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Itzhak Ben-David
Mark J. Johnson
René M. Stulz

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ABSTRACT

With the onset of the COVID-19 crisis in March 2020, small business lending through fintech lenders collapsed. We explore the reasons for the market shutdown using detailed data about loan applications, offers, and take-up from a major small business fintech credit platform. We document that while the number of loan applications increased sharply early in March 2020, the supply of credit collapsed as online lenders dropped from the platform and the likelihood of applicants receiving loan offers fell precipitously. Our analysis shows that the drying up of the loan supply is most consistent with fintech lenders becoming financially constrained and losing their ability to fund new loans.

Itzhak Ben-David
The Ohio State University
Fisher College of Business
606A Fisher Hall
Columbus, OH 43210-1144
and NBER
ben-david.1@osu.edu

Mark J. Johnson
Brigham Young University
Department of Finance
Provo, UT 84602
markjjohnson@byu.edu

René M. Stulz
The Ohio State University
Fisher College of Business
806A Fisher Hall
Columbus, OH 43210-1144
and NBER
stulz@cob.osu.edu

1. Introduction

In this paper, we examine how small business fintech lenders were affected by and responded to the COVID-19 shock as it unfolded during March 2020. For this paper, fintech credit is defined as non-deposit takers making unsecured loans online. We use a novel and unique database that tracks the evolution and outcome of all applications for loans from a large fintech credit platform that matches small businesses with online lenders. Our data is unique in that it allows us to study the demand for loans separately from the supply of loans as we observe loan applications, offers made in response to these applications, and loans that were eventually funded. As a result, we can study the evolution of the demand for credit separately from the supply of credit.

The COVID-19 shock was a stress test for the financial system as a whole, but it was also the first time that fintech lenders were confronted with a large economic shock. In practice, this shock led to a sharp contraction in fintech lending to small businesses around the onset of the crisis. Digital lending in the second quarter of 2020 declined by 75% relative to its $16 billion level in the fourth quarter of 2019.[1] Another perspective on the contraction is that, out of 16 small business fintech lenders originating loans before the COVID-19 shock in 2020, only six were still originating loans in the third quarter of 2020.[2] There is no evidence of an equivalent collapse in bank loans to small businesses during the same period. As considerable attention from academics, practitioners, and regulators has focused on fintech in recent years,[3] assessing the circumstances which led to the sharp decline in fintech lending during the COVID-19 crisis is important to understand the strengths and weaknesses of the fintech lending model and the extent to which fintech lending can substitute for bank lending.

[1] According to S&P Global, digital lending in the fourth quarter of 2019 amounted to $16 billion. In the second quarter of 2020, this amount had fallen to $4 billion. See "US digital lender originations expected to rebound strongly after painful 2020," by Nimayi Dixit, S&P Global Market Intelligence, February 4, 2021. René Stulz consults for financial institutions and is retained by their attorneys for expert testimony.

[2] "The seesaw journey of alternative lenders during the COVID-19 pandemic," by Tanvi Anand and Sachin Goel, ABFJournal, January 27, 2021.

[3] For reviews of the literature and surveys of fintech activity see CGFS (2017), IMF (2019), Philippon (2016), Stulz (2019), and Thakor (2019). Claessens, Frost, Turner and Zhu (2018) and Cornelli, Frost, Gambacorta, Rau, Wardrop, and Ziegler (2021) review more directly the state of fintech lending.

Fintech lenders are different from banks on multiple dimensions and these differences can help explain why fintech lenders responded to the crisis differently from banks. First, fintech lending is transactional in nature and does not rely on long-term relationships. Second, fintech lenders do not take deposits and finance their lending through debt (often secured by the loans they make), loan sales (including securitization), or equity. In this respect, banks have an advantage in times of crisis, as they rely on their deposit franchise for most of their funding and typically receive large inflows of deposits during a crisis, so that they can fund credit line drawdowns and new loans (Gatev, Schuermann, and Strahan, 2009). Consequently, fintech lenders are exposed to different dynamics in crises: they are more likely to experience financial constraints and a drop in interest from investors. Furthermore, fintech lenders disburse the loans that they make as cash, meaning that they need to have the cash on hand. In contrast, when banks make loans, they fund a deposit account, so that funds remain with the bank initially. Finally, fintech small business lenders do not normally require collateral but rather request a personal guarantee from the business owner, while banks often rely on physical collateral when making loans (Gopal and Schnabl, 2020; Beaumont, Tang, and Vansteenberhe, 2020).

We begin with studying the demand for loans and document a surge in loan applications by small businesses. For many small businesses, the COVID-19 shock was the equivalent of what the international finance literature calls a sudden stop: Suddenly, revenue fell sharply or stopped entirely (Fahlenbrach, Raggetz, and Stulz, 2021). Yet, small businesses with fixed charges still had to fund these charges, which was problematic as the typical small business had cash on hand to cover only a month or two of expenses (Bartik, Bertrand, Cullen, Glaeser, Luca, and Stanton, 2020). Not surprisingly, many businesses became inactive. Fairlie (2020) shows that the number of active business owners in the U.S. fell by 22% from February to April 2020. As revenue fell, many businesses had to borrow in order to cover running expenses. Compared to the same period in 2019, we find that the number of loan applications on the platform doubled. Loan applicants in March 2020 were of higher credit quality, were larger in terms of sales and employees, and appeared to be in a better position financially at least by historical measures. These facts are consistent with many businesses applying for fintech loans as they needed immediate liquidity or wanted to hoard liquidity in the face of the crisis. Towards the end of March 2020, the demand for loans fell as potential borrowers contemplated the use of the Paycheck Protection Program (PPP) of the CARES Act. The CARES Act was signed into law by President Trump on March 27, 2020.

Next, we turn to studying the supply of fintech credit. In contrast to the demand for loans increasing during the first three weeks of March, the supply fell sharply starting with the second week of March. This drop in the supply was such that a loan applicant with given observable characteristics became much less likely to receive a loan. The observable characteristics are historical characteristics and hence do not account for the impact of COVID-19. A plausible explanation for the decrease in the supply of loans is the direct impact of COVID-19 on the creditworthiness of applicants. We would expect applicants more exposed to the impact of COVID-19 to be less likely to be approved as their actual default probability would be higher than the default probability predicted based on their historical characteristics. We isolate the impact of exposure to COVID-19 of potential borrowers on the supply of loans. Indeed, we find that the supply of loans decreased more for the restaurant industry than for other industries. Also, we show that the supply of loans fell more for borrowers in states that were in lockdown and in states where the proportion of the labor force working from home increased more. However, these effects only explain a small portion of the drop in supply.

To investigate why the supply of fintech credit decreased so much, we turn to how the COVID-19 shock affected the business model of fintechs. First, the crisis affected the funding sources available to fintech lenders and made them financially constrained (the financial constraint channel). Loans on fintech platforms are funded in two different ways: balance sheet funding and loan sales (either directly to investors or through securitization). With balance sheet funding, a lender raises funds through equity and debt issuance that it then uses to fund loans that stay on the balance sheet. With loan sales, a lender funds loans temporarily using its own cash, with the intent to sell the loans to investors directly or securitize the loans, so that the loans do not stay on the balance sheet. Both approaches imply that an unexpected increase in the default risk of existing loans causes a decrease in the supply of loans unless new equity or debt are raised. This is the case for balance sheet lending because the lender has to build a buffer that absorbs the higher expected future losses from existing loans. With loan sales, the demand from investors can dry up during a crisis for many reasons, including that new loans are harder to assess in the midst of a crisis and that potential investors may be financially constrained because of losses in their portfolios. Furthermore, with securitizations, the lender has to keep some risk or has to provide excess collateral. A weakened lender will not be in a position to bear this additional risk without raising additional equity. Lenders could raise more equity to support the greater risk of loans, but such an effort takes time and may be impeded by a debt overhang created by the loss of value of existing loans.

Second, the economic shock could have reduced the loan supply because it made some loans too risky to be profitable (the uncertainty channel). The COVID-19 shock was an unprecedented shock that increased uncertainty about future performance of small businesses as well as about fintechs' ability to assess credit risks. In risk management language, the COVID-19 shock increased model risk. The increased uncertainty about future performance corresponds to an increase in the volatility of future cash flows, which increases the probability of default of loans (Merton, 1974). The ability of lenders to assess risk decreased because of the unprecedented nature of the crisis. Specifically, historical characteristics and performance data of applicants become less instructive about credit risk when the economic environment changes in ways not experienced before. For example, historical data about the borrower's cash flows and profits are not useful when there may be no revenue and no profits for some time because of an unprecedented event. Modern data analytics that rely on past data may not be reliable in predicting default risk in a situation never observed before and, faced with such a lack of reliability, lenders may retrench. As a result, we hypothesize that the increase in uncertainty reduced the supply of loans because the credit risk of existing and potential borrowers increased and became harder to assess.

The financial constraint channel and the uncertainty channel of the impact of the COVID-19 shock have different implications for the evolution of credit supply. A lender who suddenly becomes financially constrained will stop making loans. With an increase in uncertainty, a lender will reduce the risk of the loans it is granting and increase their price. We find that the evidence is more supportive of the financial constraint channel than of the uncertainty channel. Lenders did not increase the price of loans and, conditional on COVID-19 exposure, did not decrease the risk of loans they made. Instead, lenders dropped out during the month. Strikingly, the typical pattern is that a lender kept making loans at the same level as in February until the level of lending suddenly dropped to a trivial amount or zero. Such an evolution seems consistent with what we would expect if lenders became financially constrained.

We would expect that lenders to riskier borrowers would have become financially constrained faster than lenders who made safer loans. Riskier borrowers are closer to default, so that an adverse shock will affect the performance of their loans more quickly and hence weaken the balance sheet of the lenders faster. We find a clear relation between the time a lender dropped out and the risk of the loans made by that lender. Johnson (2021) shows that the fintech lenders have preferred habitats that can be characterized by the FICO scores of the borrowers with whom they transact. We find that the order in which lenders dropped out is inversely related to the median FICO score of their borrowers from the previous year. In other words, with some exceptions, the lenders who made the riskiest loans prior to the crisis dropped out first. Further, we show that more conservative lenders keep making loan offers to applicants that are turned down by riskier lenders, which we view as further evidence that the riskier lenders are financially constrained.

We also provide additional evidence for the role of financial constraints in the drop in the supply of loans by studying publicly-available information about fintech lenders. Unfortunately, almost all fintech lenders in the sample are private companies, meaning that there is little data available for us to explore more directly why they dropped out. Nevertheless, we use public information where some of the firms discuss explicitly dropping out or having a lending pause. More importantly, we show that asset prices tied to marketplace lending collapsed during the month of March. For example, a lender called Kabbage had a securitization issued under Rule 144a. The price of its B-Note dropped from 100 to less than 10 and then bounced back to almost 100. We also show that the stock price of the only U.S. publicly traded fintech lender that specialized in small business loans at the time, On Deck, experienced a sharp stock price drop in March and it did not recover before the lender was acquired by another company. On Deck is one of several small business fintech lenders that did not survive as independent entities following the COVID-19 crisis of March 2020.

Overall, our results indicate that the COVID-19 shock reduced the supply of credit by fintech small business lenders sharply. The decrease in the supply of credit cannot be explained by exposure of potential borrowers to the COVID-19 shock alone. We find that the evidence is consistent with the supply having decreased because lenders became financially constrained. However, it is also plausible that the supply decreased in part because loans became riskier and because of increased model risk for fintech lenders.

Our paper contributes to multiple literatures. First, the paper contributes to the literature on fintech lending to small firms. In this literature, Gopal and Schnabl (2020) show that the increase in lending by finance companies and fintech lenders substituted for a reduction in lending to small businesses by banks after the global financial crisis. Barkley and Schweizer (2020) show that fintech credit has become an important source of loans for small businesses and that it makes loans accessible to businesses that otherwise would not be able to receive bank credit. Berger and Black (2011) argue that large banks make small business lending based on hard information and small banks make loans based on soft information. Balyuk, Berger, and Hackney (2020) argue that fintech lenders make loans using technologies similar to those of large banks. They study small business loans made through the platform Prosper and show that fintech lenders can substitute for lending by large banks, but not for lending by small banks. Beaumont, Tang, and Vansteenberhe (2020) show that fintech lending can help banks obtain bank credit subsequently as it helps firms acquire assets that they can use as collateral for banks loans. Johnson (2021) shows how small business fintech lenders have preferred risk habitats. Cornelli, Frost, Gambacorta, Rau, Wardrop, and Ziegler (2021) find that digital lending by Big Tech firms as opposed to stand-alone fintech lenders has increased rapidly. We add to this literature by showing how fintech lending demand and supply respond to an external shock.

Second, the paper advances our understanding of the contraction of credit during crises. Credit can contract because the demand for loans falls as investment opportunities disappear, because the supply falls as lenders become capital constrained, or because the supply falls as the risk of loans increases. Most recently, Chang, Gomez, and Hong (2020) find that the banks lending to the riskiest firms cut lending the most during the global financial crisis. They show that an increase in the cost of holding loans explains the decrease in aggregate lending during the Great Recession. In our paper, we observe demand and supply separately. We find that both the increase in risk and the increase in holding costs affects the supply of loans for fintech small business lenders.

Third, we contribute to the literature on the impact of the COVID-19 shock. As shown by Bartik et al. (2020), Fairlie (2020), Gourinchas, Kalemli-Ozcan, Penciakova, and Sander (2020), and others, the COVID-19 shock had a dramatic impact on small businesses. This is not surprising as small businesses generally have fragile economic conditions. We show that the decrease in credit supply for the riskiest businesses was dramatic. Though PPP appears to have led some fintech lenders to stop making unsecured loans, PPP provided credit when the supply of credit to the riskiest firms from fintech lenders had essentially dried up. As the literature has shown, fintech lenders became important distributors of PPP loans as they were used to dealing with and were accessible to a clientele that had no banking relationships (Erel and Liebersohn, 2020), but Griffin, Kruger, and Mahajan (2021) present evidence that some fintech lenders had a rate of fraudulent PPP loans.

Though we are not aware of a study of the impact of COVID-19 on small business fintech lending, Bao and Huang (2021) explore the impact of COVID-19 on fintech personal loans in China. They find that fintech lenders expanded lending more than banks, but subsequently they experienced poor loan performance even though historically the loan performance for fintech lenders was similar to the loan performance of banks.

The paper is organized as follows. In Section 2, we describe the fintech small business lending space and introduce the platform through which we obtain our data. In Section 3, we show how the amount of loans made evolves in the first three months of 2019 compared to the first three months of 2020. We document how the demand for loans increases in March 2020 in Section 4. In Section 5, we turn to documenting the evolution of the supply. In Section 6, we explore predictions about the evolution of the supply at the lender level. In Section 7, we provide additional data from lenders with public securities. We conclude in Section 8.

2. Fintech lending and lending platforms

This section describes the fintech lenders in the small business lending space and provides institutional details regarding the platform through which we obtain the data. We begin by defining who the fintech lenders are and how they differ from other lending institutions. We discuss their business models, the competitive advantages that they may hold over banks, and their importance relative to banks and other finance companies. We then describe how the platform operates in connecting these lenders with potential borrowers.

2.1. Fintech Lending

In this paper, fintech lenders are non-deposit taking institutions that make loans online either directly or through an online platform. Instead of relying on deposits to fund loans, they raise capital through private equity, bank credit facilities, securitization, and in some cases public debt and equity markets. The inability to raise cheap funds through federally-insured deposits can be both a blessing and a curse for fintech firms. The funding advantage of banks comes at the cost of tighter regulations imposed in the form of capital requirements, financial reporting and disclosures, as well as other federal or state rules. Banks are also limited by regulatory guidance in their ability to make loans to low FICO borrowers.[4] The lack of regulations may allow fintech lenders to economize on overhead and make lending to risky borrowers less costly. Existing evidence shows that the fact that fintech lenders are subject to less regulation than banks plays an important role in their growth (Buchak, Matvos, Piskorski, and Seru, 2018).

The role of fintech lending as a source of financing for small businesses has increased dramatically over the last decade. Gopal and Schnabl (2020) estimate that the volume in loan originations to small

[4]From the FDIC manual of examination policies: "Subprime lending should only be conducted by institutions that have a clear understanding of the business and its inherent risks, and have determined these risks to be acceptable and controllable given the institution's staff, financial condition, size, and level of capital support. In addition, subprime lending should only be conducted within a comprehensive lending program that employs strong risk management practices to identify, measure, monitor, and control the elevated risks that are inherent in this activity. Finally, subprime lenders should retain additional capital support consistent with the volume and nature of the additional risks assumed. If the risks associated with this activity are not properly controlled, subprime lending may be considered an unsafe and unsound banking practice." See https://www.fdic.gov/regulations/safety/manual/section3-2.pdf, 3.2.-77.

businesses from banks and non-fintech finance companies was roughly $243 billion in 2016. Assuming similar magnitudes in 2019, fintech loan originations of $13 billion comprise 5% of loans in volume.[5] However, this underestimates the potential impact of fintech lending as the average dollar size of fintech loans is substantially smaller than those made by banks and finance companies.[6] In other words, while total lending volume may be relatively small, the number of businesses using fintech loans is large. A recent survey by the Federal Reserve found that 1 in 5 businesses have used an online lender in the last 5 years which amounts to millions of loans. Importantly, evidence suggests that these loans are typically being used by businesses that have the most difficulty obtaining finance elsewhere.[7]

The legal structure through which these lenders originate loans typically follows one of two models. The first is to obtain licenses from each state as a non-depository financial institution and make loans directly to businesses. The second approach is to partner with an industrial bank that has a national charter to lend across the country.[8] In these partnerships, the fintech lender screens the applicant and the partner bank originates the loan. The loan is subsequently purchased from the bank by the fintech lender. The advantage of this origination model is the simplification in lending across states. Any usury laws or other state level lending requirements are exported from the state where the industrial bank is chartered.[9]

The business model of fintech lenders is similar to that of a bank in that profits come from the spread between the cost of funds and the interest and fees paid by borrowers net of losses. However, fintech lenders differ from banks in how they fund the loans they make as they have no deposit funding. Lenders typically hold the loans they originate on their balance sheet, but in some cases sell some of these loans to investors.[10] In recent years before the COVID-19 shock, as discussed more later, an increasing number of securitizations

[5] The S&P Global Market Intelligence US Fintech Market Report 2021 estimates that SME focused fintech originations totaled roughly $13 billion.
[6] See, for instance, https://www.valuepenguin.com/average-small-business-loan-amount.
[7] See for example Barkley and Schweitzer (2020) as well as statistics released by the Federal Reserve in the Small Business Credit Survey (2020).
[8] Industrial banks are also known as Industrial Loan Corporations or ILC's (see Barth and Sun, 2018).
[9] For example On Deck capital makes loans in partnership with Celtic Bank, an ILC chartered in Utah. Loans made through Celtic Bank to an individual in Texas are not required to be capped by the usury laws in Texas. See https://www.wsj.com/articles/fintech-firms-look-to-enter-banking-via-century-old-tactic-1518085801.
[10] Mills (2020) provides greater detail about the business models and identifies the differences in business models among small business fintech lenders.

were completed that allowed lenders to move assets off their balance sheets and secure additional funds. In troubled times, banks often see large inflows of deposits that increase their ability to fund loans (see Gatev, Schuermann, and Strahan, 2009). Fintech lenders do not fund loans through deposits. Instead of seeing an inflow of deposits in a crisis, they are more likely to be confronted by an investor strike as investors sit out the crisis because of excessive uncertainty or financial constraints. In addition, a bank that has excess capital can easily make a loan by granting the loan. As the loan is made, the money finds its place initially in a deposit account and hence does not leave the bank. Over time, the loan has to be funded. With fintech credit, the lender has to provide all the cash it lends when it agrees to a loan and hence has to have it on hand when it makes the loan.

Much of the research on fintech credit focuses on lenders and platforms that cater to consumers. However, as discussed later, some of the literature also addresses the provision of credit to small firms. The existing literature on fintech small firm credit shows that the provision of credit by fintech firms involves transactional loans often facilitated by big data analytics (see Mills, 2019). Borrowers have no relationships with these transactional lenders and these lenders do not offer products other than loans that could enable them to develop a relationship with borrowers or garner information from borrowers.

Similar to banks, fintech lenders offer a variety of loan products including merchant cash advances, lines of credit, term loans, and business credit cards. Merchant cash advances, sometimes referred to as short-term loans, are those made based on the frequency and timing of the borrower's cash flows. Equal payments are typically drawn from the borrower's bank account at a daily or weekly frequency. Lines of credit from these lenders allow borrowers to draw down credit up to some limit and are similar to merchant cash advances in the frequency of payments after a draw. Term loans are typically longer maturity loans with less frequent payments and lower interest rates resembling a more traditional bank loan. However, unlike banks or finance companies, all of these loan products are almost exclusively unsecured, but they typically have a personal guarantee from the business owner.[11] Business owners waive the limited liability

[11] Gopal and Schnabl (2020) note the key differences between finance companies and fintech with the primary difference being the collateral that is pledged.

of the company through a personal guarantee which allows the lender to seek recourse through collection agencies, court proceedings, or by placing liens on business or personal assets.

Fintech lenders have differentiated themselves by speeding up and simplifying the application and funding processes. The most often cited challenges that small businesses face working with traditional banks are the long wait times and the difficult application process.[12] Fintech lenders have a greatly simplified application process, condensing application times down to minutes instead of hours or days. Many lenders boast the ability to make decisions within minutes and for funds to hit the owner's bank account within 24 hours. The speed, convenience, and probability of receiving funding are the primary reasons that firms apply to online lenders relative to banks.[13]

2.2. The role of marketplace platforms

Marketplace platforms are fintech firms that connect potential borrowers with lenders. Two basic models of marketplace platform lending exist for consumers and businesses. The first is often referred to as peer-to-peer lending (or P2P platforms). These platforms accept applications for financing, evaluate and price risk, and then invite retail or institutional investors to fund the loans at the prices set by the platform. The peer-to-peer name has become somewhat a misnomer in the U.S. as institutional investors have become the primary investors and retail or peer investors have been pushed out. Before the COVID-19 crisis, the largest and most well-known P2P platforms in the U.S. were LendingClub and Prosper, both of which focused primarily on consumer loans with a small number of business loans.[14] In 2020, LendingClub changed its business model and became a bank.

The second model of marketplace lending centralizes the application process to reduce search costs for both lenders and borrowers. These marketplaces make no attempt to price risk, but instead disseminate applications to multiple lenders and assist the borrower in finding the best offer. The largest and most well-

[12] https://www.fedsmallbusiness.org/medialibrary/FedSmallBusiness/files/2020/2020-sbcs-employer-firms-report.

[13] Firms that applied to online lenders were nearly twice as likely to report that contributing factors for applying were the speed and probability of being funded relative to those that applied to banks. https://www.fedsmallbusiness.org/medialibrary/FedSmallBusiness/files/2020/2020-sbcs-employer-firms-report.

[14] Balyuk, Berger, and Hackney (2020) study small business loans made through Prosper.

known marketplace platforms of this type are LendingTree, Fundera, and Lendio with the latter two focusing solely on small business lending. The data used in this paper come from a platform using this second model of marketplace lending and it will be referred to through the remainder of the paper as "the platform."

The process from application to obtaining a loan through one of these platforms is relatively simple. Small business owners apply through the platform website by answering questions about the business, stating the amount of money they are seeking, and uploading documents to verify certain aspects of the application. For example, a driver's license may be uploaded to verify the identity of the owner or images of bank statements may be required to examine the cash flows of the business. After submitting the application, the platform forwards the information to multiple lenders and requests offers.

The platform has relationships with dozens of lenders, but typically an application is forwarded to only a handful of lenders. The reason for this is that many lenders request that the platform send to them only applications with certain attributes. For example, many lenders have hard cutoffs related to firm age, owner credit score, annual revenues, or industries (Johnson, 2021). The platform also uses its own data analysts in deciding where to send applications based on the likelihood of acceptance and the financing needs of the borrower.

In a matter of hours or days, applicants may receive offers from one or multiple lenders. On average, about 20% of applicants are approved by at least one lender, so about 80% of applicants do not receive any offers.[15] Applicants who receive offers are assisted by the platform's loan agents in understanding the loan terms for each offer. Each offer includes the cost of the loan, maturity, offer amount, payment amount, payment frequency, and loan type. If the applicant selects an offer, the lending firm sends loan documents to the agent for the applicant to sign and typically within 1-3 days the funds arrive at the borrower's bank account via direct payment. The platform receives commissions from each lender set as a percentage of the loan amount for a completed transaction.

[15] Note that we include all applications in this calculation, even those where the applicant did not respond to requests for further information because they were incomplete.

3. The COVID-19 shock and platform lending volume

Before investigating the loan demand and the loan supply separately, we present statistics about the lending volume on the platform both before March 2020 and during March 2020. We first report the five previous business days moving average (five business day moving average) for the three months ending in March 2019 and March 2020.

Figure 1, Panel (a), shows five business day moving averages for the number of loans from January to March 2019 and 2020. The number of loans in 2020 exceeds the number of loans in 2019 until the middle of March. The number of loans in 2020 increases in March before falling precipitously almost to zero. Though the number of loans becomes trivially small in April once PPP is in effect, the number of loans falls sharply before PPP is proposed and almost all of the fall takes place before the stimulus package is approved by Congress. Figure 1, Panel (b), shows similar results for the amount of loans funded. Again, the amount funded plummets and becomes a fraction of what it was in 2019.

In the remainder of the paper, we focus on explaining the evolution of the supply and the demand for loans to understand why the number of loans funded fell so dramatically. A drop in the number of loans could result from a drop in demand or a drop in supply. With our data, we can examine the evolution of the demand for loans separately from the supply for loans.

4. COVID and the demand for fintech small business loans

In this section, we first describe the applicants for loans on the platform. We use data from March 2019 so that we can compare how the characteristics of applicants changes in March 2020. We then show how the number of applications changes from March 2019 to March 2020. We finally turn to an examination of the evolution of applications within March 2020.

Table 1 shows the characteristics of loan applicants. Panel A compares the characteristics of applicants in March 2019 to those of applicants in March 2020. We call these characteristics "historical characteristics" as they are measured before the application date. Because the loans are personally guaranteed, the applicant's FICO score is a key metric used to evaluate creditworthiness. The average FICO score in March 2019 is 648. This average score reflects, depending on the classification chosen, a subprime score or a near-prime credit score.[16] Applying small businesses on average have annual sales of $616,866 and are 38 months old. The average number of employees for applicants is 6.4. The average bank balance is $18,203. Very few applicants appear to have a seasonal business.

The application pool in March 2020 is twice as large as in March 2019, and firm applicants are more established, larger, and with better FICO score than applicants a year earlier. Average sales are 45% higher. The average age of the business of the applicants is 23% higher. While the average applicant in 2019 was a near-prime or subprime applicant, the average applicant in 2020 is a prime applicant with a FICO score of 668. Bank balances are 43% higher. In sum, the applicants are overall more creditworthy based on the attributes reported in the table.

As the crisis worsens during March 2020, the volume of applications increases and their credit quality as measured by historical characteristics improves. Panel B of Table 1 compares applicant characteristics for the first half of March to the second half of March. The number of applicants in the second half of March is higher than in the first half of March by 56.6%. Surprisingly, the creditworthiness of the applicants based on historical characteristics is higher on average in the second half of March than in the first half. Average sales and bank balances are significantly higher in the second half of March than in the first half.

The data in Table 1 suggests that the decline in lending is unlikely to be due to a drop in demand. To understand better the evolution of demand, we show in Figure 2 plots for the daily number of applicants and the daily total amount of financing sought for March 2019 and March 2020. In each plot, we show the amounts for 2019 and for 2020. In Panel (a), we see that the number of applicants is higher throughout March 2020 than in March 2019. After March 9, 2020, the number of applicants increases sharply and

[16] There is no consensus definition of the FICO score below which a borrower is considered a subprime borrower. On its website, the credit reporting company Experian classifies a borrower with a FICO score below 660 as a subprime borrower. The FDIC examination manual also treats a FICO score below 660 as evidence that the borrower is subprime (see https://www.fdic.gov/regulations/safety/manual/section3-2.pdf, 3.2.-78). The Consumer Financial Protection Bureau classifies a FICO score of 648 as a near-prime credit score (https://www.consumerfinance.gov/data-research/consumer-credit-trends/student-loans/borrower-risk-profiles/).

almost doubles over one week. The number of applicants subsequently decreases, but it is higher on every day of the month in 2020 than it was in 2019. The evolution of the total amount of financing sought shown in Panel (b) is similar.

Figure 1 suggests that the demand for fintech loans drops as aid to small businesses through a stimulus package becomes more likely. The White House first proposed $500 billion worth of aid to small businesses on March 17, which corresponds to a sharp drop in the demand for loans.[17] On March 20, the senate rejected the stimulus program, which is followed by an increase in the demand for loans. The demand for loans falls after it becomes certain that the stimulus package will become law on March 23. However, despite the prospect of the stimulus program, the number of applicants stays higher than in 2019.

The historical credit quality of applicants at the onset of the COVID-19 crisis may not be a good predictor of loan performance because it does not reflect the anticipated impact of the COVID-19 shock on the business. For instance, a borrower who owns a restaurant could appear creditworthy based on information available when the loan application is made, but this restaurant owner may be expecting to have to close the restaurant the next day. Hence, even though demand increases and the creditworthiness of borrowers increases based on the historical characteristics we observe, it is important to investigate how the applicants are affected by the COVID-19 shock based on their industry and location. In the remainder of this section, we explore the evolution of the demand in greater detail.

To understand better the sources of the heightened demand in 2020 relative to March 2019, we normalize the March 2020 daily demand by the average daily demand for March 2019. For instance, if we look at the demand for loans from restaurants on March 12, 2020, we divide that demand by the average daily demand for loans from restaurants in March 2019. We interpret the normalized demand as abnormal demand. We report in Panel (a) of Figure 3 the abnormal demand across firm size. We see that the highest abnormal demand is for small businesses with 25 employees or more.

[17] Wall Street Journal and Washington Post articles on March 17, 2020 detail the White House's $1 trillion proposal including $500 billion to small businesses. See https://www.wsj.com/articles/trump-administration-seeking-850-billion-stimulus-package-11584448802, and https://www.washingtonpost.com/us-policy/2020/03/17/trump-coronavirus-stimulus-package/.

In Panel (b) of Figure 3, we show the demand by state restrictiveness. We consider a state to be restrictive if it has announced a lockdown by March 23. We see that in most days there is no difference between restrictive states and other states. The exceptions are on the days when the demand appears to spike. On these days, the demand spike seems to be driven by the restrictive states. This evidence does not necessarily mean that a lockdown causes an increase in demand as the lockdown may simply be the result of a high impact of the virus on the respective state and this high impact could have the same effect on loan demand absent a lockdown. However, this evidence shows that on a few days the demand is higher for states that are more restricted and, on most days, there is no difference in demand between states that have early lockdowns and other states.

Lastly, in Panel (c) of Figure 3, we show abnormal demand by industry. The figure shows that demand moves in tandem across industries. In particular, during the time that demand is particularly elevated, abnormal demand is elevated across all industries. There is no evidence of a demand shift towards the industries most vulnerable to the COVID-19 shock. Oddly, the finance industry seems to experience the highest abnormal demand. However, the economic relevance of this finding is questionable because the demand for loans from the finance industry is extremely small. During the period of peak demand, the restaurant and construction industries have the highest demand, but they also have the highest demand before the period of peak demand. The figure shows data for ten industries including the "Other" category. The "Other" category includes those businesses that classify themselves as "other services", or those that are not covered by the other 19 2-digit NAICS classifications.

We now turn to a more formal analysis. We first assess whether the demand is abnormally high during some portion of March 2020. We show the results in Table 2. For our analysis, we proceed as follows. We regress the daily number of applicants on indicator variables for each week. We only report the coefficients on the indicator variables for the weeks of March 2020 in Column (1), but our sample period is January, February, and March 2020. The omitted week is the first week of the year. We see that the daily demand is higher in the week of March 11-17 by 540 applications and the week following sees a similar daily increase of 400 applications. In Column (2), we estimate the same model for 2019. Not surprisingly, none of the weeks during that month experience a significantly different level of demand. Lastly, in Column (3), we estimate the regression for 2019 and 2020. We add an indicator variable for 2020. We find the same result as in Column (1), namely that the demand for the weeks of March 11-17 and March 18-24 is significantly higher than in the omitted week, but the demand for the first and last weeks of March is not. The other coefficients are not significant. It is noteworthy that the week indicator variables explain little of the daily variation in demand in 2019, but they explain much more of the daily variation in 2020.

5. Aggregate supply of loans made by fintech lenders

Next, we investigate the evolution of the supply of loans. We focus on loan offers that lenders make in response to applications, rather than on actual loans made. The reason is that the number of loan offers measures the supply of loans, whereas the number of loans made measures the intersection of the demand and supply curve of loans. Before receiving an offer, applicants do not know the terms on which they can borrow; after receiving the offer, applicants often reject the offer. Presumably, some of these rejections are because the applicants expected better terms. As a result, the supply of loans is quite distinct from the number of loans made.

Figure 4, Panel (a), shows the evolution of the number of loan offers for March 2019 and 2020. Panel (a) conveys a clear message: the number of loan offers is high until mid-March and then it collapses. The drop in offers is striking. The number of offers reaches a peak of slightly more than 500 offers on March 15, but it then plummets to less than 100 in the last days of the month. We saw in Section 4 that the number of applications changes during March. We therefore show in Panel (b) the number of offers per applicant. We find a dramatic drop as well. Consequently, the supply falls in aggregate—i.e., number of offers—but also falls as a fraction of applications.

We now turn to a more formal analysis of the evolution of loan offers. In Table 3, we show estimates of a regression similar to the one presented in Table 2 but for loan supply instead of loan demand. In Table 3, the dependent variable is an indicator variable that takes a value of one if an applicant receives an offer. The variables of interest are indicator variables for the different weeks in March 2019 and March 2020.

Table 3 shows that the supply falls in the second week of March 2020 and decreases steadily through the rest of the month. In the last week, the supply is 10 percentage points lower than at the beginning of March. At the beginning of March, the unconditional probability of acceptance is 20% meaning that by the end of the month the unconditional probability of acceptance is 10%. In Column (2), we re-estimate the regression with applicant controls (FICO, size of business, and age of business). We see the same steady decrease in supply, but it is larger in absolute value. The explanation for the difference between Columns (1) and (2) is that the creditworthiness of applicants increases in March, so that the acceptance rate is higher unconditionally than when controlling for the creditworthiness of the applicant. The next two columns repeat the regressions of Columns (1) and (2) but use the sample period from January to March. The same results hold except that the last week of March is not worse than the third week of March. The supply of the third week of March is lower by 14.5% from the first week of January, which means that an applicant is 14.5 percentage points less likely to receive an offer. By the second week of March, supply is already down by 9.8 percentage points. Column (5) shows the regression estimated for January to March 2019 and no indicator variable for March has a significant coefficient. Finally, Column (6) uses the sample of January to March 2019 and 2020. The regression includes week indicator variables, an indicator variable for 2020, applicant controls, and industry fixed effects. In the third week of March, applicants are 15.4 percentage points less likely to receive an offer relative to applicants with similar characteristics prior to the onset of the pandemic.

A possible explanation for the decrease in supply is that supply falls because the COVID-19 shock makes applicants riskier in a way that is not captured by the applicant characteristics for which we control. For instance, an applicant could own a restaurant and the restaurant is losing customers rapidly and may have to close as customers become worried about COVID-19 spread. The lenders may be informed of these current circumstances, but the applicant characteristics we control for would not reflect this risk or would reflect it poorly.

In Table 4 we propose a simple way to examine the possibility that the supply is impacted by the increasing risk of applicants. The table shows regression results of our indicator variable for whether an applicant receives an offer on indicator variables for the industry, controls, an indicator variable for the period starting on March 12, 2020, which is when the World Health Organization (WHO) declared a pandemic emergency, and an interaction of the industry indicator variable with the post-March 12 indicator variable. Our industries are North American Industry Classification System (NAICS) sectors that match to the industries surveyed in the Census Pulse Business Survey. We report the results in Table 4. The results are very similar whether we estimate the regression on data from March 2020, January-March 2020, or January-March 2019 and 2020. The variable of interest is the interaction of the industry and of the post-March 12 indicator. The restaurant industry is the only industry with a significantly negative interaction irrespective of the sample period. It is also the industry in the initial Census Pulse Business Survey from April 26-May 2, 2020 that reports the largest fraction of businesses saying that they are strongly negatively affected by COVID-19. When we use the longest sample period, the interaction has a coefficient of -0.099, so that supply to the restaurant industry is abnormally low by 9.9 percentage points compared to other industries. Three industries have a positive coefficient on the interaction with the longest sample period. These industries are arts and entertainment, education, and wholesale. The coefficient for arts and entertainment is especially puzzling since, in the initial Pulse Survey, this industry is second only to restaurants for the fraction of businesses saying that they were strongly negatively affected by COVID-19.

An alternative approach to estimate the impact of COVID-19 risk on the supply of loans is to investigate whether COVID-19 developments at the state level affect the supply of loans. We estimate regressions where the dependent variable is the indicator variable for whether an applicant receives an offer. We use a difference-in-differences framework where the treatment effect is the imposition of a state lock-down. We also use the percentage of the population staying at home as the treatment. The data is obtained from SafeGraph which uses cell phone data to track mobility. For the U.S. as a whole, the percentage staying home reported by SafeGraph evolves from 23.8% on March 1 to 39.9% on March 31. We report the estimates in Table 5. In the first three columns, we estimate the regression for March and have no controls. In Column (1), we have an indicator variable for whether a state is in lockdown. The coefficient on the indicator variable for whether a state is in lockdown is insignificant both statistically and economically. In Column (2), we have a variable corresponding to the percent of the population working from home at the county level. The coefficient on percent of the population working from home is significant and positive, so that it would appear that the loan supply expanded in areas where more individuals were working from home. Lastly, in Column (3), we use a seven-day average for the percentage of the population working from home. This coefficient is significant and positive as well. In the next three columns, we add applicant controls, county fixed effects, and industry fixed effects. Now, the indicator variable for whether a state has a lockdown is significantly negative in Column (4), but the economic magnitude of the coefficient is small as it corresponds to a decrease in the probability of an offer of 1.5%. The coefficient on the population working from home is significantly negative in Columns (5) and (6). An increase in the percentage staying at home of 16.1 percentage points, which is the increase for the U.S. during March, reduces the likelihood of an offer by 4.67 percentage points using the coefficient in Column (5) and by 7.89 percentage points using the coefficient in Column (6). Lastly, in Columns (7) to (9), we re-estimate the regressions of Columns (4) to (6), but include January-March 2019 in the sample. The results are similar.

We have seen that the supply falls sharply. The drop is significant in the restaurant industry and in the counties where the percentage of the population staying at home increases sharply. The overall impact of lockdowns seems rather limited. When we re-estimate the regressions of Table 3 with the addition of the lockdown and working from home variables (untabulated), the weekly indicator variables exhibit little change, so that our COVID-19 exposure variables do not by themselves explain the drop in supply.

We now explore the other dimension of supply, which is the terms of loans. Applicants could receive an offer, but the rate might be higher than they anticipated, which could reduce the take-up rate of offers. We report the results in Table 6. In Panel A of Table 6, we estimate regressions for offer terms similar to the regressions for the supply of loans of Table 3. We regress offer terms on an indicator for the week of the offer, the applicant's FICO, age of the business, log sales of the business, industry fixed effects, and lender fixed effects. We also estimate the regressions without lender fixed effects and the overall conclusions are similar. Columns (1) and (2) show results when the dependent variable is the Annual

Percentage Rate (APR). In Column (1), the week indicators are never significant. Since that regression only uses data from March 2020, the interpretation is that the APR does not change within March. As expected, the APR falls as FICO increases, as the age of the business increases, and as sales increase. In Column (2), we use data from January to March 2020. We find that APR is significantly lower in the first two weeks of March relative to the omitted week, which is the first week of January. In Columns (3) and (4), the dependent variable is the maturity of loans. None of the week indicator variables are significant. Finally, in Columns (5) and (6), the dependent variable is the loan amount. As expected, the maturity and size of the loan increase with FICO, age of the business, and log sales. Column (5) shows that the loan amount falls during the month. In Column (6), the loan amount is lower the last week only. In summary, there is no evidence that interest rates increase or that the maturity falls, as one would expect with tighter credit conditions, but there is some evidence that loan amounts fall.

In Panel B, we regress each offer's Annual Percentage Rate (APR) on the applicant's FICO, age of the business, log sales of the business, and the COVID-19 exposure variables used in Table 5. We use in Column (1) an indicator variable for whether the state is in lockdown. The coefficient on whether the state is in lockdown is not significant. In Column (2), we include in the regression the percentage of the population staying at home. Again, this variable does not have a significant coefficient. The 7-day average of that variable does not have a significant coefficient in Column (3). We explore next in the table whether the maturity is lowered or the loan amount is lowered as the applicant comes from a county more affected by COVID-19. We find no evidence of an impact of COVID-19 on the maturity of the loan offered or on the amount of the loan offered.

We analyze whether the exposure of the industry of a business to COVID-19 affects the terms of the loan in Panel C. Our variables that proxy for COVID-19 exposure are an indicator variable for the period of March after the WHO declares a pandemic emergency and an indicator variable for high exposure industries. High exposure industries are identified using the Small Business Pulse Survey which asked "overall how has the COVID-19 pandemic affected your business?" in the initial survey from April 26-

May 2, 2020.[18] To determine exposure we assign industries that are above the median in responding that they experienced a "large negative impact".[19] We then interact these two variables. We find that the indicator variable for the period after the declaration of emergency is insignificant for APR and maturity. It has a negative significant coefficient in one of the regressions for loan amount. The interaction between the temporal indicator variable and the exposure indicator variable is not significant for APR and maturity, but it is positive and significant for loan amount.

The conclusion of this section is that the supply of loans falls sharply. However, loans do not become more expensive. The effect of lockdowns on the supply of credit are weak. The effect of the percentage of the population staying at home is stronger and so is the effect for the restaurant industry. Hence, COVID-19 exposure does appear to explain part of the drop in the supply. In the next section, we analyze the potential channels that caused the dry up in supply.

6. Why did the supply fall?

We saw earlier that during the second and third weeks of March 2020, the demand for loans increases sharply. At the same time, the supply falls. As a result, the number of offers per loan application decreases keeping constant the borrower historical characteristics for which we control. Despite this decrease in the number of offers and despite the increase in demand, loan interest rates do not appear to increase.

In this section, we consider possible explanations for this pattern. In the first part of the section, we explore the economics of fintech lenders to show how the COVID-19 shock affected fintech lenders' supply of loans through a financial constraint channel and an uncertainty channel. In the second part of the section, we provide evidence showing that fintech lenders dropped from the platform. Lastly, we attempt to

[18] See https://portal.census.gov/pulse/data/.

[19] The responses are averaged first at the state and the two-digit NAICS sector. We then take the average across states and assign industries above median to be "high exposure" industries. These industries are (1) Accommodation and Food Services, (2) Arts, Entertainment, and Recreation, (3) Educational Services, (4) Health Care and Social Assistance, (5) Other Services, (6) Mining, Quarrying, and Oil and Gas Extraction, (6) Transportation and Warehousing, (7) Real Estate and Rental and Leasing, and (8) Information.

disentangle whether lender supply cuts are more directly explained by the financial constraint channel or the uncertainty channel.

6.1. The economics of fintech small business lenders

The mode of operation of fintech lenders is fundamentally different from that of banks. Banks mostly fund loans through deposits. Their loans are not marked to market. In crises, their deposits increase sharply as their customers seek safety. It follows that during crises banks have liquidity to make loans as long as they are sufficiently well capitalized. The fintech lenders considered in this paper are mostly non-banks. These non-banks fund new loans relying on equity, debt facilities (e.g., lines of credit), and loan sales (including securitization). We first discuss the behavior of an all-equity fintech lender and then discuss the behavior of a lender relying on debt funding.

Consider a fintech lender with a balance sheet that has loans and cash on the asset side and equity on the liability side. Suppose that the fintech lender has access to frictionless financial markets where it can invest its cash and that its lending is purely transactional so that not making loans has no reputation or franchise costs. A shock like COVID-19 reduces the value of its existing loans as borrowers suddenly become more risky. The fintech lender therefore makes a loss and its equity falls. However, the demand for loans increases. With its cash and with loan repayments, the lender has resources to make more loans. It will lend if it finds loans that have a positive NPV. As a result of the increase in demand, it can make loans at a higher interest rate. It will decrease its holdings of cash and will attempt to raise equity to lend more if the demand is high enough.

For a given level of borrower risk and loan attributes, we would expect the demand for loans to decrease as the lending interest rate increases. We would also expect the supply of loans to increase as the lending rate increases and to be zero below the rate that makes the NPV of the loans equal to zero. A demand increase in this setting would lead to an increase in the quantity of loans and an increase in the loan rate.

We observe a demand increase in the data, but see no evidence of an increase in rates. This result may not be as counterintuitive as it initially seems given the nature of the COVID-19 shock because applicants who would be willing to pay the higher rates may be too risky. With the COVID-19 shock in March 2020, potential borrowers face an interruption in revenue that is potentially long lasting. This means that the probability of default on loans could be much larger than predicted for a loan to the same borrowers before the COVID-19 shock. There may be no rate that makes the loans positive NPV projects. Hence, even an all-equity lender may choose not to make loans simply because there is too much default risk. This risk will not be captured by observable characteristics that are even a few weeks old, so that the decision of not making a loan will be driven by risks that we cannot observe from applicant historical characteristics. Note that this increase in the probability of default will be much more consequential for riskier borrowers who cannot offer collateral. Such borrowers seem precisely to be the borrowers that use the platform.

A simple example helps make clear why a borrower willing to pay a higher rate may not get a loan. Suppose a small business wants to borrow $20,000 to buy a machine that will produce goods worth $30,000. As long as the interest paid is less than $10,000 the small business makes a profit if the goods can be sold. However, consider now the case where there is 50% chance the goods cannot be sold because of COVID-19 and a 50% chance they can be sold for their value. In this case, the project is a negative NPV project for the business if it finances the machine out of equity. However, with a loan that has 40% interest, the project is worthwhile for the business but not for the lender. The business expects to earn $1,000. The lender is making a loan of $20,000 where the expected repayment is $15,000. There is no interest rate for which a loan is a positive NPV project for the lender.

Suppose now that the lender receives a mix of applicants. Some applicants are unaffected by COVID-19. Absent an impact on loan rates from macroeconomic conditions, these applicants would pay the same rate as before. Other applicants are affected by direct exposure to COVID-19. They have higher risk but also a higher demand for loans. If the risk of these applicants is perceived to be high enough by lenders, these applicants are simply rejected. Hence, with this scenario, we would expect demand to increase from the riskiest borrowers, but these borrowers would not receive loans. The borrowers who receive loans would not be riskier and their rates would stay the same. The greater risk of borrowers explains the drop in supply. However, the greater risk of borrowers is magnified by the fact that credit models were not built using data from an event like the COVID-19 shock, so the reliability of these models becomes questionable when such a shock occurs. We call the uncertainty channel the impact of the COVID-19 shock on the supply of loans through its effect on the risk of borrowers and the model risk of lenders.

Next, consider a fintech lender that funds loans with a debt facility. This lender has debt liabilities. With the COVID-19 shock, the value of its loans on its balance sheet falls. It therefore becomes more highly levered. If the institutions funding the lender require mark-to-market leverage, the lender may not be able to make new loans unless it raises more equity. At that point, the lender has a debt overhang (Myers, 1977). Raising equity would enable the lender to make more loans, but it would also make its debt more secure and hence could mostly benefit debtholders. For a levered firm in this situation, no new loans may be positive NPV projects even if some new loans would be positive NPV projects if it were an all-equity firm. Alternatively, the institutions funding the lender might require the weekly delinquency rate to be above a threshold. A surge in delinquencies would then make the lender unable to fund new loans. If the lender uses securitization, it may no longer be able to sell loans to the securitization trust because of the decline in the quality of the existing loans. This puts the lender in a position where it has to raise alternative sources of funding to make new loans. Such funding may be too expensive to make loans positive NPV projects or may simply not be available in the short run. As a result, the lender cannot lend because it is financially constrained. We call the impact of the COVID-19 shock on the supply of loans due to funding difficulties of lenders the financial constraint channel.

A complicating factor in this analysis is that eventually the CARES Act was signed into law by President Trump and PPP was implemented. As the adoption of the CARES Act became highly likely, the lenders could expect the demand for their loans to fall as potential borrowers would anticipate switching to PPP loans. They could also see that lending through the PPP program would be more profitable for them than to keep making the loans they were making as these loans would mostly disappear for a while. However, lending through the PPP program would require reconfiguring their systems and hence might require them to stop lending to do so. It was not entirely clear prior to the disbursal of PPP funds whether these lenders would be included as certified distributors and many were not cleared to do so until after banks had already begun to fulfill the demand.[20] In the last week of March, we would expect lenders to drop out as they anticipate being involved in PPP.

6.2. How did the supply fall?

The supply of loans could fall because lenders gradually reject more applications. With the uncertainty channel, we expect fewer loans to be made as more applicants are rejected, so that progressively a lender makes fewer and fewer loans. With the financial constraint channel, we expect a lender to stop lending when it becomes constrained. We find that lenders did not progressively reduce their lending as predicted by the uncertainty hypothesis but instead they dropped out suddenly during the month. A lender has a fairly steady acceptance rate, but suddenly that acceptance rate goes to almost zero or zero. Panel (a) of Figure 5 gives an example of a fairly typical evolution. After the collapse in the acceptance rate, the number of applications went to zero because the platform was no longer sending applications to this particular lender as the lender had dropped out. Panel b of Figure 5 shows the decrease in the number of active lenders. The decrease is steady through the last three weeks of March. This evidence is supportive of the role of the financial constraint channel.

Another way to look at the decrease in the number of lenders is to consider the timeline of lenders dropping out when we define dropping out as making no loans:

1) March 17, one lender,
2) March 19, four lenders,
3) March 20, one lender,
4) March 21, one lender,
5) March 23, one lender,
6) March 25, two lenders,

[20] Kabbage was the first fintech lender to be approved for PPP lending and this occurred on April 7, 2020—Four days after the first loans were made by banks. See https://newsroom.kabbage.com/news/kabbage-partners-with-sba-authorized-bank-to-deliver-paycheck-protection-program-loans-to-small-businesses/.

7) March 24, three lenders.

We have focused on a specific definition of lenders dropping out, namely the lender makes zero loans going forward. An alternative approach is to focus on lenders making almost no offers. When we use that measure, lenders generally dropped out almost a week earlier.

We would expect lenders making riskier loans to experience a greater weakening of their balance sheet and to be financial constrained faster than other lenders. Johnson (2021) shows that lenders have preferred habitats with respect to FICO scores. We define a lender's habitat in this paper using the median FICO score on loans that were transacted in 2019. In Figure 6, we show how lenders exit in relation to their FICO scores. The horizontal axis has time and the vertical axis has the lender's median FICO score on loans transacted in the previous year. The figure shows that lenders with higher median FICO scores, who are safer lenders, drop out later. Given the small number of observations, a more formal analysis is problematic. Nevertheless, when we consider only the month of March, there is a significant relation between the time that a lender dropped out and the median FICO score of that lender. However, three lenders with a low median FICO score did not drop out in March. If we extend the analysis to April, the significant relation does not hold because of these three lenders.

Our evidence is that supply dropped because lenders dropped out. It does not appear that their offer rate slowly fell, so that they eventually ended with no offers. Instead, it seems that it was almost business as usual until fairly close to their exit. Such a pattern is hard to reconcile with the view that lenders exited because it became harder for lenders to find acceptable borrowers because of an increase in risk. It is a pattern that one would expect with the financial constraint channel. However, we cannot exclude the possibility that lenders concluded that uncertainty was too high to make loans and hence shut down their lending. In particular, they could have concluded that their lending models were no longer capturing risk adequately, so that they stopped lending because they found that the loans they accepted were too risky for reasons not captured by their models. While both of these explanations likely played a role in lender supply cuts as we discuss further in Section 7, we first test whether potentially profitable loan opportunities were passed up by the lenders most likely to have experienced a shortfall in funding. Such evidence would be supportive of the role of the financial constraint channel.

6.3 Did riskier lenders pass up viable lending opportunities?

The two possible channels for lender supply cuts have different predictions on the way that lenders respond to credit solicitations from a particular applicant. If supply falls because lenders perceive risk as being too high or that their current models do not accurately capture risk in the new environment, the likelihood that an applicant receives an offer from any lender would fall and might reasonably decline more from lenders that were previously more conservative in extending credit. Lenders willing to accept more risk in normal times might see this as an opportunity to make loans that other lenders would pass up due to conservative lending practices. On the other hand, if financial constraints are the primary source for lender supply cuts then we would anticipate that lenders most susceptible to funding shortfalls would be the first to forego potentially profitable lending opportunities. These lenders are likely those that, prior to the pandemic, engaged in the riskiest lending and are the first to run out of cash as delinquencies increase. We call these lenders riskier lenders.

Loan applications submitted to the platform are almost always sent to multiple lenders to solicit loan offers if they have made it past the initial screening. The data allow us to identify not only when an offer is made, but also when these credit solicitations are rejected by lenders. This provides an avenue for identifying the likelihood that an offer will be extended to a particular applicant based on the characteristics of the *lender*. In particular we can use application fixed effects to test how the lender's habitat influences the probability of extending an offer by controlling perfectly for borrower characteristics. As before, we define a lender's habitat as the median FICO on the transacted loans in 2019. We test whether this habitat influences the probability of extending an offer by regressing an offer indicator on lender habitats. Unsurprisingly, prior to the pandemic crisis riskier lenders (those with lower median FICO loans) are relatively more likely to extend an offer as seen in Column (1) of Table 7. However, this relationship diminishes greatly when only looking at March 2020 in Column (2). Furthermore, when interacting a lender’s median FICO with the crisis period, after March 12, the relationship vanishes almost entirely. Summing the coefficients of median FICO with its crisis interaction yields an effect that is near zero. The fact that riskier lenders were the first to drop from the platform and would subsequently not show up in these regressions only biases the results in such a way that it would be more difficult to observe such a result. In other words, if applications had been sent without regard to the lender’s active participation on the platform we would likely see an even larger positive coefficient on median FICO interacted with the crisis.

To address the possibility that the median FICO does not adequately describe a lender’s habitat, we run the same tests using the median interest rate on closed loans for each lender in 2019. This serves as a market-based summary variable for the riskiness of the loans made by the lender and is not necessarily correlated with the median FICO of their borrowers. The results using this measure are reported in Panel B of Table 7 and the interpretation is nearly identical to the previous results, though perhaps slightly stronger as median APR has no impact on offer likelihood during the month of March.

The evidence presented in this section supports the view that riskier lenders were simply unable to make loans that safer lenders deemed profitable. The alternative interpretation of the evidence would be that riskier lenders became more cautious in their underwriting during the crisis for reasons unrelated to funding availability. Because it is impossible to know whether the offers being made by safer lenders were ex-post profitable investments, one cannot rule out the alternative interpretation, but it seems unlikely that the degree to which lenders are conservative in underwriting would suddenly flip during a crisis.

7. Evidence from the securitization market and individual lenders

This section presents evidence drawn from public information available about the collapse of the credit supply by small business fintech lenders in March 2020. We discuss lenders for whom information is available. Some of the lenders we discuss were not lenders on the platform from which we obtain the data used in the earlier sections of this paper and others were. An important funding source for small business fintech lending is loan sales to institutional investors either directly or through securitization. We first show some evidence on the evolution of securitization markets during March 2020. We then provide some publicly available evidence about the reasons small business fintech lenders dropped out. Lastly, we discuss evidence from banks.

7.1. Securitization markets during March 2020

Small business fintech lenders have to finance the loans they make. By March 2020, a number of fintech lenders financed loans through securitization programs. With such programs, the securitization trust buys loans from the lender and the trust uses the proceeds from loan repayments to buy new loans provided that loans in the trust meet a quality threshold. Examples of small business fintech lenders with securitizations in March 2020 include Funding Circle, Kabbage, Credibly, Fora Financial, National Funding, RFS, On Deck, RapidAdvance, and Strategic Funding Source.

The securitization market between March and June 2020 provided only limited funding to fintech lenders. In general, securitizations use tranching, so that they have a large highly rated tranche and then riskier tranches. The top-rated tranche of the securitizations that were underwritten before March 2020 did not have top ratings from any rating agency at issuance. One exception is the On Deck securitization in April 2019, which was rated by Kroll and received an AAA rating for its safest tranche. The largest securitization was the Kabbage securitization in 2019. It issued notes for $700 million. The top-rated notes had a rating of AA by Kroll at issuance. In March 2020, Kroll put 10 small business ABS deals on downgrade watch due to COVID-19.[21] Subsequently, by June, six transactions had entered rapid amortization.[22] A rapid amortization occurs when the loans in the trust fail to meet a quality threshold. At that point, repayments are disbursed to investors and loans are no longer purchased by the trust. In sum, these developments for securitizations are inconsistent with the securitization market being open for those issuers.

[21] See KBRA, ABS Surveillance Report, U.S. small business ABS watch downgrade surveillance report, March 30, 2020.
[22] See KBRA, ABS Surveillance Report, KBRA affirms two U.S. small business ABS ratings; 27 remain on watch downgrade, June 30, 2020.

The secondary market for securitization notes offers another perspective on the withdrawal of investors. Many securitizations are private transactions so that prices are not available. However, the Kabbage securitization is a 144a issuance, so that prices are available on TRACE. Perhaps not surprisingly, there are almost no trades. The tranches were issued at 100 in 2019. Figure 7 shows prices for the A-Note in Panel A and the B-Note in Panel B. The securitization also has tranches C and D, but these tranches are not traded in March and April. The A-Note trades slightly above 100 on March 1. It falls to 72 on April 6, but it then trades the next day at 90. The B-Note trades initially slightly above 100, but then it has a trade for 6.31 on April 3 and another for 6.45 on April 7. By July 16, it has a trade at 90. The evolution of the prices of the Kabbage notes is consistent with the view that funding markets essentially closed for marketplace lending during the March crisis. The rebound in prices is dramatic. It seems inconsistent with markets still expecting a high default rate in the summer.

7.2. The experience of individual fintech lenders

Some fintech lenders stopped lending without public explanation. Other lenders provided some information about their lending and the issues they faced. Public companies are the ones with the most information available, but there is only one U.S. public company specialized in small business fintech lending.

7.2.a. On Deck Capital Inc.

In March 2020, On Deck was a publicly traded small business fintech lender. In contrast to other publicly traded fintech lenders in the U.S., On Deck only lent to small businesses. It held loans on its balance sheet. It used debt facilities and securitization to finance loans. Figure 8 shows the evolution of its stock price. The stock price dropped from $3.52 at the start of March 2020 to $1.54 at the end of the month. During March, the stock price was $0.65 on March 18. It rebounded sharply after it became clear that the CARES Act would be adopted. The company filed an 8-K form on March 23, 2020. In that form, it said that it recently experienced both an increase in loan applications and slower collections. The increase in loan applications is consistent with the results we present in Section 3.

On Deck's first quarter in 2020 ended at the end of March. At that time, it had current loans and receivables of $922 million. Of these $922 million, $203 million, or 22%, were non-paying. For comparison, at the end of the fourth quarter of 2019, it had loans of $1,098 million and receivables of $84 million, i.e., 7.6% of loans were non-paying. The difference between non-paying loans at the end of 2019 and the end of the first quarter of 2020 is due to loans that are past due by 1 to 14 days. These are the loans that bore the brunt of the COVID-19 shock. In its 10-Q filing, On Deck added that at the end of April 2020, 45% of its loans were one day or more delinquent. On Deck financed loans with a variety of debt facilities from financial institutions and through securitization. Moreover, it explained that it had suspended making new loans to preserve liquidity. It stated that "In order to resume normal lending when the economy reopens, we will require adequate liquidity, which may not be available."

In its earnings call for Q1, 2020, on April 30, On Deck explained that the surge in loan applications in March represented "a higher degree of risk" so that they "proactively tightened credit policies and slowed originations dramatically. We suspended new originations to certain industries, limited draws on certain customer lines of credit, tightened underwriting standards".[23] It then reported that it was working with lenders to amend certain debt facilities. It discussed suspending new term loan and credit line originations to support the PPP program. The CFO stated in the call that "Our liquidity and funding position became our top priority as the COVID crisis emerged. We quickly took actions to bolster our available cash, fully drawing on our corporate line, and managing both origination and operating cost outflows."

On Deck was purchased by Enova for $1.38 a share in July 2020. Strikingly, before 2020, On Deck had a peak market capitalization of $1.6 billion. It lost much value before COVID-19. Enova purchased On Deck for $90 million. Enova is a publicly traded diversified fintech firm.

[23] Q1 2020 On Deck Capital Inc. Earnings Call, April 30, 2020, Thompson Reuters.

7.2.b. Kabbage

The CEO of Kabbage posted a statement on April 2, 2020, that Kabbage had paused lending on March 29 to convert its systems to process loans through PPP. However, before that, there was much discussion that Kabbage had cut and/or suspended credit lines. It had also furloughed a "significant number" of its 500 U.S. employees. According to Bloomberg, Kabbage said that it took these actions to conserve cash to be able to continue operate.[24] Kabbage relied on securitization as we have discussed. Its securitization structures were such that it was responsible for some of the losses on the loans included in securitization trusts. The president of Kabbage was quoted in the Financial Times saying "We securitize our receivables and we are on the hook for loan performance, which is suffering because of delinquencies, because our customers have no revenue, because they are closed".[25] As reported by the Financial Times, Kabbage eventually processed more loans for the PPP program than it had lent in the previous year: $3.5 billion PPP loans by May 8, 2020, versus $2.8 billion loans in 2019.[26]

7.2.c. LendingClub

LendingClub, as discussed in Section 2, is built on the peer-to-peer lending model. As the business model evolved, the investors in the loans became financial institutions and professional investors rather than individuals. Most of the loans from LendingClub are loans to individuals rather than businesses, but some of the loans of LendingClub are loans to small businesses. The company itself also acquires loans. In the fourth quarter of 2019, LendingClub originated loans for $3,083 million. In the first quarter of 2020, the origination volume dropped to $2,521 million. The origination volume dropped by 18.2% even though March is only one of three months in the quarter. In the "Current Economic and Business Environment" section of its 10-Q form, LendingClub stated:

[24] "Softbank-backed lender Kabbage cuts off businesses as cash needs mount," by Zeke Faux and Jennifer Surane, Bloomberg, April 1, 2020.
[25] "Online lender stops making loans to small US businesses," by Robert Amstrong, April 1, 2020.
[26] "Kabbage rebounds after accessing US loan programme," by Miles Kruppa and Robert Amstrong, Financial Times, May 18, 2020.

> "There has been a reduction in investor demand on our platform reflecting market dislocation for unsecured personal loans driven in part by wider credit spreads and increased liquidity constraints. Similarly, the Company has temporarily ceased purchasing loans to preserve capital due to the lack of investor demand for our Structured Program transactions and whole loan sales. The reduction in investor demand on our platform has had a direct impact on the reduction in loan origination and transaction fees earned by the Company from our issuing banks."[27]

LendingClub attributed the decrease in originations to the lack of investor demand for loans. Eventually, during 2020, it ceased to be a peer-to-peer lender and became a bank.

7.3. Banks

Additional insights could potentially be drawn from the evolution of bank lending to small businesses during March 2020. Li, Strahan, and Zhang (2020) document that commercial and industrial (C&I) loans increased by $482 billion between March 11 and April 1. During the same period, deposits increased by almost $1 trillion. Banks did not have trouble funding the loans they made even though the increase in lending that took place had no precedent within the period of 1973 to 2021. Much of the increase in loans corresponded to firms drawing down lines of credit. Chodorow-Reich, Darmouni, Luck, and Plosser (2021) examine drawdown of credit lines for small firms during the COVID-19 crisis and show that small firms did not draw down credit lines in the same way as large firms as they appear to have credit lines that are more subject to lender discretion. The evolution of credit for banks was dramatically different from the evolution of credit we observe for the platform. The comparison between banks and fintech lenders is made more difficult by the fact that the loans made by fintech lenders on the platform were to small firms and were uncollateralized. The fact that bank credit increases so much does not mean that credit increased for small businesses.

[27] 10-Q filings for the quarter ending on March 31, 2020, p. 59.

Evidence supporting the idea that fintech lenders decreased small business lending more sharply than banks comes from a survey by biz2credit. A small business lending platform, biz2credit, distributes a small business lending index. This index reports acceptance rates of applications made through the platform to various types of lenders. It computes the index based on a sample of 1,000 applications. It is not possible to know how representative this sample is of conditions for small-business loan applications in general as opposed to applications on that platform. It is also not possible to know what type of institutions are included in the platform. However, it is reasonable to assume that the index is built consistently across months, so that month-to-month comparisons are instructive. The index shows that the acceptance rate of banks with assets greater than $10 billion dropped from 27.3% in March 2019 to 15.4% in March 2020. In contrast, the acceptance rate of small banks was much larger in March 2019, 49.4%, and dropped much less as it was 38.9% in March 2020. The platform includes loans made by institutional lenders. Their approval rate dropped from 65.2% to 41.2%. Lastly, the index has a category corresponding to alternative lenders. This category's acceptance rate dropped from 57.3% to 30.4%. It follows from the biz2credit small business lending index that there was an overall decrease in the acceptance rate for small business loans, but less so for small banks.

For banks, the survey only shows acceptance rates for banks that lend on the biz2credit platform. The Federal Reserve Bank of Kansas City (FRBKC) publishes a survey of small business lending by banks.[28] This survey queries banks generally. That survey reports different approval rates from those of the biz2credit index. The FRBKC survey has much higher acceptance rates for banks and, further, finds an unchanged approval rate for the first quarter of 2020. That survey further shows an increase in small business lending during the first quarter of 2020 compared to the same quarter in 2019. The same survey reports that about 20% of respondents experienced an increase in credit line usage. The survey has mixed evidence on overall loan demand as on net small banks reported a decrease in loan demand but the other banks report an increase. From this survey evidence, it is clear that the experience of banks differs from the

[28] See Federal Reserve Bank of Kansas City Small Business Lending Survey, June 24, 2020.

experience of the platform from which we obtain our data. A plausible explanation is that the loan applicants on the platform as well as on the biz2credit platform are riskier. This makes sense since many applicants are subprime borrowers and banks often have a minimum FICO threshold for loans that excludes subprime borrowers (see Johnson and Lee, 2021).

8. Conclusion

In this paper, we examine the evolution of fintech small business lending during the COVID-19 crisis period of March 2020 using unique data from a lending platform that allows us to examine separately the demand and the supply for loans. We find that the demand increased in response to the COVID-19 shock and the applicants for loans became more creditworthy using historical characteristics. However, the supply fell sharply. Surprisingly, while the supply fell, the terms of the loans were mostly unaffected by the COVID-19 shock. We show that the supply fell because lenders dropped out. The typical lender kept lending during March with an acceptance rate that stayed relatively stable. Suddenly, that acceptance rate collapsed and the lender dropped out. It seems difficult to rationalize a decrease in supply taking place this way by simply an increase in risk resulting from the COVID-19 shock that affected borrowers. This is because the decrease in supply is to a large extent the result of lender exits. Lender exits are more likely to take place because lenders become financially constrained. We would expect the lenders with the riskiest borrowers before the COVID-19 shock to have their balance sheet weakened the most by the shock and hence would be financially constrained first. As a result, they would drop out first and, being financially constrained, would reject the opportunity to make safer loans. We find support for this hypothesis. We show that the lenders with the riskiest borrowers dropped out first. We show that these lenders rejected safer loans. We also show that the prices of securitization notes fell sharply but then bounced back. The dramatic evolution of securitization prices seems to support an explanation where lenders stopped lending at least in part because they were concerned about running out of funding.

Our evidence points to both strengths and weaknesses of the fintech small business lending model. The model makes loans available to small businesses that are unlikely to find funding from banks because their creditworthiness is not high enough. It also makes loans available quickly and conveniently. However, because these loans are transactional loans and borrowers do not have a relationship with the lender, the lender has to rely on hard information to make loans. With the COVID-19 shock, such information became less useful. Further, the fintech small business lending relies on loan sales and debt facilities collateralized by loans to fund loans. Such a funding model becomes problematic when existing loans lose value and default more. As a result, small business fintech firms reduced lending in March because they became financially constrained and experienced an increase in risk.

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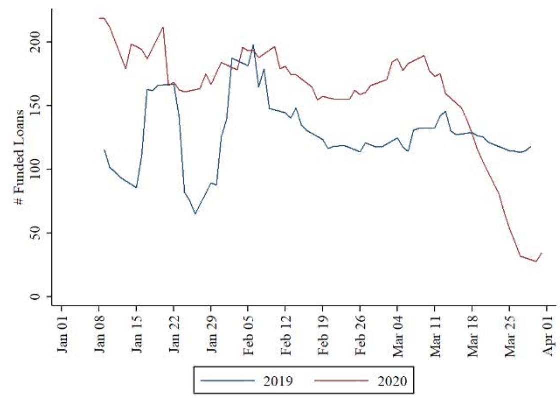
Figure 1. Fintech loan volume

These figures depict the evolution of funded loans in the first three months of 2020. Panel A plots a five-business day moving average of the number of funded loans in 2020 relative to 2019. Panel B plots a similar moving average but for total amount funded.

(a) Number of funded loans



(b) Total amount funded

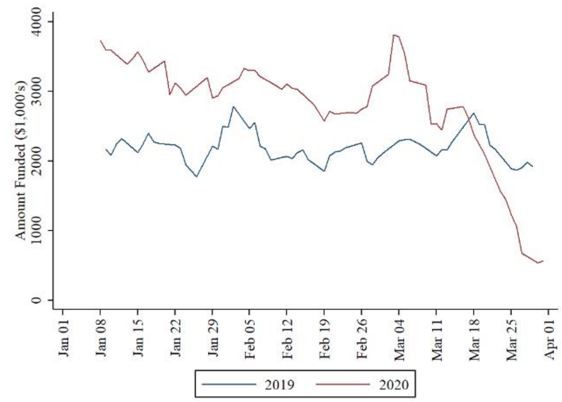


Figure 2. Loan demand

The figures show how demand evolved in the month of March 2020 relative to the same month in 2019. Panel A shows the number of unique small businesses that applied for financing and Panel B shows the sum of all financing requested in millions of dollars for each weekday in the month of March. Weekends are excluded.

(a) Number of applicants

(b) Total amount requested (Millions)

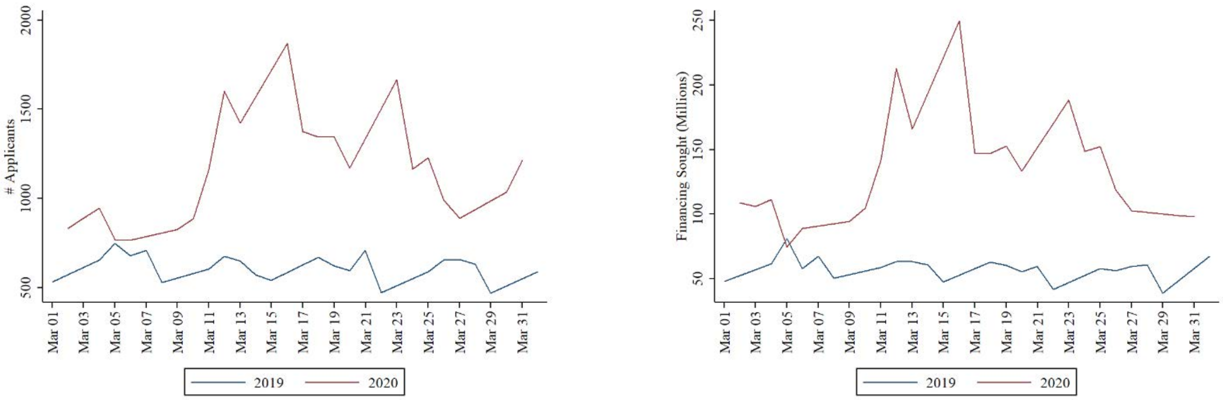
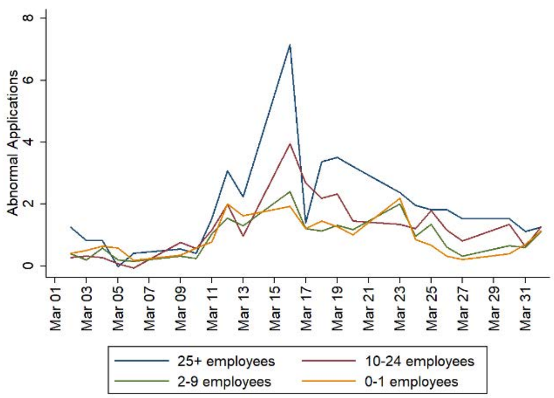


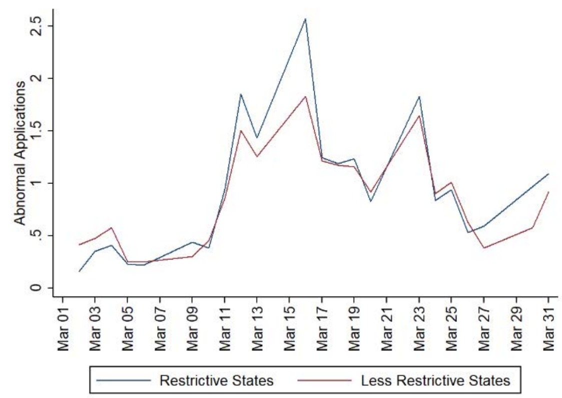
Figure 3. Abnormal demand for fintech loans

These figures depict abnormal demand in March 2020 based on applicant firm size, state restrictiveness, and industry. Abnormal demand is defined as the number of applications on a given day divided by the average number of daily applicants in March 2019 minus one. Panel A shows abnormal demand based on firm size. Panel B shows the differences in abnormal demand based on the owners' state restrictiveness. "Restrictive States" are those that first enacted statewide lockdowns—namely California, Washington, Oregon, Louisiana, Illinois, Ohio, New York, New Jersey, and Connecticut. Panel C shows abnormal demand for the 10 largest industries by volume.

(a) Firm size



(b) State restrictiveness



(c) Industry

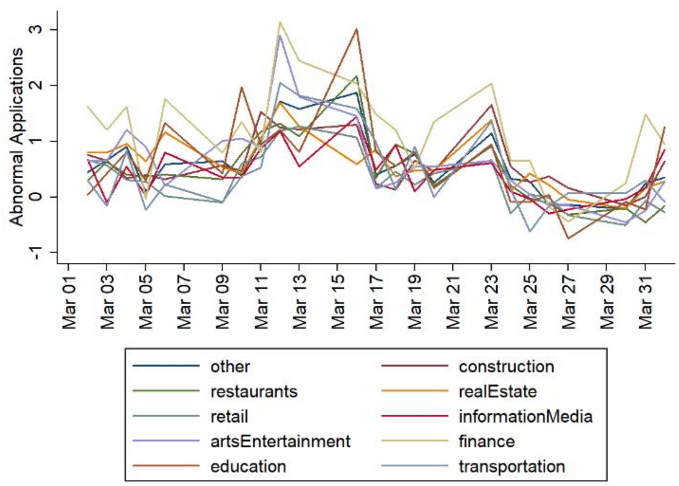


Figure 4. Loan supply

These figures show how supply changes during the crisis. Applicants receive anywhere from zero to 5+ offers from multiple lenders. Panel A reports the total number of offers made through the platform in the month of March. Panel B reports the average number of offers that an applicant receives. Weekends are excluded

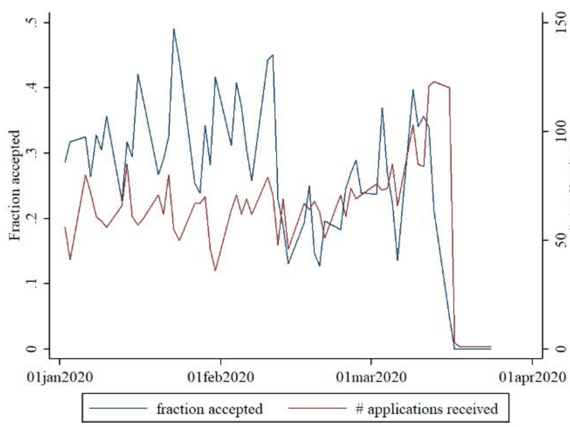
(a) Number of offers

(b) Number of offers per applicant

Figure 5. Lender dropouts

These figures provide evidence on the supply shock to credit at the lender level. Panel A depicts the fraction of applicants that a particular lender accepts in the first three months of 2020 as well as the number of applications the lender received from the platform. The fraction accepted drops to zero precipitously in the middle of March. Such patterns are common for many of these lenders. Panel B shows the average number of daily active lenders from the prior business week. A lender is considered active if on a given day it extends an offer to at least one individual. Weekends and observed holidays are excluded from weekly averages.

(a) Lender dropout example



(b) Active lenders (moving average)

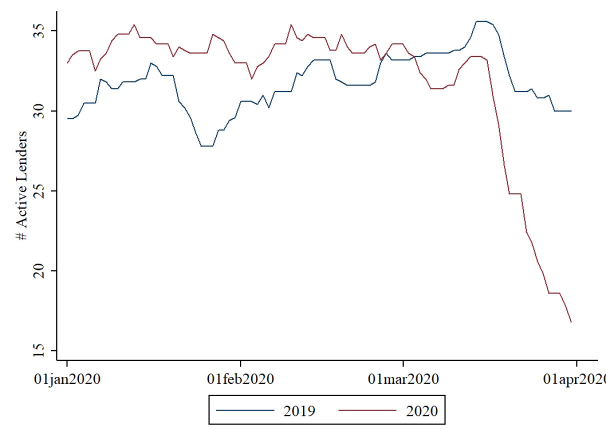


Figure 6. Lender dropouts by average lender risk

This figure shows the relationship between a lenders' last day extending offers and the average risk of the borrowers with whom they transacted in the previous year. *Supply cut date* on the x-axis refers to the date when the lender makes zero offers and makes no offers in the following month. *Lender MedianFICO* on the y-axis refers to the median borrower FICO score with whom the lender transacted in the previous year. This can be viewed as a proxy for a lender's risk appetite.

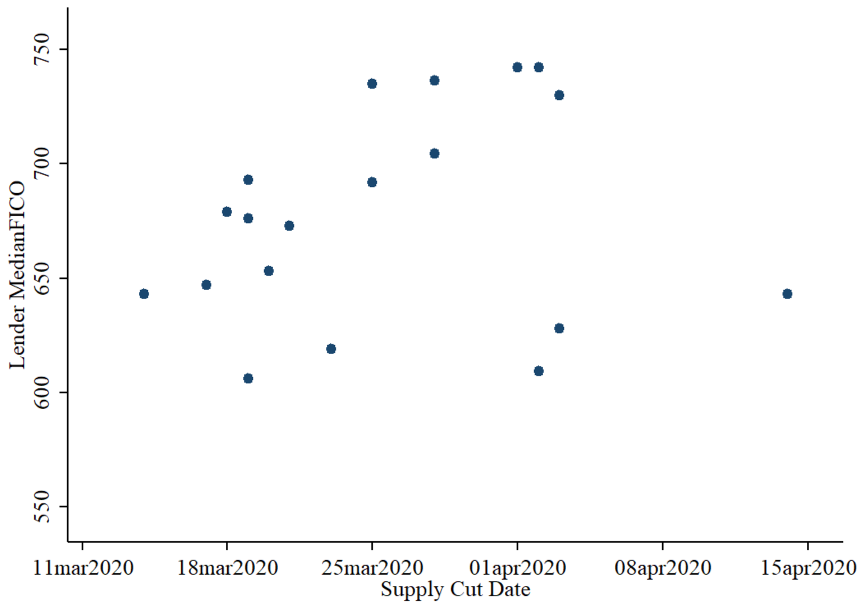
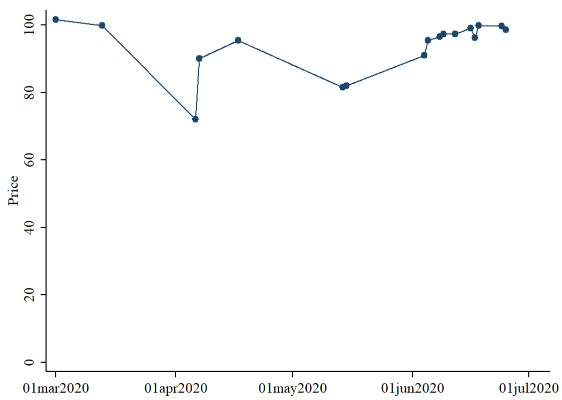


Figure 7. Securitization prices

These figures show the changes in transacted prices on securitized notes issued by Kabbage in 2019. Panel A shows the price changes for higher quality A-Notes during and after the March 2020 while Panel B does the same for lower quality B-Notes. For most days transacted prices are unavailable.

(a) A-Note securitization prices (Kabbage)



(b) B-Note securitization prices (Kabbage)

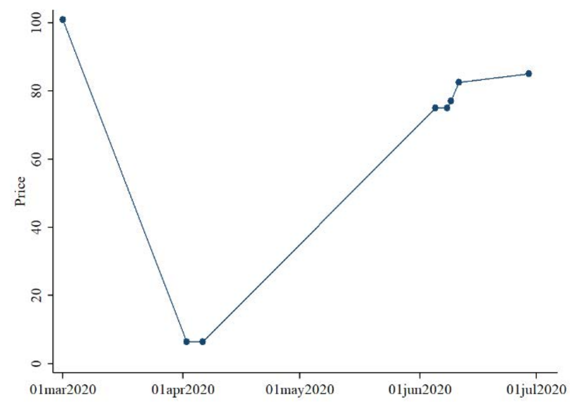


Figure 8. On Deck Capital stock price evolution

This figure shows On Deck Capital's equity prices during the first part of 2020. On Deck is the only public fintech lender that focuses only on small business lending. The stock price dropped from $3.52 at the start of March 2020 to $1.54 at the end of the month. The stock price was $0.65 on March 18.

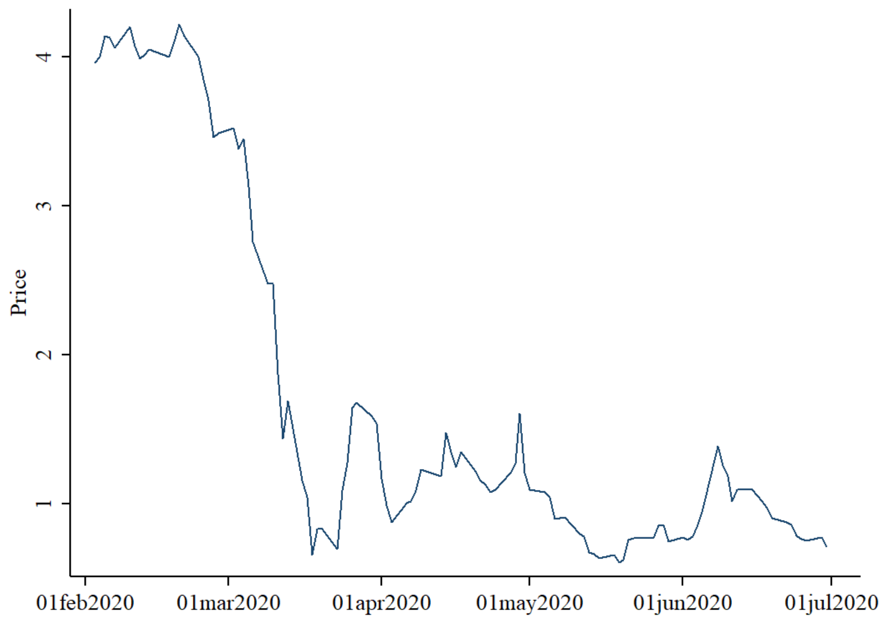


Table 1. Applicant comparative statistics

This table compares applicant characteristics between those that applied prior to the Covid-19 shock and those after. Panel A compares applicants in March 2019 with those in March 2020 while Panel B compares those in the first part of March with those in the latter part. *Days with NSF* is the number of days where the bank account balance of the business owner was insufficient to meet the charges to the account (Not Sufficient Funds). *Bank Balance* is the average daily balance in the owner's or business account. *Seasonal business* is an indicator equal to one if the business defines itself as seasonal. Difference in means and t-statistics are reported in the last two columns.

Panel A

	March 2019		March 2020		Difference	
Variable	Mean	St. Dev	Mean	St. Dev	b	t
FICO	647.8	89.5	667.5	93.4	19.76***	22.12
Annual Sales	616,866	1,018,703	893,804	1,279,542	276,937***	23.66
Age(Months)	38.48	46.03	47.49	43.19	9.01***	20.32
# Employees	6.39	11.39	7.54	12.88	1.15***	7.02
Days with NSF	1.56	3.13	1.2	2.8	-0.36***	-6.58
Bank Balance	18,203	37,473	26,061	49,138	7,857***	10.66
Seasonal Business	0.06	0.24	0.06	0.24	-0.00	-1.30
I(Offer)	0.19	0.39	0.14	0.34	-0.06***	-15.08
APR (%)	112.29	67.71	99	64.17	-13.28***	-8.23
Observations	15,611		30,751		46,362	

Panel B

	March 1-14, 2020		March 15-31, 2020		Difference	
Variable	Mean	St. Dev	Mean	St. Dev	b	t
FICO	654.9	91.6	675.6	93.6	20.71***	19.14
Annual Sales	751,584	1,194,898	975,530	1,318,853	223,945***	14.48
Age(Months)	39.82	39.57	52.39	44.66	12.57***	25.77
# Employees	6.83	12.16	7.92	13.23	1.09***	5.41
Days with NSF	1.43	3.09	1.07	2.62	-0.36***	-5.87
Bank Balance	21,874	43,525	28,490	51,968	6,616***	6.84
Seasonal Business	0.07	0.25	0.06	0.23	-0.01**	-2.59
I(Offer)	0.18	0.38	0.11	0.32	-0.06***	-15.09
APR (%)	108.03	64.38	90.05	62.7	-17.99***	-8.98
Observations	11,980		18,771		30,751	

Table 2. Demand for loans in March 2020

This table examines the effect of the pandemic on the demand for loans. For each day starting January 1 and ending March 31, the number of applicants to the platform are summed up and regressed on an indicator for the week of the year. In specification 1, the sample period is January to March of 2020 while specification 2 looks at the same months in 2019. In each of these specifications, the first week of the year (January 1-7) is omitted. In the last column both years are included along with an indicator variable for the year 2020. In the last specification, the first weeks in both 2019 and 2020 are omitted. Robust standard errors are reported. * p<.1; ** p<.05; *** p<.01.

	Number of Applicants		
	(1)	(2)	(3)
Mar 4-10 (2020)	-49.14		-127.00
	(127.25)		(164.08)
Mar 11-17 (2020)	540.85***		488.71**
	(173.75)		(199.86)
Mar 18-24 (2020)	400.57**		370.14*
	(160.61)		(188.96)
Mar 25-31 (2020)	103.92		86.81
	(149.95)		(184.37)
Mar 5-11 (2019)		77.85	77.85
		(103.57)	(103.52)
Mar 12-18 (2019)		52.14	52.14
		(98.67)	(98.63)
Mar 19-25 (2019)		30.42	30.42
		(99.46)	(99.41)
Mar 26-Apr 1 (2019)		17.11	17.11
		(107.27)	(107.22)
Sample Period	Jan-Mar 2020	Jan-Mar 2019	Jan-Mar 2019-2020
R-squared	0.40	0.10	0.49
N	90	90	181

Table 3. Supply of loans and timing in March 2020

This table examines the impact of the crisis on the supply of credit by estimating the likelihood that a firm receives an offer in relation to the week that the application is submitted. The dependent variable is an indicator equal to one if the applicant received at least one offer. Firm controls are included in all but the first and third columns. These controls include the FICO score of the owner, log of firm, log of sales, and fixed effects for industry. To save space only the coefficients on indicators for weeks in March are included, but all week indicators are included in regressions where the sample period extends prior to March. The first two specifications limit the sample period to applications received in March 2020, the next two specifications include January and February 2020, the fifth is limited to January-March of 2019, and the last includes January-March for both years. Standard errors are clustered by application date. Robust standard errors are reported. * p<.1; ** p<.05; *** p<.01.

	I(Offer)					
	(1)	(2)	(3)	(4)	(5)	(6)
Mar 4-10 (2020)	-0.00	0.00	-0.00	-0.01		-0.01
	(0.02)	(0.02)	(0.02)	(0.02)		(0.02)
Mar 11-17 (2020)	-0.04**	-0.07***	-0.04**	-0.10***		-0.10***
	(0.02)	(0.01)	(0.02)	(0.02)		(0.02)
Mar 18-24 (2020)	-0.08***	-0.12***	-0.09***	-0.14***		-0.15***
	(0.01)	(0.01)	(0.02)	(0.02)		(0.02)
Mar 25-31 (2020)	-0.10***	-0.12***	-0.10***	-0.14***		-0.14***
	(0.01)	(0.01)	(0.02)	(0.01)		(0.02)
Mar 5-11 (2019)					-0.01	-0.00
					(0.02)	(0.01)
Mar 12-18 (2019)					0.00	0.00
					(0.02)	(0.02)
Mar 19-25 (2019)					0.01	0.01
					(0.02)	(0.02)
Mar 26-Apr 1 (2019)					-0.01	-0.00
					(0.02)	(0.02)
Sample Period	March 2020	March 2020	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2019	Jan-Mar 2019, 2020
Controls		X		X	X	X
Industry FE		X		X	X	X
Cluster	App Date	App Date	App Date	App Date	App Date	App Date
R-squared	0.01	0.07	0.01	0.11	0.10	0.10
N	30,751	20,924	74,148	52,415	34,971	87,411

Table 4. Industry exposure and the supply of loans in March 2020

This table examines which industries were most impacted by the reduction in the supply of credit in the latter half of March. The dependent variable is an indicator variable that takes value 1 if an application received an offer. An indicator variable equal to 1 if the application was submitted on or after March 12 identifies the applicants that were "treated" to the reduction in supply. This treated indicator is interacted with firm characteristics including FICO score, log(age), log(sales) and industry. For ease in reporting, the table includes only the coefficients on industries in the treated half of March. The omitted industry indicator is the "other" category which is the largest most frequently reported industry. The coefficients can be interpreted as the differential impact in the likelihood of receiving an offer for an applicant from that industry relative to the change in likelihood of receiving an offer if the applicant had belonged to "other". Standard errors are clustered by application date. Robust standard errors are reported. * p<.1; ** p<.05; *** p<.01.

	I(Offer)		
	(1)	(2)	(3)
agricultureForestry * I(Post 3/12)	-0.02	0.04**	0.02
	(0.04)	(0.02)	(0.01)
artsEntertainment * I(Post 3/12)	0.01	0.04***	0.03**
	(0.02)	(0.01)	(0.01)
automotive * I(Post 3/12)	0.03	0.05**	0.04***
	(0.03)	(0.02)	(0.02)
construction * I(Post 3/12)	-0.01	-0.03**	-0.02
	(0.02)	(0.01)	(0.01)
education * I(Post 3/12)	0.06	0.07***	0.07***
	(0.04)	(0.03)	(0.02)
finance * I(Post 3/12)	0.02	0.04*	0.02
	(0.03)	(0.02)	(0.02)
freightTrucking * I(Post 3/12)	-0.05	-0.05*	-0.03
	(0.04)	(0.03)	(0.03)
healthcare * I(Post 3/12)	-0.00	0.02	0.02
	(0.04)	(0.02)	(0.02)
informationMedia * I(Post 3/12)	0.01	-0.00	0.00
	(0.03)	(0.02)	(0.02)
legalServices * I(Post 3/12)	0.04	0.08	0.06
	(0.07)	(0.07)	(0.07)
manufacturing * I(Post 3/12)	-0.09**	-0.04**	-0.02
	(0.04)	(0.02)	(0.02)
realEstate * I(Post 3/12)	0.05**	0.02	0.02
	(0.02)	(0.02)	(0.01)
restaurants * I(Post 3/12)	-0.10***	-0.10***	-0.10***
	(0.02)	(0.01)	(0.01)
retail * I(Post 3/12)	-0.01	-0.03*	-0.03*
	(0.02)	(0.01)	(0.01)
transportation * I(Post 3/12)	-0.04	-0.03	-0.02
	(0.04)	(0.02)	(0.02)
wholesale * I(Post 3/12)	0.01	0.04*	0.05**
	(0.04)	(0.02)	(0.02)
Sample Period	March 2020	Jan-Mar 2020	Jan-Mar 2019-2020
Controls	X	X	X
Cluster	App Date	App Date	App Date
R-squared	0.07	0.11	0.11
N	18,925	47,201	76,443

Table 5. Loan supply and geographic exposure to Covid-19

This table shows the effect of geographic exposures to the pandemic on the likelihood that a firm receives an offer. The dependent variable is an indicator equal to one if the applicant received at least one offer. *I(State Lockdown)* is an indicator for whether the state has been ordered to be on lockdown. *% Population Home* is the fraction of individuals in the county that are home all day on the date the application was submitted. *% Population Home (7 day average)* is the average fraction home all day in the county from the prior week. Standard errors are clustered by application date. Robust standard errors are reported. * p<.1; ** p<.05; *** p<.01.

	I(Offer)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
I(State Lockdown)	-0.01			-0.01			-0.03***		
	(0.01)			(0.01)			(0.01)		
% Population Home		0.26***			-0.29**			-0.31***	
		(0.05)			(0.13)			(0.09)	
% Population Home (7 day average)			0.24***			-0.50***			-0.56***
			(0.07)			(0.16)			(0.12)
FICO				0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln(Age)				0.04***	0.04***	0.04***	0.06***	0.06***	0.06***
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln(Sales)				0.05***	0.05***	0.05***	0.06***	0.06***	0.06***
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.18***	0.12***	0.13***	-0.67***	-0.59***	-0.54***	-0.91***	-0.83***	-0.77***
	(0.00)	(0.02)	(0.02)	(0.06)	(0.06)	(0.07)	(0.04)	(0.05)	(0.05)
Sample Period	March 2020	March 2020	March 2020	March 2020	March 2020	March 2020	Jan-March 2020	Jan-March 2020	Jan-March 2020
App Date FE	X	X	X	X	X	X	X	X	X
Industry FE				X	X	X	X	X	X
County FE				X	X	X	X	X	X
Cluster	App Date	App Date	App Date	App Date	App Date	App Date	App Date	App Date	App Date
R-squared	0.02	0.02	0.02	0.17	0.17	0.17	0.20	0.20	0.20
N	23,455	18,884	18,884	13,153	13,153	13,153	32,895	32,895	32,895

Table 6. Offer terms and exposure to Covid-19

This table shows the effect of time and geographic exposures to the pandemic on offered loan terms. The dependent variables are the interest rate of the loan in APR, the maturity in months, and the natural log of loan amount. Panel A examines whether offered loan terms change over the course of the March 2020 controlling for firm characteristics and holding constant the lender. Panel B looks at the effect of COVID-19 exposure on terms using the same key independent variables as in Table 5. Specifically, *I(State Lockdown)* is an indicator for whether the state has been ordered to be on lockdown, *% Population Home* is the fraction of individuals in the county that are home all day on the date the application was submitted, and *% Population Home (7 day average)* is the average fraction home all day in the county from the prior week. In Panel C, the proxies for COVID-19 exposure are an indicator variable for the period of March after the WHO declares a pandemic emergency (Post 3/12) and an indicator variable for high exposure industries. High exposure industries are identified using the Small Business Pulse Survey which asked "overall how has the COVID-19 pandemic affected your business?" in their initial survey. Industries that were above median in responding that they experienced a "large negative impact" are identified with the dummy *I(HighIndExposure)*. Standard errors are clustered by application date and lender. Robust standard errors are reported. * p<.1; ** p<.05; *** p<.01.

Panel A						
	APR		Maturity		ln(Loan Amount)	
	(1)	(2)	(3)	(4)	(5)	(6)
Mar 4-10	-0.77	-2.29**	-0.05	-0.05	-0.06***	0.01
	(1.16)	(1.09)	(0.07)	(0.20)	(0.01)	(0.03)
Mar 11-17	0.05	-1.36	0.05	0.03	-0.06	-0.00
	(2.14)	(1.47)	(0.12)	(0.20)	(0.04)	(0.03)
Mar 18-24	1.01	0.00	0.02	0.19	-0.09	-0.03
	(2.59)	(1.27)	(0.32)	(0.34)	(0.08)	(0.06)
Mar 25-31	1.15	0.54	-0.16	-0.02	-0.19	-0.11
	(3.26)	(2.15)	(0.57)	(0.53)	(0.12)	(0.10)
FICO	-0.06***	-0.07***	0.01***	0.01***	0.00***	0.00***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln(Age)	-0.06***	-0.07***	0.01***	0.01***	0.00***	0.00***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
ln(Sales)	-4.63***	-4.04***	0.53***	0.47***	0.07***	0.05***
	(1.22)	(0.91)	(0.17)	(0.15)	(0.02)	(0.02)
Constant	-1.64*	-2.42**	0.01	0.07	0.52***	0.56***
	(0.92)	(1.17)	(0.06)	(0.05)	(0.03)	(0.03)
Sample Period	March 2020	Jan-Mar 2020	March 2020	Jan-Mar 2020	March 2020	Jan-Mar 2020
Industry FE	X	X	X	X	X	X
Lender FE	X	X	X	X	X	X
Cluster	App Date, Lender	App Date, Lender	App Date, Lender	App Date, Lender	App Date, Lender	App Date, Lender
R-squared	0.83	0.83	0.95	0.88	0.67	0.67
N	5,334	18,684	5,334	18,684	5,334	18,684

Table 6. Offer terms and exposure to Covid-19 (Cont.)

Panel B									
	APR			Maturity			ln(Loan Amount)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
I(State Lockdown)	2.85			-0.79			0.08		
	(2.06)			(0.49)			(0.07)		
% Population Home		7.04			0.68			-0.15	
		(10.23)			(1.24)			(0.33)	
% Population Home (7 day average)			25.10			1.30			-0.64
			(18.61)			(3.00)			(0.59)
FICO	-0.07***	-0.07***	-0.07***	0.01***	0.01***	0.01***	0.00***	0.00***	0.00***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln(Age)	-4.44***	-4.45***	-4.44***	0.47***	0.47***	0.47***	0.06***	0.06***	0.06***
	(1.02)	(1.02)	(1.02)	(0.14)	(0.14)	(0.14)	(0.01)	(0.01)	(0.01)
ln(Sales)	-2.19*	-2.20*	-2.20*	0.04	0.04	0.04	0.55***	0.55***	0.55***
	(1.21)	(1.21)	(1.21)	(0.06)	(0.06)	(0.06)	(0.03)	(0.03)	(0.03)
Constant	181.13***	179.74***	175.35***	6.11***	5.87***	5.71***	1.89***	1.94***	2.05***
	(22.54)	(23.47)	(23.02)	(1.29)	(1.17)	(1.09)	(0.49)	(0.51)	(0.51)
Sample Period	Jan-March 2020	Jan-March 2020	Jan-March 2020	Jan-March 2020	Jan-March 2020	Jan-March 2020	Jan-March 2020	Jan-March 2020	Jan-March 2020
App Date FE	X	X	X	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X	X	X	X
Lender FE	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Cluster	App Date, Lender	App Date, Lender	App Date, Lender	App Date, Lender	App Date, Lender	App Date, Lender	App Date, Lender	App Date, Lender	App Date, Lender
R-squared	0.84	0.84	0.84	0.98	0.98	0.98	0.72	0.72	0.72
N	10,517	10,517	10,517	10,517	10,517	10,517	10,517	10,517	10,517

Table 6. Offer terms and exposure to Covid-19 (Cont.)

Panel C						
	APR		Maturity		ln(Loan Amount)	
	(1)	(2)	(3)	(4)	(5)	(6)
I(Post 3/12)	-1.08	1.00	0.20*	0.01	0.03	-0.13***
	(1.40)	(1.47)	(0.12)	(0.13)	(0.04)	(0.04)
I(HighIndExposure)	-1.32*	-1.85***	0.21	0.24	-0.15***	-0.02
	(0.76)	(0.67)	(0.16)	(0.14)	(0.04)	(0.02)
I(Post 3/12) X I(HighIndExposure)	-0.31	0.04	0.37	0.33	0.10**	0.08*
	(1.30)	(1.16)	(0.26)	(0.25)	(0.05)	(0.04)
FICO		-0.07***		0.01***		0.00***
		(0.01)		(0.00)		(0.00)
ln(Age)		-4.81***		0.62***		0.07***
		(1.14)		(0.19)		(0.02)
ln(Sales)		-2.10		0.06		0.57***
		(1.31)		(0.08)		(0.04)
Constant	88.51***	182.17***	12.97***	4.83***	10.55***	1.68***
	(0.48)	(23.31)	(0.09)	(1.69)	(0.02)	(0.53)
Sample Period	Jan-March 2020	Jan-March 2020	Jan-March 2020	Jan-March 2020	Jan-March 2020	Jan-March 2020
Lender FE	X	X	X	X	X	X
Cluster	App Date, Lender	App Date, Lender	App Date, Lender	App Date, Lender	App Date, Lender	App Date, Lender
R-squared	0.81	0.83	0.97	0.97	0.37	0.69
N	8,040	8,040	8,040	8,040	8,040	8,040

Table 7. Supply cuts and lender risk: Within applicant tests

This table tests whether lenders with riskier portfolios are more likely to reject applicants during the crisis relative to lenders with more conservative portfolios. Regressions use application fixed effects to assess the relative likelihood of extending an offer based on lender characteristics. The dependent variable, *I(Offer)*, indicates whether an offer is extended by a lender conditional on that lender having received the application. The independent variables are measures of the lender's risk appetite based on the portfolio of transacted loans in 2019. In Panel A this measure is the median FICO score and in Panel B it is the median annual interest rate charged (Annual Percentage Rate; APR). An indicator variable equal to 1 if the application was submitted on or after March 12 identifies the applicants that were "treated" to the pandemic shock. This treated indicator is interacted with measures of lender risk. Robust standard errors are reported. * p<.1; ** p<.05; *** p<.01.

Panel A				
	I(Offer)			
	(1)	(2)	(3)	(4)
MedianFICO	-0.24***	-0.09**	-0.23***	-0.20***
	(0.06)	(0.04)	(0.06)	(0.05)
MedianFICO*I(Post 3/12)			0.21***	0.19***
			(0.06)	(0.06)
I(Post 3/12)			-141.57***	-128.92***
			(41.34)	(37.50)
Constant	180.79***	78.92***	171.14***	156.09***
	(40.83)	(28.10)	(37.93)	(32.81)
Sample Period	Jan-Feb 2020	March 2020	Jan-March 2020	Jan-March 2019-2020
Applicant FE	X	X	X	X
R-squared	0.28	0.30	0.29	0.29
N	67,833	30,967	99,127	152,530

Panel B				
	I(Offer)			
	(1)	(2)	(3)	(4)
MedianAPR	0.17***	0.05	0.16***	0.16***
	(0.05)	(0.03)	(0.04)	(0.04)
MedianAPR*I(Post 3/12)			-0.19***	-0.19***
			(0.03)	(0.03)
I(Post 3/12)			16.21***	10.72***
			(3.58)	(3.56)
Constant	8.60*	14.55***	8.18*	10.97***
	(4.66)	(3.81)	(4.26)	(3.83)
Sample Period	Jan-Feb 2020	March 2020	Jan-March 2020	Jan-March 2019-2020
Applicant FE	X	X	X	X
R-squared	0.29	0.31	0.3	0.31
N	65,743	29,680	95,735	147,791