a Granger causality test. The data indicate a unidirectional effect from lagged Prosper loans to consumer loans. The absence of an effect of consumer loans on Prosper loans is corroborated by prior findings that lenders on P2P platforms do not factor banking conditions in their decision to extend credit to borrowers (Butler et al., 2017).

[Tables 2 – 5 About Here]

In Tables 4 and 5, we ran robust OLS regressions with Net Consumer Loans (LHS), Lagged Prosper Loans, and NASDAQ Returns (RHS). The different columns report different time periods. As we drop the earlier years, we can see that the models' explanatory power improves. This suggests that Prosper loans became more prominent over time and evolved as a lead indicator for consumer loans in the banking sector. In the last two columns of Tables

4 and 5, we split the data into two timeframes (2015-2018, 2019-2020). We find that in the former, Prosper loans were not a significant indicator of bank consumer lending. However, in the latter, they are significant. This evidence further supports the notion that Prosper loans have evolved to be a lead indicator of consumer loan activity.

Summing our graphical depictions and empirical analyses, we indicate that P2P loans evolved as a lead indicator for bank consumer lending starting in 2019. COVID-19 significantly affected P2P markets to a very large degree. The impact of COVID-19 on bank consumer lending was significantly delayed and more pronounced. The benefits of the U.S. policy response to COVID-19 – the CARES Act – are seen in the bank consumer lending market, not the P2P market. P2P lending, while serving risker and smaller borrowers, turns out to be much more stable, timely, and resilient in a crisis than bank consumer lending. To investigate the effect of COVID-19 on individual loan applications we turn to P2P loan application data for several reasons. First, P2P platforms provide rich unparalleled data at the individual loan application level, such individual loan application data cannot be accessed from banks (Butler et al., 2017; Lin, Prabhala, & Viswanathan, 2013). Second, peer lenders' financing decision is similar to that of sophisticated investors (Iyer, Khwaja, Luttmer, & Shue, 2016). Hence, inferences regarding credit allocation in a crisis can be drawn from our analysis. Third, given our findings that P2P loan markets serve as a lead indicator for bank consumer lending, the effects found can be used to anticipate shifts in bank consumer lending activity. In the next section we proceed with presenting the data and methodology that will be used in the micro-level analysis of P2P loan applications.

3. COVID-19 and Credit Allocation: Data and Methodology

3.1 Dataset

The data used in our analysis cover all individual loan applications on Prosper from January 1st, 2019, up to June 30th, 2020. In total, this includes 229,226 loan listings, out of which 221,178 were approved by investors. We gather loan applicants' credit profile information, income and employment data, loan characteristics and listings' outcomes from Prosper.com. Since our focus, in this study, is to see how the COVID-19 pandemic has affected investor behavior in P2P lending markets, we merge this data with daily COVID-19 infections at the state-level for the loan applicant. This daily state infection-rate data are retrieved from the webpage of the Centers for Disease Control and Prevention (retrieved from CDC.gov). To control for market conditions, our dataset is merged with NASDAQ returns (retrieved from NASDAQ.com) and weekly consumer loan balances for all U.S. banks' balance sheets (retrieved from FRED.stlouisfed.org).

3.2 Measures

3.2.1 Dependent Variable

For our analysis, we are interested in looking at whether credit is allocated to loan applicants. The dependent variable *Credit Allocation* is a dummy variable which captures funding success. It takes the value of 1, if the loan applicant is allocated credit by Prosper's investors, and 0 otherwise. As detailed in Section 2, when Prosper switched from an auction-type model to a preset rate mechanism in 2010, it started allowing the partial funding of loans. If the applicant opted for partial funding, Prosper allows for the origination of loans if investors' commitments fund at least 70% of the requested amount. Therefore, for loan applications opting for partial funding, *Credit Allocation* takes the value of 1, if the amount funded surpasses the 70% threshold.

3.2.2 Independent Variables

The first independent variable in our analysis is *COVID-19*. This dummy variable captures the outbreak of COVID-19 in the United States. As the first COVID-19 case in the U.S. was detected on January 20th, 2020, this variable takes the value of 1 for the period January 20th, 2020 – June 30th, 2020. The second independent variable *Daily state COVID-19 infections* is a continuous variable that tracks the number of COVID-19 infections in the applicant's state on the day of the loan application. The third independent variable is the *CARES Act*. The Coronavirus Aid, Relief, and Economic Security (CARES) Act is an over-$2 trillion economic relief package pursued at protecting citizens from COVID-19 impacts on their health and the economy. It was "passed by Congress with overwhelming bipartisan support and signed into law by President Trump on March, 27th, 2020" (U.S. Department of the Treasury, 2020). The *CARES Act* is, therefore, a dummy variable, which takes the value 1 for the period March 28th, 2020 – June 30th, 2020.

3.2.3 Interaction Variables

For our analysis, we are interested in knowing how the pandemic affected the allocation of credit by investors on P2P lending platforms given the loan applicant's risk profile. To do that, our independent variables are interacted with three variables that gauge the loan applicant's risk profile. These variables are: *Interest Rate*, *Employment History,* and *Repeat Borrower*.

Interest Rate is a continuous variable which measures loan risk. As explained in Section 2, the interest rate is automatically allocated to the loan applicant by Prosper's proprietary algorithm, which assigns a risk measure to the borrower. Listings from higher (lower) risk applicants are assigned higher (lower) rates. Prior research shows that borrowers with lower interest rates are more likely to receive funding (Serrano-Cinca, Gutiérrez-Nieto, and López-Palacios, 2015). Similar conclusions can be drawn from the studies of Ryan, Reuk, and Wang (2007) and Zhang et al. (2017). *Employment History* is a continuous variable which captures the number of years that the applicant has accumulated. It is a measure of human capital. The specific effect of this variable on credit allocation has not been investigated; however, Serrano-Cinca, et al. (2015) fail to reject the null hypothesis that there is no difference in employment length between defaulted and non-defaulted loans. This suggests that this could play a role in investors' decisions to fund a specific loan request. Since borrowers who defaulted on previous Prosper loans are not allowed to request a subsequent loan, being a repeat borrower on the platform is a signal of quality. We operationalize *Repeat Borrower* as a dummy variable, which takes the value 1 if the loan applicant has previously acquired a loan through Prosper, and 0 otherwise. Indeed, Ryan et al. (2007) show that a higher number of recent listings increases the probability of getting funded.

3.2.4 Control Variables

We acknowledge that the investors' decisions to allocate credit to a specific loan could be affected by multiple other factors. Hence, we control for a battery of variables that relate to three different dimensions: i) loan characteristics, ii) loan applicant's profile, and iii) market conditions. As for loan characteristics, similar to prior research, we control for the *Loan Amount Requested*, which is a continuous variable measuring the loan amount in dollars (Ryan et al., 2007; Herzenstein et al., 2008; Puro et al., 2010) and the *Listing Term,* which takes the value of 0, if the loan term is 36-month, and 1, if it is a 60-month loan. Additionally, we control for the loan purpose by using *Loan Purpose Category Dummies* (Serrano-Cinca et al., 2015). On Prosper there are 20 different loan purpose categories (e.g., debt consolidation, home improvement, business and personal loan, etc.). Moreover, given that loans can either be whole or fractional, we control for this using *Investment Type Dummies*. Moving to the loan applicant's profile, we start by controlling for the applicant's annual income using *Income Range* (Serrano-Cinca et al., 2015). This is a categorical variable that captures the loan applicant's annual income category. We also control for the applicant's employment status. *Employment status* is a categorical variable that takes the value of 1 for full-time employment, 2 for self-employment, and 3 for other. Finally, we control for whether the loan applicant is also an active investor on the platform. *Active lender* is a dummy variable, which takes the value of 1, if the loan applicant is an active lender on the platform, and 0 otherwise. To control for market conditions, we use two proxies: The *NASDAQ Return*, which is a continuous variable that measures the NASDAQ daily percentage return, and *Consumer Loans*, which is a continuous variable that captures the sum of consumer loans on U.S. banks' balance sheets. Due to the skewedness of our control variables and the zero and negative values encountered, we transform all the variables using the inverse hyperbolic sine transformation. The inverse hyperbolic sine transformation has the same interpretation as that of the natural log transformation (Burbidge, Magee, and Robb, 1988; Sauerwald, Lin, and Peng, 2016). A variable description list is presented in Table 6.

[Table 6 About Here]

3.3 Descriptive Statistics

Table 7 exhibits the descriptive statistics (number of observations, mean, standard deviation, and minimum and maximum values) of the variables considered in the model. We also calculate Pearson's correlation coefficients between variables, which are exhibited in Table 8. The highest correlation with the dependent variable, *Credit Allocation*, is found for *COVID-19* (ρ = -0.260), followed by *Daily State COVID-19 Infections* (ρ = -0.243) and

CARES Act (ρ = -0.227). The high correlation between the independent variables: *COVID-19* and *CARES Act* (ρ = 0.623), *Daily State COVID-19 Infections* and *COVID-19* (ρ = 0.740), and *Daily State COVID-19 Infections* and *CARES Act* (ρ = 0.870) is non alarming, since these independent variables will be used in separate estimation models. The remaining correlation coefficients are not high; we note that the greatest linear relationship between the control variables is between *Loan Amount Requested* and *Listing Term* (0.248). Hence, multicollinearity issues are not a concern.

[Tables 7 and 8 About Here]

Figure 3 graphically shows the success in P2P loan applications. P2P loan success did not drop off significantly until COVID-19 was widely recognized in the U.S.

[Figure 3 About Here]

3.4 Estimation Methods

In the first stage, to investigate the effect of COVID-19 on the crowdlending market, we apply a probit regression model to the whole sample of loan requests (229,226 observations). In this model, *Credit Allocation* is regressed on the independent variable *COVID-19*, and its interaction with *Interest Rate*, *Employment History,* and *Repeat Borrower* (interaction variables). For a given loan *i* referred to time *t,* if *x* is a vector of information about loan characteristics, the loan applicant's profile, and market conditions, we estimate:

$$Pr(Credit\ allocation_{it}|x_{it}) =$$

$$\Phi\begin{pmatrix} \alpha + \beta_1 COVID19_t + \beta_2 COVID19_t \times \\ Interaction\ Variable_i + \beta_5 Loan\ Controls_i + \beta_6 Market\ Controls_t \end{pmatrix} \quad (1)$$

where Φ denotes the standard cumulative normal distribution, and j can take the values of 1, for the interaction variable *Interest Rate*; 2, for *Employment History*; or 3, for *Repeat Borrower*. *Loan Controls* includes the control variables related to the loan characteristics and the loan applicant's profile. *Market Controls* comprises the control variables related to market conditions (*NASDAQ Return* and *Consumer Loans*).

In both the second and third stage of our analysis, to properly tackle our research question and avoid differences in loan characteristics between periods, we use a matched sample. Matching allows "controlling for the confounding influence of pretreatment control variables in observational data" (Iacus, King, and Porro, 2011). Its main objective is reducing imbalance between treated and control groups by pruning some of the observations. As a result, the empirical distributions of the covariates (*X*) of the treatment and control groups are more alike. The most widely used matching techniques belong to the ''equal percent bias reducing'' (EPBR) class, which does not guarantee imbalance reduction. To avoid this limitation, this study uses Coarsened Exact Matching (CEM). This technique decreases the imbalance in covariates between treated and control groups by eliminating multivariate nonlinearities, interactions, moments, quantiles, co-moments, and other distributional differences beyond the specified level of coarsening (which is selected by the user). It is also faster and simpler to understand than previous matching methods and does not require any assumptions about the data generating procedure (Blackwell et al., 2009; Iacus, King, and Porro, 2011).

With regard to the process implied by CEM, this technique involves first applying exact matching to temporarily coarsened data. Then, uncoarsened values of the matched sample are retained, and the coarsened data are removed. More specifically, after coarsening data, a set of strata, say $s \in S$, is created. Each stratum s has the same coarsened value of X.

Those units in strata with at least one treated and control unit are retained, and the remaining are pruned. CEM assigns the following weights to each matched unit *i* in stratum *s* (Blackwell et al., 2009; Iacus, King, and Porro, 2011):

$$w_i = \begin{cases} 1, & i \in T^s \\ \dfrac{m_c}{m_t}\dfrac{m_T^s}{m_C^s}, & i \in C^s \end{cases},$$

where T^s and C^s denote, respectively, the treated and control units in stratum *s* and m_T^s, and m_C^s is the number of treated and control units in the stratum. The number of matched units are $m_T = \cup_{s \in S} m_T^s$ for treated and $m_C = \cup_{s \in S} m_C^s$ for controls. A weight $w_i = 0$ is given to the unmatched units. In our sample, the matching is made across different loan and applicant characteristics (loan amount, loan term, loan rating, loan category, applicant's FICO range, applicant's annual income range, applicant's employment history, and whether the applicant was a repeat borrower).

In the second stage of our analysis, we look into whether investors on P2P lending platforms are more reluctant to invest in loans requested by borrowers from states with higher daily COVID-19 infection rates. Using CEM to match loan applications from states with an outbreak of COVID-19 infection to similar loan applications prior to the COVID-19 outbreak, we have a matched sample of 58,891 loan applications (29,448 loan requests during COVID-19 matched to 29,443 loan applications prior to COVID-19). Given the binary nature of our dependent variable, we apply a probit regression model using the matched sample, where *Credit Allocation* is regressed on the independent variable *Daily State COVID-19 Infections*, and its interaction with *Interest Rate*, *Employment History,* and *Repeat Borrower.* Therefore, our probit specification can be expressed as follows:

$$\Pr\left(Credit\ Allocation_{it} | x_{it}\right) =$$

$$\Phi\begin{pmatrix}\alpha + \beta_1 Daily\ State\ COVID19\ Infections_t + \beta_2 Daily\ State\ COVID19\ Infections_t\ \times \\ Interaction\ Variable_i + \beta_5 Loan\ Controls_i + \beta_6 Market\ Controls_t\end{pmatrix} \quad (2)$$

In the third stage of our analysis, we look at the effect of the CARES Act on investors' willingness to invest in loans requested on crowdlending markets. Using CEM to match loans after the introduction of the CARES Act with loan applications during the COVID-19 outbreak but prior to the CARES Act (loan applications between March 28th, 2020 – June 30th, 2020 were matched with applications between January 20th, 2020 – March 27th, 2020), we have a matched sample of 27,913 observations (13,951 loan applications prior to the CARES Act and 13,962 loan applications after the CARES Act). We run separate probit regressions for each group, applying the same model described in Equation (3), where we label loan requests prior to the CARES Act as "Prior" and loan requests after the CARES Act as "Post." As in the second stage of our analysis, *Credit Allocation* is regressed on the independent variable *Daily State COVID-19 Infections*, and its interaction with *Interest Rate*, *Employment History*, and *Repeat Borrower.* For all three stages of our analysis, we control for different loan applicant profiles, loan characteristics, and market conditions.

4. COVID-19 and Credit Allocation: Results

In the following subsections we present the results for the three stages of our analysis. In the first stage, we present the general effects of COVID-19 on individual loan applications and how these effects differ given the loan applicant's profile. In the second stage, we check whether borrowers from states with higher infection rates were more susceptible to the adverse effects of COVID-19. In the third stage, we investigate the effect of the CARES Act on credit allocation decisions.

4.1 The effect of COVID-19 on credit allocation in P2P markets

Our base model specifications for the determinants of fully funded loans are shown in Table 9. In Model 1 of Table 9, we present the control variables, which account for market conditions, loan characteristics, and the loan applicant's profile. These control variables are extended to Models 2-5. Across the models, many of the control variables are significant in ways that we would expect, which is consistent with the prior literature on the determinants of credit allocation in P2P loan markets. For example, repeat borrowers are approximately 1.6% to 2.4% more likely to be fully funded at any time, regardless of COVID-19. Relative to being a full-time employee, being self-employed reduces the likelihood of full funding by 1.8% to 2.0%. A 60-month loan is 0.2% less likely to be fully funded relative to a 36-month loan. An additional 10 years in employment history increases the probability of full funding by 1.4% to 2.3%.

Turning to the effects of COVID-19 on the probability of credit being allocated to the loan applicant, the data indicate that the COVID-19 shock reduced funding probability by 4% in the most conservative estimate (Model 2) and by 9.6% in the least conservative estimate (Model 3). In Models 3-5, we investigate how the adverse effects of COVID-19 are different given the loan applicant's risk profile. The results show that the negative effects of COVID-19 were more pronounced for higher risk loans which are associated with higher interest rates (Model 3), but they were less severe for repeat borrowers on the P2P lending platform (Model 5). Employment history had no impact on mitigating or exacerbating the adverse effects of COVID-19 (Model 4). Thus, in general, during COVID-19 lenders were more reluctant to extend credit to riskier borrowers. While capital was channeled towards safer borrowers who had an established borrowing history on the platform.

[Table 9 About Here]

Table 10 complements the findings shown in Table 9 by presenting regression estimates with different model specifications. In Models 1 and 2, given that credit is allocated to a high percentage of loan applications, a rare events logistic regression model is estimated. As for Models 3-8, alternative dependent variables for credit allocation are used. Namely, funding percent obtained (Models 3 and 4), time-to-funding failure (Models 5 and 6), and time-to-funding success (Models 7 and 8). In Model 2, the marginal effect of COVID-19 is very similar to that reported in Table 5 at an 8.6% reduction in the probability of credit being allocated by the crowd. Model 4 shows that the percentage of funding obtained decreases by 0.70% due to COVID-19. From Model 6 we compute COVID-19's hazard ratio, which is 8.14[4], meaning that loans are 8 times more likely to fail as time passes. From Model 8 we find that COVID-19's hazard ratio is 0.7921, meaning that during COVID-19, loan requests are 20.78% (*1-0.7922*) less likely to succeed as time passes. All these results further support the initial finding that COVID-19 has caused a negative shock to the P2P lending market.

[Table 10 About Here]

4.2 The effect of higher COVID-19 infection rates on borrowers from these states

Having validated the adverse effects of COVID-19 on credit being allocated, we proceed to see whether investors on P2P lending platforms factor daily COVID-19 infections in their decision to extend credit to loan applicants. The goal is to identify whether loan applicants from states with higher infection rates are at a larger disadvantage relative to applicants from states with lower infection rates. We repeat the analysis conducted in Table 9 using the CEM sample of loans pre- and post-COVID-19; we also measure COVID-19 not

[4] In Cox, proportional hazard models, the Hazard Ratio = exp(coefficient), $e^{2.0969} = 8.1413$

by a binary variable but, instead, by the number of daily infections per loan applicant's state. The results are presented in Table 11.

[Table 11 About Here]

The data indicate that although all borrowers are at a disadvantage as a result of COVID-19, a 10% increase in infections in the applicant's state reduces the probability of credit allocation by 0.1380% to 0.140%. In Models 3-5, we investigate how the adverse effects of daily infections in the loan applicant's state were moderated by the loan's risk profile. Similar to the results presented in Table 9, the results show that the negative effects of daily COVID-19 infections were more pronounced for loans with higher interest rates (Model 3). However, the advantage of having a less risky loan profile, due to having more years of employment history or being a repeat borrower, was weakened for applicants from states with higher daily infection rates. Hence, our findings suggest that lenders are more likely to allocate credit to applicants from states with lower infection rates.

4.3 The effect of the CARES Act on credit allocation in P2P markets

To investigate the policy implications of the CARES Act on the ability to secure credit through P2P loan markets, we compare the effect of daily COVID-19 infection rates pre- and post-CARES Act. The estimation is run on a CEM sample of loan applications where all observations included are after the COVID-19 outbreak in the United States. The results are presented in Table 12.

[Table 12 About Here]

The data indicate that prior to the CARES Act, an increase in the daily infection rates in the loan applicant's state reduced the probability that investors extended credit to the loan applicant. This concurs the findings presented earlier in Table 11. When looking at the two samples, pre- and post- CARES Act, we note that although the P2P loan market suffered a negative shock in general during COVID-19, the CARES Act did not cause a rebound to credit allocation rates on P2P lending platforms. However, all else being equal, the daily COVID-19 cases did not reduce the loan applicant's probability of securing funding in the post-CARES Act period. This suggests that, at best, the CARES Act neutralized an already stabilized level of P2P lending.

5. Conclusions

This paper examined the impact of COVID-19 on consumer lending markets. We compared the impact of the COVID-19 crisis on consumer banking loans and P2P loans, which is a fintech solution that connects borrowers and lenders through an online platform and without the involvement of a traditional banking financial institution. We highlighted the relationship between these two lending channels. Additionally, we investigated the effect of COVID-19 on credit allocation in P2P markets.

We first showed that COVID-19 affected consumer bank loans in a differential way. Intermediated bank loans are smoothed over time relative to P2P loans; hence, consumer bank loans reacted much later to COVID-19 relative to P2P loans. Even though P2P loans serve marginal, riskier borrowers, the data show that P2P loans dropped in total dollar value 2 months prior to the drop in consumer bank loans in response to COVID-19. The differences in the normalized dollar value of consumer bank loans versus P2P loans is enormous: consumer bank loans fell off at least twice as much relative to P2P loans.

Second, we showed exactly the extent to which impact of COVID-19 on P2P loans was pronounced. The U.S. data examined show that COVID-19 lowered the probability of P2P complete funding success by 9.5%. In terms of funding percentages obtained relative to those sought, COVID-19 reduced funding percentages obtained by 40%. Duration models show that COVID-19 caused a decreased likelihood of funding success by 21% with the passage of time. Furthermore, COVID-19 increased the likelihood of funding failure by 810% with the passage of time.

Third, we highlight that the policy response – the Coronavirus Aid, Relief, and Economic Security (CARES) Act – caused a substantial rebound to bank consumer lending and NASDAQ. Surprisingly, the CARES Act had an insignificant impact on P2P lending. The CARES Act, therefore, appears to have benefited those who use financial institutions more than marginal borrowers who seek financing through P2P fintechs.

The data here suggest many ideas for future research and policy implications. Are P2P loans as stable in other countries, or have there been differential reactions across countries? Do financial institutions in other countries lag P2P market developments as much as they do in the U.S.? To what extent have other policy responses in other countries affected the P2P market versus the consumer loans market? Is it welfare improving to design policy that enables financial institutions to rebound quicker in response to a crisis? Or, should policy be geared directly towards consumers in the market? These and other related questions could usefully inform future scholars, practitioners, and policymakers alike.

Figures and Tables

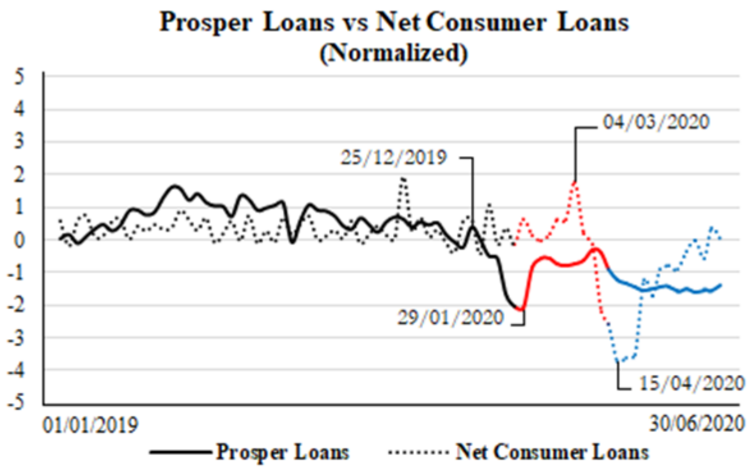

Figure 1: Weekly loans raised on Prosper.com and Net Consumer Loans issued by banks in the United States for the period 01/01/2019 to 30/06/2020. The red section presents the start of the COVID-19 outbreak in the United States, and the blue section marks the implementation of the CARES Act. The normalized standard deviation before the COVID-19 outbreak is 0.6907 for Prosper Loans and 0.4050 for Net Consumer Loans. The normalized standard deviation after the COVID-19 outbreak is 0.4799 for Prosper Loans and 1.4621 for Net Consumer Loans. The decrease in volatility of Prosper Loans is not statistically significant (*p-value* = 0.5267). However, the increase in volatility of net consumer loans is statistically significant (*p-value* = 0.0000).

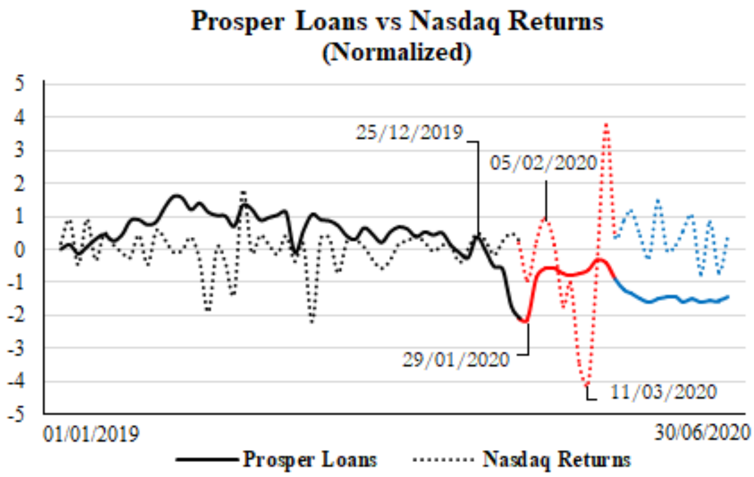

Figure 2: Weekly loans raised on Prosper.com and NASDAQ returns for the period 01/01/2019 to 30/06/2020. The red section presents the start of the COVID-19 outbreak in the United States, and the blue section marks the implementation of the CARES Act. The normalized standard deviation before the COVID-19 outbreak is 0.6907 for Prosper Loans and 0.6194 for NASDAQ Returns. The normalized standard deviation after the COVID-19 outbreak is 0.4799 for Prosper Loans and 1.5689 for NASDAQ Returns. The decrease in volatility of Prosper Loans is not statistically significant (*p-value* = 0.5267). However, the increase in volatility of NASDAQ Returns is statistically significant (*p-value* = 0.0004).

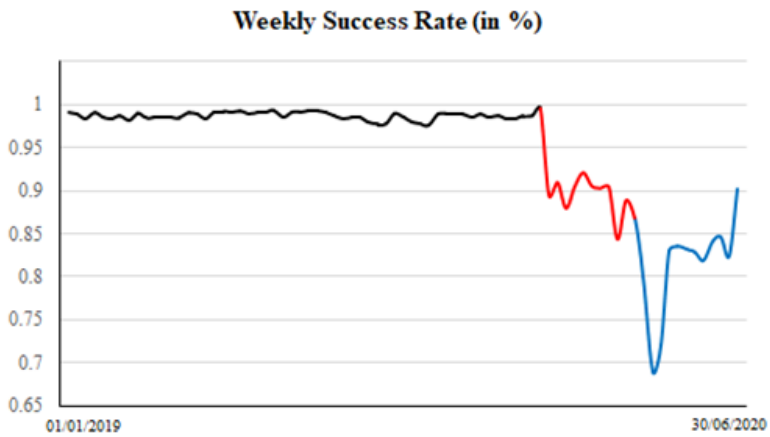

Figure 3: Weekly success rates of loan requests on Prosper.com for the period 01/01/2019 to 30/06/2020. The red section presents the start of the COVID-19 outbreak in the United States, and the blue section marks the implementation of the CARES Act.

Table 1
Difference in Means (Pre and Post COVID-19).

Variable	**Pre-COVID-19**	**Post-COVID-19**	**Two tailed t-test**
Credit Allocation	98.70%	85.80%	***
Credit Allocation SD	0.43%	6.44%	***
Prosper Loans (in thousands)	$ 47,166	$ 19,844	***
Prosper Loans SD	$ 13,120	$ 8,086	
Funding Percent	97.98%	93.47%	***
Funding Percent SD	3.30%	5.97%	***
Campaign Duration	8.12	21.42	***
Campaign Duration SD	3.62	16.15	***
Net Consumer Loans (in thousands)	$ 1,734,013	$ (3,103,117)	***
Net Consumer Loans SD	$ 1,807,080	$ 6,584,968	***
NASDAQ Returns	0.61%	0.43%	
NASDAQ Returns SD	2.09%	5.31%	***
Number of Weeks	55	24	

Table 4 presents the two-tailed t-test, which is applied to compare means between pre- and post-COVID-19 for the period 01/01/2019 to 30/06/2020. The difference in means was calculated using weekly data for Credit Allocation (the % of loan applications approved on Prosper), Prosper Loans (the weekly dollar amount raised on Prosper), Funding Percent (the funding rate of loans), Campaign Duration (the hours needed to complete funding round), Net Consumer Loans (the difference between the current and the previous week's Consumer Loan balances), and NASDAQ Returns (weekly NASDAQ returns). This test is also applied to compare variables' volatility as gauged by its standard deviation.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2
Vector Autoregression (VAR) Model.

	Net Consumer Loans $_t$	**Prosper Loans $_t$**	**NASDAQ Returns $_t$**
	β/s.e	*β/s.e*	*β/s.e*
Net Consumer Loans $_{t-1}$ (Weekly)	0.2904***	0.0146	-0.0537
	(0.0570)	(0.0295)	(0.0675)
Net Consumer Loans $_{t-2}$ (Weekly)	0.3374***	0.0329	-0.1241*
	(0.0566)	(0.0293)	(0.0671)
Prosper Loans $_{t-1}$ (Weekly)	0.2325**	0.6075***	-0.1116
	(0.1089)	(0.0563)	(0.1290)
Prosper Loans $_{t-2}$ (Weekly)	-0.1830*	0.3096***	0.0839
	(0.1089)	(0.0563)	(0.1290)
NASDAQ Returns $_{t-1}$ (Weekly)	-0.0390	-0.0419	-0.0952
	(0.0511)	(0.0264)	(0.0605)
NASDAQ Returns $_{t-2}$ (Weekly)	0.0570	-0.0027	0.0075
	(0.0513)	(0.0265)	(0.0608)
N	284	284	284
R-squared	0.3115	0.8168	0.0343

Table A1 provides VAR models. Weekly Net Consumer Loans, Weekly Prosper Loans, and Weekly NASDAQ Returns are regressed on up to two lagged terms of each of these variables. Data correspond to the period between January 1st, 2015 and June 30th, 2020. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3
Granger Causality Tests

Eq (1)	Excluded	Prob	Eq (2)	Excluded	Prob	Eq (3)	Excluded	Prob
Net Consumer Loans			**Prosper Loans**			**NASDAQ Returns**		
	Prosper Loans	0.093		Net Consumer Loans	0.310		Net Consumer Loans	0.043
	NASDAQ Returns	0.364		NASDAQ Returns	0.284		Prosper Loans	0.668
	All	0.162		All	0.199		All	0.095

Table A2 reports the results of the Granger Causality Tests between weekly Net Consumer Loans, Weekly Prosper Loans, and Weekly NASDAQ Returns. Data correspond to the period between January 1st, 2015 and June 30th, 2020.

Table 4
Robust OLS Regression (Standardized Variables)

	Dependent Variable: Net Consumer Loans $_t$					
	(1) $\beta/s.e$	(2) $\beta/s.e$	(3) $\beta/s.e$	(4) $\beta/s.e$	(5) $\beta/s.e$	(6) $\beta/s.e$
Period	**2015-2020**	**2016-2020**	**2017-2020**	**2018-2020**	**2015-2018**	**2019-2020**
Prosper Loans $_{t-1}$	0.1770***	0.2395**	0.5675***	0.8338***	0.0209	1.2122***
	(0.0601)	(0.0946)	(0.1723)	(0.2463)	(0.0364)	(0.3017)
NASDAQ Returns $_t$	-0.2208**	-0.2489**	-0.2552**	-0.2579**	-0.0557	-0.3668**
	(0.0966)	(0.1099)	(0.1170)	(0.1186)	(0.0593)	(0.1549)
N	286	235	183	131	207	79
R-squared	0.0852	0.0934	0.1477	0.2020	0.0055	0.2974

Table A3 reports the results of the Robust OLS regression. Weekly Net Consumer Loans are regressed on the weekly NASDAQ returns and 1-week-lagged weekly Prosper Loans. Data correspond to the period between January 1st, 2015 and June 30th, 2020. Weekly net consumer loans, weekly prosper loans, and weekly NASDAQ returns are standardized. In Column (1) we run a robust OLS regression on the full sample of 286 weekly observations. In Columns (2)-(4) we drop subsequent years in order, since P2P markets were less developed in the early years. The model's explanatory power improves significantly. In Column (5) we run the OLS regression models for the first period (2015 – 2018), weekly prosper loans no longer play a significant role in predicting net consumer loans. However, they do for the period 2019-2020. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5
Robust OLS Regression (Inverse-hyperbolic sine transformation)

	Dependent Variable: Net Consumer Loans $_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
	β/s.e	*β/s.e*	*β/s.e*	*β/s.e*	*β/s.e*	*β/s.e*
Period	**2015-2020**	**2016-2020**	**2017-2020**	**2018-2020**	**2015-2018**	**2019-2020**
Prosper Loans $_{t-1}$	0.6183***	0.6425***	1.1256***	1.4165***	0.0982	1.8938***
	(0.1601)	(0.2022)	(0.2658)	(0.3071)	(0.1238)	(0.3490)
NASDAQ Returns $_t$	-0.1204**	-0.1341**	-0.1243*	-0.1227	-0.0546	-0.2205*
	(0.0544)	(0.0654)	(0.0750)	(0.0826)	(0.0520)	(0.1133)
N	286	235	183	131	207	79
R-squared	0.1004	0.0890	0.1507	0.2009	0.0089	0.3266

Table A4 reports the results of the Robust OLS regression. Weekly Net Consumer Loans are regressed on the lagged weekly Prosper Loans and weekly NASDAQ returns. Data correspond to the period between 2015 and 2020. The analysis is identical to that of Table 2a; however, the variables are transformed using the inverse hyperbolic sine transformation. The inverse hyperbolic sine transformation has the same interpretation as the natural logarithm transformation, however it can be used when zero and negative values are encountered. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6
Variable Definitions.

Variable	Description	Source
Credit Allocation	A dummy variable = 1, if the loan applicant is allocated credit by the investors on the platform.	PROSPER.com
Funding Percent	Amount of loan funded as a percentage of loan amount requested.	PROSPER.com
Campaign Duration	Time to successfully raise loan amount requested in hours.	PROSPER.com
COVID-19	A dummy variable = 1 for the period 20/01/2020 - 30/06/2020.	CDC.gov
CARES Act	A dummy variable = 1 for the period 28/3/2020 - 30/06/2020.	TREASURY.gov
Daily State COVID-19 Infections	The number of COVID-19 infections in the applicant's state on the day of the loan application.	CDC.gov
NASDAQ Return	The NASDAQ daily percentage return.	NASDAQ.com
Consumer Loans	The dollar value of the sum of consumer loans on all U.S. banks' balance sheets (weekly)	FRED.stlouisfed.org
Loan Amount Requested	The loan amount that the applicant is requesting in dollars.	PROSPER.com
Interest Rate	The interest rate that the platform has allocated to the loan applicant.	PROSPER.com
Employment History	The number of years that the applicant has accumulated.	PROSPER.com
Repeat Borrower	A dummy variable = 1, if the loan applicant has previously acquired a loan on the platform.	PROSPER.com
Listing Term	A dummy variable = 0, if the loan term is 36-month and = 1 if the loan term is 60-month.	PROSPER.com
Income Range	Loan applicant's annual income category.	PROSPER.com
Employment Status	Loan applicant's employment status (1 = Full-time, 2 = Self employed, 3 = Other).	PROSPER.com
Active Lender	A dummy variable = 1, if loan applicant is an active lender on the platform.	PROSPER.com
Investment Type Dummies	A categorical variable for the investment type (Whole or Fractional).	PROSPER.com
Loan Purpose Category Dummies	20 dummy variables for different loan purpose categories.	PROSPER.com

Table 1 reports the definitions of the variables used in the regression models. It includes variables related to a loan's characteristics, a loan's applicant profile, and market conditions. All continuous variables were transformed using the inverse hyperbolic sine transformation due to the variables' skewness and zero values encountered. The inverse hyperbolic sine transformation has a similar interpretation to that of log transformed variables.

Table 7
Descriptive Statistics.

Variable	Obs	Mean	Std.Dev.	Min	Max
Credit Allocation	229,226	0.96	0.18	0	1
Funding Percent	229,226	0.98	0.14	0	1
Campaign Duration	221,182	9.48	30.63	0	336
COVID-19	229,226	0.17	0.38	0	1
CARES Act	229,226	0.08	0.26	0	1
Daily State COVID-19 Infections	229,226	95.02	518.69	0	13,262
NASDAQ Returns (in %)	229,226	0.12	1.646	-12.321	9.346
Consumer Loans (in $ billions)	229,226	1,551.49	29.50	1,498.68	1,612.50
Loan Amount Requested (in $)	229,226	13,939.06	8,672.29	2,000.00	40,000.00
Interest Rate (in %)	229,226	0.15	0.06	0.05	0.318
Employment History (in years)	229,226	9.35	9.14	0.08	41.5
Repeat Borrower	229,226	0.38	0.48	0	1
Listing Term	229,226	0.32	0.46	0	1
Active Lender	229,226	0.01	0.10	0	1

Table 2 reports the summary statistics of the variables used in the probit regression models. The sample consists of 229,226 loan listings posted in Prosper.com between January 1st, 2019 and June 30th, 2020. COVID-19-related data, information on political measures (CARES Act), and market variables (*NASDAQ Returns* and *Consumer loans*) are merged with a loan's characteristics and a loan applicant's profile data. Variables are defined in Table 1.

Table 8
Correlation Matrix.

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	Credit Allocation	1												
(2)	Funding Percent	0.743***	1											
(3)	Campaign Duration	-0.201***	-0.261	1										
(4)	COVID-19	-0.260***	-0.109***	0.190***	1									
(5)	CARES Act	-0.227***	-0.154***	0.243***	0.623***	1								
(6)	Daily State COVID-19 Infections	-0.243***	-0.143***	0.241***	0.740***	0.870***	1							
(7)	NASDAQ Returns	-0.004**	-0.010***	0.018***	-0.012***	0.100***	0.069***	1						
(8)	Consumer Loans	-0.045***	0.011***	0.038***	0.315***	-0.188***	-0.029***	-0.108***	1					
(9)	Loan Amount Requested	-0.024***	-0.034***	0.003	-0.013***	-0.014***	-0.009***	0.000	-0.018***	1				
(10)	Interest Rate	-0.017***	-0.012***	-0.005**	-0.038***	-0.055***	-0.051***	-0.006***	0.036***	-0.133***	1			
(11)	Employment History	0.027***	0.015***	0.015***	-0.017***	-0.013***	-0.017***	-0.002	-0.009***	0.059***	-0.041***	1		
(12)	Repeat Borrower	0.076***	0.059***	-0.028***	0.015***	-0.004**	-0.002	-0.003	0.031***	0.029***	-0.020***	0.164***	1	
(13)	Listing Term	0.001	-0.002	-0.061***	0.023***	0.021***	0.023***	-0.002	0.018***	0.248***	0.099***	0.034***	0.056***	1
(14)	Active Lender	0.007***	0.005**	-0.006***	0.000	-0.001	0.000	0.003	0.000	0.023***	-0.019***	0.005	0.094***	0.010***

Table 3 exhibits the Pearson’s correlation coefficients between variables and their significance. Variables are defined in Table 1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9
Probit Regression.

	Dependent Variable: Credit Allocation				
	(1) *β/s.e.*	(2) *β/s.e.*	(3) *β/s.e.*	(4) *β/s.e.*	(5) *β/s.e.*
COVID-19		-1.1463***	-0.9061***	-1.1507***	-1.1612***
		(0.0136)	(0.0323)	(0.0274)	(0.0148)
COVID-19 x Interest Rate			-1.6415***		
			(0.2011)		
COVID-19 x Employment History				0.0019	
				(0.0104)	
COVID-19 x Repeat Borrower					0.0699**
					(0.0284)
NASDAQ Return (in %)	-0.0106	0.0058	0.0059	0.0058	0.0059
	(0.0065)	(0.0052)	(0.0053)	(0.0052)	(0.0053)
Consumer Loans (in $)	-5.6796***	2.1200***	2.4069***	2.1199***	2.1323***
	(0.3179)	(0.2929)	(0.2959)	(0.2929)	(0.2927)
Loan Amount Requested (in $)	-0.1604***	-0.2301***	-0.2284***	-0.2301***	-0.2309***
	(0.0104)	(0.0117)	(0.0117)	(0.0117)	(0.0117)
Interest Rate (in %)	-1.0471***	-1.5451***	-0.8559***	-1.5452***	-1.5502***
	(0.0910)	(0.1045)	(0.1359)	(0.1045)	(0.1044)
Employment History (in years)	0.0433***	0.0400***	0.0399***	0.0390***	0.0398***
	(0.0049)	(0.0054)	(0.0054)	(0.0074)	(0.0054)
Repeat Borrower	0.4508***	0.5430***	0.5455***	0.5429***	0.5011***
	(0.0132)	(0.0148)	(0.0148)	(0.0148)	(0.0216)
Listing Term (0 = 36 month, 1 = 60-month)	-0.0303**	0.0472***	0.0484***	0.0472***	0.0471***
	(0.0122)	(0.0136)	(0.0136)	(0.0136)	(0.0136)
<u>Income Range</u> <u>(less than $25,000 or unverified)</u>					
$25,000 - $49,999	0.0561	0.0190	0.0115	0.0189	0.0191
	(0.0670)	(0.0739)	(0.0747)	(0.0739)	(0.0741)
$50,000 - $74,999	0.1243*	0.0982	0.0903	0.0981	0.0984
	(0.0674)	(0.0743)	(0.0751)	(0.0743)	(0.0744)
$75,000 - $99,999	0.1535**	0.1327*	0.1241	0.1326*	0.1330*
	(0.0682)	(0.0752)	(0.0761)	(0.0752)	(0.0754)
$100,000 or above	0.0325	0.0452	0.0360	0.0451	0.0455
	(0.0682)	(0.0753)	(0.0762)	(0.0753)	(0.0755)
<u>Employment Status (Full-Time)</u>					
Self Employed	-0.2693***	-0.4011***	-0.3998***	-0.4011***	-0.4016***
	(0.0197)	(0.0206)	(0.0207)	(0.0206)	(0.0206)
Other	-0.1994***	-0.2389***	-0.2390***	-0.2389***	-0.2392***
	(0.0212)	(0.0233)	(0.0233)	(0.0233)	(0.0233)
Active Lender	0.0280	-0.0154	-0.0170	-0.0154	-0.0146
	(0.0651)	(0.0723)	(0.0719)	(0.0723)	(0.0716)
Investment Type Dummies	Yes	Yes	Yes	Yes	Yes
Loan Purpose Category Dummies	Yes	Yes	Yes	Yes	Yes
N	229,226	229,226	229,226	229,226	229,226
R-squared	0.1155	0.2387	0.2396	0.2387	0.2387
chi2	7,696.74	16,983.31	17,257.93	16,989.64	17,453.06

Table 5 provides the results of the probit model applied to the whole sample of loan requests (229,226 observations from January 1st, 2019 to June 30th, 2020) to investigate the effect of COVID-19 on the crowdlending market. In this model, Credit Allocation is regressed on the independent variable *COVID-19*, and its interaction with *Interest Rate*, *Employment History,* and *Repeat Borrower* (interaction variables). Variables are defined in Table 1. Standard errors are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10

Alternative Model Specifications: Credit Allocation, Funding Percentage, and Campaign Duration

Dependent Variable:	**Credit Allocation**		**Funding Percent**		**Campaign Duration (A)**		**Campaign Duration (B)**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	β/s.e	*β/s.e*	*β/s.e*	*β/s.e*	*β/s.e*	*β/s.e*	*β/s.e*	*β/s.e*
COVID-19		-2.3900***		-0.4140***		2.0969***		-0.2330***
		(0.0315)		(0.0153)		(0.0281)		(0.0065)
NASDAQ Return (in %)	-0.0173	0.0137	-0.0043	0.0052	0.0065	-0.0077	0.0030	0.0052**
	(0.0150)	(0.0105)	(0.0081)	(0.0071)	(0.0107)	(0.0090)	(0.0023)	(0.0023)
Consumer Loans (in $)	-10.9133***	4.3276***	4.0200***	5.2281***	13.6250***	-1.3669**	0.2902**	1.7798***
	(0.7412)	(0.5955)	(0.3914)	(0.3641)	(0.6093)	(0.5674)	(0.1164)	(0.1250)
Loan Amount Requested (in $)	-0.3802***	-0.4884***	-0.2904***	-0.3061***	0.0279	0.1557***	0.0064*	0.0011
	(0.0238)	(0.0253)	(0.0150)	(0.0153)	(0.0206)	(0.0211)	(0.0037)	(0.0037)
Interest Rate (in %)	-2.5694***	-3.4771***	-1.8724***	-1.8724***	2.4706***	2.9818***	1.2876***	1.2481***
	(0.2027)	(0.2285)	(0.1257)	(0.1288)	(0.1888)	(0.1979)	(0.0357)	(0.0357)
Employment History (in years)	0.0923***	0.0805***	0.0320***	0.0302***	-0.0767***	-0.0725***	0.0069***	0.0062***
	(0.0105)	(0.0114)	(0.0064)	(0.0065)	(0.0103)	(0.0105)	(0.0020)	(0.0020)
Repeat Borrower	0.9957***	1.1202***	0.4835***	0.5051***	-0.8446***	-0.8940***	0.0528***	0.0540***
	(0.0307)	(0.0316)	(0.0171)	(0.0174)	(0.0299)	(0.0300)	(0.0046)	(0.0046)
Listing Term (0 = 36 month, 1 = 60-month)	-0.0772***	0.1229***	-0.0245	0.0094	-0.0133	-0.1328***	-0.0514***	-0.0467***
	(0.0268)	(0.0288)	(0.0162)	(0.0166)	(0.0254)	(0.0255)	(0.0048)	(0.0048)
<u>Income Range (less than $25,000 or unverified)</u>								

$25,000 - $49,999	0.1208	0.0392	0.0826	0.0589	0.0497	0.0522	0.0080	0.0091
	(0.1436)	(0.1552)	(0.0873)	(0.0885)	(0.1350)	(0.1348)	(0.0280)	(0.0280)
$50,000 - $74,999	0.2805*	0.2028	0.1719*	0.1483*	0.0597	0.0368	0.0514*	0.0536*
	(0.1445)	(0.1561)	(0.0879)	(0.0891)	(0.1357)	(0.1356)	(0.0280)	(0.0280)
$75,000 - $99,999	0.3490**	0.2976*	0.1958**	0.1721*	0.0574	0.0378	0.0742***	0.0775***
	(0.1465)	(0.1582)	(0.0891)	(0.0903)	(0.1376)	(0.1374)	(0.0283)	(0.0283)
$100,000 or above	0.0909	0.1038	0.1136	0.1071	0.3572***	0.2297*	0.0947***	0.1027***
	(0.1466)	(0.1584)	(0.0893)	(0.0906)	(0.1375)	(0.1375)	(0.0283)	(0.0283)
Employment Status (Full-Time)								
Self-Employed	-0.5799***	-0.8957***	-0.3219***	-0.3604***	0.3770***	0.5408***	-0.1040***	-0.1054***
	(0.0418)	(0.0435)	(0.0255)	(0.0254)	(0.0395)	(0.0398)	(0.0091)	(0.0091)
Other	-0.4448***	-0.4820***	-0.3052***	-0.3104***	0.1363***	0.1796***	-0.0053***	-0.0623***
	(0.0454)	(0.0492)	(0.0260)	(0.0263)	(0.0441)	(0.0440)	(0.0088)	(0.0088)
Active Lender	0.0716	0.0110	-0.0412	-0.0580	-0.0199	0.0110	0.0153	0.0143
	(0.1496)	(0.1566)	(0.0846)	(0.0857)	(0.1457)	(0.1458)	(0.0214)	(0.0214)
Investment Type Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose Category Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	229,226	229,226	229,226	229,226	229,154	221,154	229,154	221,154
R-squared/(AIC)	0.0368	0.0854	0.2088	0.2239	(159,455)	(153,279)	(4,940,652)	(4,939,330)

Table 6 provides the results of alternative model specifications for the results presented in Columns (1) and (2) of Table 5. Given that the probability of credit not being allocated is a rare event, we repeat the analysis using the rare event logistic regression model and present the main results in Columns (1) and (2). In Columns (3) and (4) we investigate the effect of *COVID-19* on loan request funding rates. We run a bounded logistic regression model, given that the funding rates are between 0 and 1. In Columns (5) and (6) we run a Cox Proportional Hazards Model to investigate the effect of *COVID-19* on exiting from the sample as time passes. Exiting from the sample takes place if the campaign fails. In Columns (7) and (8), we repeat the analysis conducted in Columns (5) and (6), but we instead define exiting from the sample when credit has been allocated to the applicant, since successful loan requests are the ones that exit the sample before campaign expiry (failed loan requests usually remain until the end of the campaign period, which is 14 days). Variables are defined in Table 1. Standard errors are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11

Probit Regression (CEM Sample)

	Dependent Variable: Credit Allocation				
	(1) *β/s.e.*	(2) *β/s.e.*	(3) *β/s.e.*	(4) *β/s.e.*	(5) *β/s.e.*
Daily State COVID-19 Infections		-0.1259***	-0.1074***	-0.1176***	-0.1205***
		(0.0026)	(0.0066)	(0.0053)	(0.0029)
Daily State COVID-19 Infections x Interest Rate			-0.1321***		
			(0.0443)		
Daily State COVID-19 Infections x Employment History				-0.0037*	
				(0.0021)	
Daily State COVID-19 Infections x Repeat Borrower					-0.0236***
					(0.0056)
NASDAQ Return (in %)	-0.0083	0.0111*	0.0112*	0.0112*	0.0113*
	(0.0068)	(0.0062)	(0.0062)	(0.0062)	(0.0062)
Consumer Loans (in $)	-0.7248*	-4.9755***	-4.8965***	-4.9749***	-5.0556***
	(0.3759)	(0.3885)	(0.3889)	(0.3888)	(0.3913)
Loan Amount Requested (in $)	-0.1539***	-0.1786***	-0.1775***	-0.1787***	-0.1761***
	(0.0147)	(0.0157)	(0.0157)	(0.0157)	(0.0157)
Interest Rate (in %)	-2.9645***	-2.7410***	-2.2377***	-2.7449***	-2.7433***
	(0.1462)	(0.1590)	(0.2286)	(0.1591)	(0.1594)
Employment History (in years)	0.0344***	0.0360***	0.0356***	0.0523***	0.0362***
	(0.0072)	(0.0076)	(0.0076)	(0.0116)	(0.0076)
Repeat Borrower	0.4552***	0.4881***	0.4883***	0.4889***	0.6017***
	(0.0182)	(0.0192)	(0.0192)	(0.0192)	(0.0336)
Listing Term (0 = 36 month, 1 = 60-month)	0.0121	0.0625***	0.0646***	0.0626***	0.0633***
	(0.0177)	(0.0187)	(0.0187)	(0.0187)	(0.0187)
<u>Income Range (less than $25,000 or unverified)</u>					
$25,000 - $49,999	0.0452	0.0293	0.0246	0.0291	0.0279
	(0.0943)	(0.0984)	(0.0989)	(0.0982)	(0.0982)
$50,000 - $74,999	0.0923	0.0885	0.0834	0.0884	0.0861
	(0.0947)	(0.0989)	(0.0994)	(0.0987)	(0.0987)
$75,000 - $99,999	0.1661*	0.1785*	0.1729*	0.1786*	0.1763*
	(0.0961)	(0.1004)	(0.1009)	(0.1002)	(0.1002)
$100,000 or above	0.0092	0.0331	0.0266	0.0331	0.0302
	(0.0961)	(0.1004)	(0.1010)	(0.1002)	(0.1002)
<u>Employment Status (Full-Time)</u>					
Self Employed	-0.4525***	-0.5429***	-0.5434***	-0.5451***	-0.5455***
	(0.0315)	(0.0321)	(0.0321)	(0.0322)	(0.0323)
Other	-0.1757***	-0.2040***	-0.2040***	-0.2041***	-0.2044***
	(0.0325)	(0.0343)	(0.0343)	(0.0344)	(0.0344)
Active Lender	0.0745	0.0815	0.0811	0.0817	0.0861
	(0.0950)	(0.1004)	(0.1002)	(0.1003)	(0.1017)
Investment Type Dummies	Yes	Yes	Yes	Yes	Yes
Loan Purpose Category Dummies	Yes	Yes	Yes	Yes	Yes
N	58,891	58,891	58,891	58,891	58,891
R-squared	0.0917	0.1598	0.1601	0.1599	0.1603
chi2	2,866.40	5,491.68	5,599.51	5,466.82	5,206.28

Table 7 provides the results of the probit model aimed at discerning whether investors on P2P lending platforms are more reluctant to invest in loans requested by borrowers from states with higher daily COVID-19 infection rates. Coarsened Exact Matching (CEM) is applied to match loan applications from states with an outbreak of COVID-19 infection to similar loans applications prior to the COVID-19 outbreak. The probit model is applied to the resulting matched sample, which is comprised of 58,891 loan applications corresponding to the period January 1st, 2019 to June 30th, 2020 (29,448 loan requests during COVID-19 and 29,443 loan applications prior to COVID-19). *Credit Allocation* is regressed on the independent variable *Daily State*

COVID-19 Infections, and its interaction with *Interest Rate*, *Employment History,* and *Repeat Borrower*. Variables are defined in Table 1. Standard errors are shown in parentheses. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12
Probit Regression (CEM Sample)

	Dependent Variable: Credit Allocation									
	(1)		(2)		(3)		(4)		(5)	
	Prior	**Post**	**Prior**	**Post**	**Prior**	**Post**	**Prior**	**Post**	**Prior**	**Post**
	β/s.e.	*β/s.e.*	*β/s.e.*	*β/s.e.*	*β/s.e.*	*β/s.e.*	*β/s.e.*	*β/s.e.*	*β/s.e.*	*β/s.e.*
Daily State COVID-19 Infections			-0.0263***	-0.0006	-0.0175***	-0.0050	-0.0309**	0.0006	-0.0232***	0.0018
			(0.0062)	(0.0094)	(0.0018)	(0.0301)	(0.0138)	(0.0221)	(0.0069)	(0.0109)
Daily State COVID-19 Infections x Interest Rate					-0.0701	0.0341				
					(0.1307)	(0.1947)				
Daily State COVID-19 Infections x Employment History							0.0020	-0.0005		
							(0.0054)	(0.0086)		
Daily State COVID-19 Infections x Repeat Borrower									-0.0152	-0.0087
									(0.0152)	(0.0210)
NASDAQ Return (in %)	0.0158*	0.0283**	0.0151*	0.0283**	0.0151*	0.0283**	0.0151*	0.0283**	0.0150*	0.0283**
	(0.0093)	(0.0110)	(0.0090)	(0.0110)	(0.0090)	(0.0110)	(0.0090)	(0.0110)	(0.0090)	(0.0110)
Consumer Loans (in $)	0.2639	6.3672***	0.6586	6.3613***	0.5389	6.4166***	0.6442	6.3617***	0.6041	6.3609***
	(3.6240)	(0.8969)	(3.6098)	(0.8983)	(3.6129)	(0.9012)	(3.6099)	(0.8983)	(3.6048)	(0.8984)
Loan Amount Requested (in $)	-0.1776***	-0.2443***	-0.1765***	-0.2443***	-0.1766***	-0.2445***	-0.1767***	-0.2443***	-0.1765***	-0.2443***
	(0.0289)	(0.0252)	(0.0290)	(0.0252)	(0.0290)	(0.0252)	(0.0290)	(0.0252)	(0.0290)	(0.0252)
Interest Rate (in %)	-2.3174***	-5.0729***	-2.3366***	-5.0731***	-2.2160***	-7.4489***	-2.3370***	-5.0732***	-2.3345***	-5.0753***
	(0.3203)	(0.2945)	(0.3200)	(0.2945)	(0.3874)	(1.3878)	(0.3200)	(0.2945)	(0.3200)	(0.2946)
Employment History (in years)	0.0253*	0.0210*	0.0239*	0.0210*	0.0240*	0.0211*	0.0203	0.0247	0.0240*	0.0211*
	(0.0142)	(0.0121)	(0.0142)	(0.0121)	(0.0142)	(0.0121)	(0.0172)	(0.0617)	(0.0142)	(0.0121)
Repeat Borrower	0.7939***	0.3926***	0.7923***	0.3926***	0.7927***	0.3937***	0.7923***	0.3926***	0.8195***	0.4539***
	(0.0392)	(0.0291)	(0.0393)	(0.0291)	(0.0393)	(0.0291)	(0.0393)	(0.0291)	(0.0483)	(0.1506)
Listing Term (0 = 36 month, 1 = 60-month)	0.0942***	0.1897***	0.0968***	0.1897***	0.0969***	0.1882***	0.0968***	0.1897***	0.0972***	0.1898***
	(0.0357)	(0.0291)	(0.0356)	(0.0291)	(0.0356)	(0.0291)	(0.0356)	(0.0291)	(0.0356)	(0.0291)
Income Range (less than $25,000 or unverified)										
$25,000 - $49,999	0.3925**	0.0164	0.3904**	0.0165	0.3897**	0.0169	0.3908**	0.0166	0.3920**	0.0162

	(0.1718)	(0.1579)	(0.1720)	(0.1579)	(0.1721)	(0.1579)	(0.1720)	(0.1579)	(0.1723)	(0.1579)
\$50,000 - \$74,999	0.4186**	0.1296	0.4177**	0.1297	0.4171**	0.1295	0.4179**	0.1297	0.4192**	0.1293
	(0.1728)	(0.1587)	(0.1731)	(0.1587)	(0.1731)	(0.1587)	(0.1731)	(0.1587)	(0.1733)	(0.1587)
\$75,000 - \$99,999	0.5535***	0.1651	0.5514***	0.1653	0.5508***	0.1648	0.5516***	0.1653	0.5531***	0.1650
	(0.1756)	(0.1608)	(0.1758)	(0.1608)	(0.1759)	(0.1608)	(0.1758)	(0.1608)	(0.1761)	(0.1609)
\$100,000 or above	0.4048**	0.026	0.4026**	0.0262	0.4016**	0.026	0.4027**	0.0263	0.4050**	0.026
	(0.1760)	(0.1610)	(0.1763)	(0.1611)	(0.1764)	(0.1611)	(0.1763)	(0.1611)	(0.1765)	(0.1611)
Employment Status (Full-Time)										
Self Employed	-0.6158***	-1.2114***	-0.6084***	-1.2113***	-0.6091***	-1.2130***	-0.6086***	-1.2113***	-0.6071***	-1.2115***
	(0.0573)	(0.0705)	(0.0571)	(0.0705)	(0.0571)	(0.0705)	(0.0571)	(0.0705)	(0.0570)	(0.0706)
Other	-0.1552**	-0.1903***	-0.1606**	-0.1904***	-0.1609**	-0.1917***	-0.1607**	-0.1904***	-0.1608**	-0.1906***
	(0.0638)	(0.0539)	(0.0640)	(0.0539)	(0.0640)	(0.0539)	(0.0640)	(0.0539)	(0.0640)	(0.0539)
Active Lender	0.0041	0.1857	0.0071	0.1856	0.0069	0.1843	0.0061	0.1856	0.0099	0.1855
	(0.1889)	(0.1532)	(0.1892)	(0.1533)	(0.1892)	(0.1534)	(0.1892)	(0.1532)	(0.1897)	(0.1531)
Investment Type Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose Category Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13,951	13,962	13,951	13,962	13,951	13,962	13,951	13,962	13,951	13,962
R-squared	0.0862	0.0811	0.0881	0.0811	0.0882	0.0814	0.0882	0.0811	0.0882	0.0811
chi2	694.91	966.96	707.10	967.09	707.33	971.07	707.68	967.18	697.30	968.16

Table 8 reports the results of the probit models aimed at assessing the effect of the CARES Act (March 28th, 2020) on investors' willingness to invest into loans requested on crowdlending markets. Coarsened Exact Matching (CEM) is used to match loan applications between March 28th, 2020 and June 30th, 2020 with applications between January 20th, 2020 and March 27th, 2020. The resulting matched sample has 27,913 observations (13,951 loan applications prior to the CARES Act and 13,962 loan applications after the CARES Act). We run separate probit regressions for each group. *Credit Allocation* is regressed on the independent variable *Daily State COVID-19 Infections*, and its interaction with *Interest Rate*, *Employment History,* and *Repeat Borrower*. Variables are defined in Table 1. Standard errors are shown in parentheses. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

References

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Vega, C. (2007). Real-time price discovery in global stock, bond and foreign exchange markets. *Journal of International Economics*, *73*(2), 251–277.

Ari, A., Chen, S., and Ratnovski, L. (2021). The dynamics of non-performing loans during banking crises: A new database with post-COVID-19 implications. *Journal of Banking & Finance*, 106140.

Allen, F., and D. Gale. 1995. A welfare comparison of intermediaries and financial markets in Germany and the U.S., *European Economic Review*, 39-2, 179-209.

Allen, F., and D. Gale. 1997. Financial markets, intermediaries and intertemporal smoothing, *Journal of Political Economy*, 105-3, 523-546.

Balyuk, T. 2016. Financial innovation and borrowers: Evidence from peer-to-peer lending. *SSRN Electronic Journal*.

Balyuk, T., A. N. Berger, and J. Hackney. 2020. What is fueling fintech lending? The role of banking market structure. *SSRN Electronic Journal.*

Beck, T. 2020. Fintech and financial inclusion: Opportunities and pitfalls. ADBI Working Paper 1165. Tokyo: Asian Development Bank Institute.

Berger, A.N., and C. H. S. Bouwman. 2013. How does capital affect bank performance during financial crises? *Journal of Financial Economics*, 109, 146-176.

Berger, A.N., and G. Udel. 2002. Small business credit availability and relationship lending: The importance of bank organistional structure, *The Economic Journal*, 112 (February), F32-F53.

Blackwell, M., S. Iacus, G. King, and G. Porro. 2009. CEM: Coarsened exact matching in Stata. *The Stata Journal: Promoting Communications on Statistics and Stata*, 9(4), 524-546.

Boot, AW.A., and A.V. Thakor. 2012. The accelerating integration of banks and markets and its implications for regulation, in *The Oxford Handbook of Banking* (Editors: Allen Berger, Phil Molyneux and John S. Wilson)

Borri, N., & Giorgio, G. di. (2021). Systemic risk and the COVID challenge in the european banking sector. *Journal of Banking and Finance*, 106073.

Burbidge, J. B., L. Magee, and A. L. Robb. 1988. Alternative transformations to handle extreme values of the dependent variable. *Journal of the American Statistical Association*, 83(401), 123.

Butler, A. W., J. Cornaggia, and U. G. Gurun. 2017. Do local capital market conditions affect consumers' borrowing decisions? *Management Science*, 63(12), 4175–4187.

Constantinou, D., and A. Ashta. 2011. Financial crisis: lessons from microfinance. *Strategic Change*, 20(5–6), 187–203.

Cull, R., and M. S. Martínez Pería. 2013. Bank ownership and lending patterns during the 2008-2009 financial crisis: Evidence from latin America and Eastern Europe. *Journal of Banking and Finance*, 37(12), 4861–4878.

Cummins, M., C. Mac an Bhaird, P. Rosati, and T. Lynn. 2020. Institutional investment in online business lending markets. *International Review of Financial Analysis*, 71, 101542.

de Roure, C., L. Pelizzon, and A. Thakor. 2019. P2P lenders versus banks: Cream skimming or bottom fishing? Working paper, Goethe University, January.

Freedman, S., and G. Z. Jin. 2014. The information value of online social networks: Lessons from peer-to-peer lending. *NBER Working Paper Series*

Hasan, I., Politsidis, P. N., & Sharma, Z. (2021). Global syndicated lending during the COVID-19 pandemic. *Journal of Banking & Finance*, 106121.

Herzenstein, M., R. Andrews, U. Dholakia, and E. Lyandres. 2008. The democratization of personal consumer loans? Determinants of success in online peer-to-peer lending communities.

Herzenstein, M., S. Sonenshein, and U. Dholakia. 2011. Tell me a good story and I may lend you my money: The role of narratives in peer-to-peer lending decisions. *SSRN Electronic Journal*.

Iacus, S. M., G. King, and G. Porro. 2012. Causal inference without balance checking: Coarsened exact matching. *Political Analysis*, 20(1), 1-24.

Iyer, R., A. I. Khwaja, E. F. P. Luttmer, and K. Shue. 2016. Screening peers softly: Inferring the quality of small borrowers. *Management Science*, 62(6), 1554–1577.

Larrimore, L., L. Jiang, J. Larrimore, D. Markowitz, and S. Gorski. 2011. Peer Lending: The relationship between language features, trustworthiness, and persuasion success. *Journal of Applied Communication Research*, 39(1), 19-37.

Li, L., P. E. Strahan, and S. Zhang. 2020. Banks as lenders of first resort: Evidence from the COVID-19 crisis. *The Review of Corporate Finance Studies*, *9*(3), 472–500.

Lin, M., N. R. Prabhala, and S. Viswanathan. 2013. Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending. *Management Science*, 59(1), 17-35.

Michels, J. 2012. Do unverifiable disclosures matter? Evidence from peer-to-peer Lending. *The Accounting Review*, 87(4), 1385-1413.

Nozawa, Y., & Qiu, Y. (2021). Corporate bond market reactions to quantitative easing during the COVID-19 pandemic. *Journal of Banking & Finance*, 106153.

Petersen, M., and R. G. Rajan. 1995. The effect of credit market competition on lending relationships, *Quarterly Journal of Economics*, 110-2, 407-443.

Puro, L., J. E. Teich, H. Wallenius, and J. Wallenius. 2010. Borrower decision aid for people-to-people lending. *Decision Support Systems*, 49(1): 52–60.

Puri, M., J. Rocholl, and S. Steffen. 2011. Global retail lending in the aftermath of the US financial crisis: Distinguishing between supply and demand effects. *Journal of Financial Economics*, 100(3), 556–578.

Rochet, J.-C., and J. Tirole. 2003. Platform competition in two-sided markets. *Journal of the European Economic Association*, 1(4), 990–1029.

Ryan, J., K. Reuk, and C. Wang. 2007. To fund or not to fund: determinants of loan fundability in the Prosper.com Marketplace, Working paper, Graduate School of Business, Stanford University.

Sauerwald, S., Z. J. Lin, and M. W. Peng. 2016. Board social capital and excess CEO returns. *Strategic Management Journal*, 37(3), 498–520.

Serrano-Cinca, C., B. Gutiérrez-Nieto, and L. López-Palacios. 2015. Determinants of default in P2P lending. *PLoS ONE*, 10(10): e0139427.

Tang, H. 2019. Peer-to-peer lenders versus banks: Substitutes or complements? *The Review of Financial Studies*, 32(5), 1900-1938.

Tedeschi, G., A. Mazloumian, M. Gallegati, and D. Helbing. 2012. Bankruptcy cascades in interbank Markets. *PLoS ONE*, 7(12).

U.S. Department of the Treasury. 2020. Retrieved from https://home.treasury.gov/policy-issues/cares

Vallée, B., and Y. Zeng. 2019. Marketplace lending: A new banking paradigm? *The Review of Financial Studies*, 32(5), 1939-1982.

Wei, Z., and M. Lin. 2017. Market mechanisms in online peer-to-peer lending. *Management Science*, 63(12), 4236-4257.

Zhang, Y., H. Li, M. Hai, J. Li, and A. Li. 2017. Determinants of loan funded successful in online P2P Lending. *Procedia Computer Science*, 122, 896-901