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ABSTRACT

FinTech small business lenders fund loans mostly through credit facilities and securitizations. This business model could make them financially constrained when a shock reduces the value of existing loans. We find evidence supporting this prediction using detailed applicant-level and lender-level data from a platform that intermediates loans between dozens of FinTech lenders and small businesses. Despite the increased demand for credit at the onset of the COVID crisis, the credit supply quickly dwindled, regardless of borrowers' credit quality. Overall, our analysis demonstrates the fragility of the FinTech lending model in the face of a crisis.

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1. Introduction

Before the COVID-19 crisis, FinTech lending had become an increasingly important source of funds for younger and riskier small businesses (Barkley and Schweitzer, 2021).[1] Because the business model of FinTech lenders differs sharply from that of banks, the two types of lenders may respond to a crisis differently. First, in contrast to banks, small business FinTech lending is transactional and does not use collateral (Gopal and Schnabl, 2020; Beaumont, Tang, and Vansteenberhe, 2020). The soft information collected through relationship lending and the use of collateral may be especially valuable during a crisis (Berger and Udell, 2006; Liberti and Petersen, 2019). These characteristics of FinTech lending make lending decisions particularly sensitive to uncertainty about borrowers' revenues. Second, because banks rely on their deposit franchise and typically receive large inflows of deposits during a crisis (Gatev, Schuermann, and Strahan, 2009), they have more resources to lend than FinTech lenders that are not depository institutions and whose funding can become too expensive during a crisis or dry up altogether. These differences between the business model of banks and the business model of FinTech lenders suggest that FinTech lenders may have had to cut back lending as a result of the COVID-19 shock in comparison to banks. We find that this was the case and show that an important part of the explanation is that FinTech lenders became financially constrained because of their business model.

In this paper, we examine how small business FinTech lending was impacted by the COVID-19 pandemic during March 2020. This period corresponds to the financial crisis period of the pandemic, which we call the COVID-19 crisis. We use unique data from a FinTech small business platform (hereafter, "the platform") that connects small businesses with dozens of the most prominent online lenders. We have data on loan applications, loan offers, the take-up rate, and the terms of loans actually made. Because we observe applications, offers, and loans, we can study the demand for loans separately from the supply of loans. During March 2020, the transacted loan volume on the platform declined sharply from its pre-crisis levels.

[1] FinTech lending is "the provision of credit facilitated by technology that improves the customer-lender interaction or lenders' screening and monitoring of borrowers" (Berg, Fuster, and Puri, 2021). Claessens, Frost, Turner, and Zhu (2018), Berg, Fuster, and Puri (2021), and Cornelli, Frost, Gambacorta, Rau, Wardrop, and Ziegler (2021) review the state of FinTech lending.

Specifically, the number of funded loans and the total amount funded declined by 80.3% and 81.0%, respectively, from February 2020 to the last week of March 2020. We show that the volume of loans dropped because of a decrease in the supply of loans.

The pattern we document is not unique to small business lending or to the platform we study. An industry report concludes that out of 16 small business FinTech lenders originating loans before the COVID-19 shock, only six were still operating in the third quarter of 2020.[2] In the United States, digital lending in the second quarter of 2020 decreased by 75% relative to its $16 billion level in the fourth quarter of 2019.[3] Using data on FinTech personal loans, we show a similar drop in loans during March 2020. In contrast, bank lending to small businesses did not experience a noticeable decrease.[4]

After documenting the decrease in lending volume of the FinTech lenders on the platform, we organize our analysis into three main parts. In the first part, we explore the evolution of the demand for loans on the platform. We rule out the possibility that a decline in demand could explain the reduction in loan volume. In sharp contrast to this hypothesis, the number of loan applications in March 2020 doubled compared to March 2019. It is also not the case that the creditworthiness of the applicants measured by traditional metrics, such as the FICO score, fell. Toward the end of March 2020, the number of applications fell as potential borrowers contemplated using the Paycheck Protection Program (PPP) of the CARES Act, which was signed into law by President Donald Trump on March 27, 2020, but by then the volume of loans had already fallen sharply.

In the second part of our analysis, we study the supply of FinTech credit. In contrast to the rising demand for loans during the first three weeks of March, the supply of credit—measured as loan offers—fell sharply starting in the second week of March. Conditional on observable pre-COVID-19 characteristics, the probability of receiving an offer drops from 48.2% to 14.4% during March, or by 70.1%. We show that

[2] "The seesaw journey of alternative lenders during the COVID-19 pandemic," by Tanvi Anand and Sachin Goel, *ABFJournal*, January 27, 2021.
[3] 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.
[4] See Federal Reserve Bank of Kansas City Small Business Lending Survey, June 24, 2020.

this fall cannot be explained by operational reasons, namely that there were so many applications that lenders could not keep up. We find that lenders responded to applications at least as quickly in March than they did before and that the time to close an offer was lower as well. In other words, the FinTech lenders appear to have been extremely efficient in coping with the increased demand for loans, but they were not able or willing to make offers.

The decrease in the loan supply to small businesses is unique to FinTech lenders. We explore two non-mutually exclusive channels that could explain the drop in the supply. The channels are both related to the lending operations of FinTech lenders and predict different empirical patterns. With the first hypothesized channel, the *uncertainty channel*, the economic shock reduced the loan supply because the unprecedented COVID-19 shock materially increased the risk of making loans for FinTech lenders so that fewer loans were positive net present value (NPV) projects. This increase in risk was worse for FinTech lenders because they lend to riskier borrowers than banks, do not have collateral, and do not have soft information. These features of the FinTech business model meant that they were more at risk of adverse selection during the crisis. For instance, a bank with a relationship with a borrower could have had valuable information about how the borrower was affected by COVID-19 and such information was not available to a FinTech lender. Concerns about adverse selection can result in a riskier borrower not receiving an offer rather than receiving an offer with poorer terms (Stiglitz and Weiss, 1981).

With the second hypothesized channel, the *financial constraint channel*, FinTech lenders stopped making new loans because they became financially constrained: they no longer had the funds to make new loans nor could they raise new funds from lenders or investors on acceptable terms. FinTech small business loans are mostly funded in two ways, and both could lead to financial constraints when an economic shock hits. Some FinTech lenders lend funds that they raise through equity and debt issuance and keep the loans on their balance sheet (called “balance sheet lending” or “portfolio loans”). Other lenders originate loans and sell them shortly afterward to investors (called “loan sales” or “originate-to-distribute loans”). Regardless of the method of sale, lenders keep loans temporarily on their balance sheets using their cash or short-term debt facilities (“warehousing”), with the intent to sell them shortly after origination. Both financing models imply that an unexpected increase in the default risk of existing loans will result in a decrease in their value and will impair lenders' ability to make new loans unless they raise new equity or debt.

With balance sheet loans, lenders suffer from a debt overhang (Myers, 1977) as the value of their loans falls. With the originate-to-distribute model, lenders become constrained because of covenants in the financing vehicles they use and losses they suffer because of having "skin-in-the-game", which also can create a debt overhang. Further, the riskiest loans tend to have frequent interest payments; if the borrowers are subject to a shock, the lenders' income will fall quickly. As a result, lenders can quickly fail to meet covenants for lending facilities when loans on their balance sheet become delinquent due to a systemic shock. Also, in the case of loan sales, the possibility that investors could hesitate to purchase additional loans (potentially because they are financially constrained themselves) would likely dissuade lenders from making these loans in the first place. Additional frictions exist in the securitization market, as defaults on existing loans in a trust can cause rapid amortization, which effectively eliminates the trust as an instrument for funding new loans because loan repayments must be disbursed rather than used for new loans. Furthermore, lenders are required to hold some risk or provide excess collateral, so that they are directly affected by a decrease in loan values.

The evolution of lending behavior in the data shows that the *financial constraint channel* played a crucial role in curtailing the supply of loans, whereas the *uncertainty channel* is likely to have had a more limited effect. The uncertainty channel works at the loan level, so that some loans become too risky to make. Hence, it predicts that lenders will tighten their loan offer terms and tilt their lending toward less risky borrowers. Furthermore, lenders should be particularly leery of lending to applicants potentially more exposed to COVID-19 risk. Our empirical analysis that examines within lender evidence shows mixed and relatively weak support for this channel. The supply of loans decreased more for the restaurant industry—which was highly impacted by lockdowns—than for other industries. We also find some evidence that the supply of loans fell more for applicants in states and counties that were affected more by COVID-19 (measured by lockdowns and work-from-home trends). However, these effects explain a relatively small portion of the overall drop in supply. Further, we find that the terms on offered loans did not materially change despite the heightened risk until the last week of March and they also seem to have been mostly unaffected by the presence of lockdowns.

In contrast, the financial constraint channel operates at the lender level, across all loans, making lending infeasible because of a lack of resources. Instead of becoming more cautious and making loans more expensive, we find that lenders dropped out entirely during the month. Strikingly, the typical pattern is that a lender kept making loans at the same level as in February until lending suddenly dropped to a trivial amount or zero. Such an evolution seems to reflect lenders' financial constraints. So does the fact that the probability of receiving a loan during March falls similarly for applicants that would have been highly likely to receive a loan before March and for applicants who would have had a low probability of receiving a loan.

We also investigate which type of lenders dropped out first. Johnson (2021) shows that FinTech lenders differ strongly in the median FICO score of the borrowers with whom they transact. The financial constraint channel implies that lenders specializing in riskier loans, that is, loans to borrowers with lower FICO scores, would be more severely impacted by the COVID-19 shock and drop out earlier. Existing loans are more likely to become delinquent for these lenders, and hence, financial constraints are more likely to bind earlier. As expected, we find a clear negative relation between the risk profile of the loans made by lenders and the time they dropped out. In other words, with some exceptions, the lenders who made the riskiest loans before the crisis dropped out first.

As a more direct test to distinguish between the financial constraint and uncertainty channel, we use a Khwaja and Mian (2008) identification approach that eliminates applicant specific risk and uncertainty. We do so by examining lending decisions made by different lenders for the same application. Absent financial constraints, we would expect an applicant to be more likely to receive an offer from a lender who makes offers to riskier applicants as they have more loose underwriting standards. Conversely, if financial constraints more strongly affect lenders that make riskier loans, we would expect the probability that an applicant receives an offer from a lender that makes safer loans to increase as this lender still has financial capacity. We find that the latter is the case: more conservative lenders kept making loan offers to applicants who were turned down by less conservative lenders, which we see as further evidence that the drop in loan supply is lender-specific rather than applicant-specific.

In the third part of the paper, we focus on lenders for which there is publicly available information. We first identify small business lenders in news reports that explicitly discussed dropping out or having a lending pause. More importantly, we use publicly available data to show that asset prices tied to FinTech lending collapsed during March. We also show that the experience of banks was very different from the experience of FinTech lenders.

Our paper contributes to multiple strands of the literature. First, we add to the body of work on FinTech lending to small firms. Gopal and Schnabl (2022) 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 of 2007-2009. Barkley and Schweizer (2021) find that FinTech credit has become an important source of loans for small businesses, making loans accessible to businesses that otherwise would not receive bank credit. Balyuk, Berger, and Hackney (2020) argue that FinTech lenders make loans using technologies similar to those of large banks, namely using hard instead of soft information (Berger and Black, 2020). They show, using small business loans made through the platforms Prosper and Funding Circle, that FinTech lenders can substitute for lending by large banks but not for lending by small banks. Beaumont, Tang, and Vansteenberhe (2020) find that FinTech lending can help firms obtain bank credit subsequently as it helps firms acquire assets that they can use as collateral for bank loans. Johnson (2021) finds that small business FinTech lenders differ strongly in the typical risk of the loans they make. We add to this literature by showing how FinTech lending demand and supply respond to an external shock.

Second, 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 (Puri, 2022). We show that the decrease in credit supply for the riskiest businesses that did not have access to bank lending was dramatic. Though PPP appears to have led some FinTech lenders to stop making unsecured loans, the program provided credit when the supply of credit to the riskiest firms from FinTech lenders had essentially dried up. Balyuk, Prabhala, and Puri (2021) and Li and Strahan (2021) show that bank relationships were helpful for PPP applications made through banks. However, FinTech lenders became important distributors of PPP loans because they were used to dealing with and were accessible to a clientele that had no banking relationships (Erel and Liebersohn, 2020; Howell, Kuchler, Snitkof, Stroebel, and Wong, 2021). PPP lending through FinTech lenders, however, came with high rates of fraud (Griffin, Kruger, and Mahajan, 2021).

Though we believe this is the first study of the impact of COVID-19 on small business FinTech lending during March 2020, Bao and Huang (2022) explore the effects of COVID-19 on FinTech personal loans in China. They find that FinTech lenders expanded lending more than banks. Still, subsequently, they experienced poor loan performance even though, historically, the loan performance for FinTech lenders was similar to that of banks.

2. FinTech lending and lending platforms

This section describes the small business FinTech lending space and provides institutional details about the FinTech small business lending platform for which we have lending data. We begin by defining who FinTech lenders are and how they differ from other lending institutions. We discuss the relative strength and weaknesses of their business models relative to those of 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 study, FinTech lenders are defined as non-deposit-taking institutions that make loans online, either directly or through an online platform. Instead of relying on deposits to fund loans, FinTech lenders raise funds through private equity, private debt, bank credit facilities, securitization, loan sales, 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 and financial reporting and disclosures as well as other federal and state rules. Banks are also limited by regulatory guidance in their ability to make loans to low-FICO-score borrowers.[5] The fact that FinTech lenders are subject to less regulation than banks appears to play an important role in their growth (Buchak, Matvos, Piskorski, and Seru, 2018), likely because FinTech lenders can economize on overhead and make lending to risky borrowers less costly.

FinTech lending to small businesses has increased dramatically over the last decade. Gopal and Schnabl (2022) estimate that the volume of loan originations to small 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.[6] However, this figure underestimates the potential impact of FinTech lending as the average dollar size of FinTech loans is substantially smaller than that of loans made by banks and finance companies.[7] 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 financing elsewhere.[8]

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

[5] 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.
[6] The S&P Global Market Intelligence U.S. FinTech Market Report 2021 estimates that SME-focused FinTech originations totaled roughly $13 billion.
[7] See, for instance, https://www.valuepenguin.com/average-small-business-loan-amount.
[8] See for example Barkley and Schweitzer (2021) as well as statistics released by the Federal Reserve in the Small Business Credit Survey (2020).

to lend across the country. In these partnerships, the FinTech lender screens applicants, and the partner bank originates the loans. Loans are 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.

Lenders who originate-to-distribute earn a fee for the screening and origination of the loans. The loans are then sold to investors directly or through securitization. This model is common in consumer lending and is also used for small business lending. Balance sheet lenders, on the other hand, are economically similar to banks in that their profits come from the spread between the cost of funds and the interest and fees paid by borrowers net of losses.[9] However, balance sheet lenders do not fund loans with deposits like banks do. Instead, they use debt facilities that often are collateralized with loans. In troubled times, banks often see large inflows of deposits that increase their ability to fund loans (Gatev, Schuermann, and Strahan, 2009). In contrast, during a crisis, FinTech lenders would be more likely to experience tighter lending conditions as debt covenants become binding and lenders are less willing to extend further credit. In addition, a bank does not necessarily have to have cash on hand equal to the loan size it makes. 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.

In contrast to many bank borrowers, FinTech borrowers have no business relationships with lenders. The literature shows that soft information is more important for small banks than large banks (Liberti and Petersen, 2019). FinTech lenders also do not have a collateral lending technology. To make loans with collateral, a lender must have the ability to monitor the collateral and dispose of it if the lender defaults. As a result, FinTech lenders are much more dependent on the cash flow of borrowers than are bank lenders, who typically require collateral. These differences between FinTech lenders and bank lenders are important when the economy as a whole becomes riskier. The value of FinTech loans will be more sensitive to the uncertainty about the cash flows of borrowers than bank loans because banks can also rely on collateral

[9] Mills (2019) provides greater detail about the business models and identifies the differences in business models among small business FinTech lenders.

(see Stulz and Johnson, 1985, for an analysis of the riskiness of collateral debt compared to uncollateralized debt).

Similar to banks, FinTech lenders offer a variety of loan products, including merchant cash advances, lines of credit, term loans, and business credit cards.[10] However, unlike banks or finance companies, all 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 of the company through a personal guarantee, which allows the lender to seek recourse through collection agencies or court proceedings, or by placing liens on personal assets.

FinTech lenders have differentiated themselves from traditional banks by speeding up and simplifying the application and funding processes, which would make them especially attractive when an unexpected shock occurs such as the COVID-19 shock. The most-often cited challenges that small businesses face when working with traditional banks are the long wait times and the difficult application process.[12] FinTech lenders have a greatly simplified application process, and many lenders boast their ability to make decisions within minutes and for funds to hit the owner's bank account within 24 hours. This convenience and speed appears to be a central driver of FinTech growth (Berg, Fuster, and Puri, 2021).[13] This timeliness advantage would seem to be especially important when firms are faced with a shock such as the COVID-19 shock that puts them in a situation where they need to raise funds quickly.

[10] Merchant cash advances, sometimes referred to as short-term loans, are 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 often 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.
[11] Gopal and Schnabl (2022) note the key differences between finance companies and FinTechs and find that the primary difference is the collateral pledged.
[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.

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 platforms (P2P). 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 of a misnomer in the U.S. as institutional investors have become the primary investors and retail (or peer) investors have mostly 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. 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-known marketplace platforms of this type are LendingTree, Fundera, and Lendio, with the latter two focusing solely on small business lending. Our data come from a platform that uses this second model of marketplace lending (hereafter "the platform"). Our best estimate is that in 2019 roughly 10% of FinTech small business lending in the United States took place through 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 the most well-known lenders. Typically, an application is forwarded to only a handful of lenders based on certain predetermined attributes. For example, many lenders have hard cutoffs related to firm age, owner credit score, annual revenues, or industry (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 applicant.

In a matter of hours or days, applicants may receive offers from one or multiple lenders. Prior to the pandemic, about 58% of applicants with completed applications were approved by at least one lender, meaning more than 40% of applicants did not receive any offers.[14] Applicants who receive offers are assisted by the platform's loan agents in understanding the loan terms of 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 in the borrower's bank account via direct payment. The platform receives commissions from lenders based on a percentage of the loan amount for completed transactions.

2.3. Data used in this study

The primary data source for this study is a marketplace platform that connects small businesses with dozens of online lenders. We observe all applications made on the platform, solicitations for offers from the platform to lenders, loan offers received from lenders, and loan deals. Completed applications include firm characteristics like age, sales, industry, and number of employees as well as variables derived from submitted bank statements from the prior three months. Industry is self-reported by the applicant from a drop-down list that includes two-digit NAICS classifications, with some notable exceptions discussed in later sections. If the industry is undisclosed or does not neatly fit into industry classifications, we use the label "other."[15]

We augment these data with geographical and industry COVID-19 exposure measures. For geographic exposure, we use data from SafeGraph that measures foot traffic based on cell phone tracking and hand-collected data on announced lockdowns at the state level. We create a measure of local impact of the

[14] 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.
[15] Missing industry classification occurs in roughly 15% of applications.

pandemic by summing the number of devices that are at home all day in a county and divide that by the total number of devices in the county. We then match applicants to these exposure measures using the applicant's county when available. For industry-specific exposure measures, we identify high-exposure industries using the Small Business Pulse Survey, which in the initial survey from April 26–May 2, 2020 asked, "Overall, how has the COVID-19 pandemic affected your business?"[16] To determine exposure, we assign industries that are above the median in responding that they experienced a "large negative impact."

Finally, we use a dataset that include daily loan originations from seven of the largest online personal loan lenders made available through a FinTech aggregator.[17] These data allow us to assess whether the trends we see from the small business platform are observed in other FinTech lending markets. Specifically, we can assess whether a similar drop in loan volume occurred. Unlike the small business data, however, we do not observe applications or lender identifiers, which limits the analysis. We apply only one filter to these data as we aggregate loan volume by origination date: we replace origination volumes on the last day of the month with the average volume from the prior week. Roughly 45% of loans in the dataset are reported as having been originated on the last day of the month, which can be attributed to the granularity of reporting by the lenders.

3. The COVID-19 shock and platform lending volume

Before separately investigating the demand for and supply of loans, we present statistics about the lending volume for small business loans made on the platform both before and during March 2020. We first report 5-previous-business-day moving averages for the three months ending in March 2019 and March 2020. For comparison, we report similar data for personal FinTech loans.

Panel (a) of Figure 1 shows moving averages for the number of loans made on the platform. The number of loans in 2020 exceeds that of 2019 until early March. The number of loans in 2020 falls precipitously in

[16] See https://portal.census.gov/pulse/data/.
[17] All loans are originated via online lenders or platforms such as LendingClub, Upstart, and Avant. This dataset encompasses the majority of all personal loans made online—roughly 70% in terms of volume since 2014.

the middle of March and, by the end of the month, is almost 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, with almost all of the decrease taking place before the stimulus package is approved by Congress. Panel (b) of Figure 1 shows similar results for the total dollar amount of loans funded. Again, the amount funded plummets and becomes a fraction of what it was in 2019.

To check whether the sharp drop in loan origination activity was unique to our platform, we examine the aggregate volume of personal loans originated using a dataset that aggregates lending statistics from seven of the largest lenders in the space and covers over 70% of loans originated in the U.S. Panel (c) of Figure 1 plots the 5-previous-business-day moving averages for the number of loans funded from January to March 2019 and 2020, and Panel (d) shows the aggregate amounts. The volume of funded personal loans is much higher in 2020 than in 2019, aside from the large dip in volume during March 2020. Average volumes were 33% higher in January and February of 2020 relative to a year prior. Yet, in the last week of March, the number of funded loans was 46.9% lower than the average week in the first two months of the year.[18] These plots affirm that the decline in FinTech loan origination was not unique to our platform but was also experienced by other large FinTech lenders.

4. COVID and the demand for FinTech small business loans

Table 1 shows the characteristics of loan applicants, conditional on having completed the entire application process. 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 or on 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 652, which, depending on the classification chosen, reflects a subprime or near-prime credit score.[19] Applying small businesses on

[18] Looking at overall lending in March 2020 including loans with time stamps on the last day of the month shows only an 8% drop relative to March 2019. However, this constitutes a 32% drop relative to the volume that would have been anticipated considering the growth in loan volume over the prior year in January and February.

[19] 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

average have annual sales of $784,138 and are 54 months old. The average applicant has 7.3 employees and a bank balance of $18,065. In the prior three months, applicants have on average 1.5 days with negative bank balances and $73,280 and $73,063 in monthly credits and debits, respectively. Very few applicants appear to have a seasonal business.

The application pool in March 2020 is more than twice as large as in March 2019. Furthermore, applicants are more established and larger, and have better FICO scores than applicants a year earlier. Average sales are 34% higher. The average age of the business of the applicants is 8% 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 671. Bank balances are 47% higher. In sum, the applicants are overall more creditworthy based on the attributes reported in the table. However, this creditworthiness is based on historical attributes. While FinTech lenders could observe these historical attributes, they could not know directly how applicants would be exposed to the COVID-19 shock going forward. As a result, application data became less predictive of loan performance. We investigate this issue when we turn to the supply of loans.

It could be that the differences in firm characteristics between March 2019 and 2020 are not indicative of changing demand during the crisis, but rather a reflection of a trend in the quality of applicants that the platform receives between the two years. To address this concern and compare applicants as the crisis worsens in March 2020, Panel B of Table 1 compares applicant characteristics for the first and second halves of March. As the crisis worsens during March 2020, the volume of applications increases, and their credit quality, as measured by historical characteristics, improves. The number of applicants in the second half of March is 80% higher than in the first half. 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.

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/).

The data in Table 1 suggest that the decline in lending is unlikely due to a drop in demand. To better understand the evolution of demand, in Figure 2 we plot the daily number of applicants and the daily total amount of financing sought on business days in March 2019 and March 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 almost doubles over one week. The number of applicants subsequently decreases, but it is higher on every day of the month in 2020 than in 2019. The evolution of the total amount of financing sought, shown in Panel (b), is similar.

Figure 2 suggests that the demand for FinTech loans dropped as aid to small businesses through a stimulus package became more likely. The White House first proposed $500 billion in aid to small businesses on March 17, which corresponds to a sharp drop in the demand for loans.[20] On March 20, the Senate rejected the stimulus program, which was followed by an increase in the demand for loans. Demand then fell after it became certain on March 23 that the stimulus package would become law. However, despite the prospect of the stimulus program, the number of applicants remained higher than in 2019.

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. We begin by regressing the daily number of applicants for each business day 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 9–15 by 162 applications, and the following week sees an increase in the daily demand of 295 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 that demand during the weeks of March 16–22 and March 23-29 is significantly higher than in the omitted week, but

[20] *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/.

demand during the first and second weeks of March is not. The other coefficients are not significant. Of note, the week indicator variables explain little of the daily variation in demand in 2019, but they do explain a considerable amount of the daily variation in 2020.

5. The COVID-19 shock and the supply of loans by FinTech lenders

Next, we investigate the evolution of the supply of loans. We first show the evolution of supply in March 2020 in Section 5.1. We then investigate the impact of COVID-19 exposure on the supply of loans in Section 5.2 for industry exposure and Section 5.3 for location exposure. In Section 5.4, we show how the terms of loans evolve and are affected by COVID-19 exposure.

5.1. The evolution of loan supply in March 2020

We focus on loan offers lenders made 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 curves of loans. Before receiving an offer, applicants do not know the terms on which they can borrow; after receiving an offer, applicants often reject it. 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 3, Panel (a), shows the evolution of the number of loan offers for March 2019 and 2020. The panel conveys a clear message: the number of loan offers is high until mid-March and then collapses. The number of daily offers reaches a peak of slightly more than 500 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—that is, the 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 like 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 and is multiplied by 100 for ease in interpreting the coefficients. The variables of interest are indicator variables for the different weeks in March 2019 and March 2020.

The results in Table 3 show that supply falls in the second week of March 2020 and decreases steadily through the rest of the month. In the last week, the probability that an applicant receives an offer is 34 percentage points lower than at the beginning of March in Column (1). At the beginning of March, the unconditional probability of acceptance is 48.1%, dropping to 14.4% by the end of the month. In Column (2), we re-estimate the regression with the following applicant controls: the owner's FICO score, the log of the age of the business, the log of sales, the average bank balance, the number of days with a negative bank balance, the monthly number of credits, the monthly credit amount, the number of monthly debits, and the monthly debit amount. 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 based on historical data increases in March, so 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), respectively, but use the sample period from January to March. By the second week of March, the probability of acceptance is already down by 14 percentage points relative to the first week January. 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 last week of March, applicants are 58 percentage points less likely to receive an offer relative to applicants with similar historical characteristics in the first week of January 2019.

5.2. Loan supply and applicant industry risk

A possible explanation for the decrease in supply is that 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 that is losing customers rapidly and may have to close it as worry about COVID-19 spread grows. 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 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, the controls of Table 3, 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 Small Business Pulse Survey by the Census Bureau, with exceptions for industries that are reported more granularly. 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 between the industry and post-March 12 indicators. Restaurants are the only industry with a significantly negative interaction, irrespective of the sample period. It is also the industry in the Census Bureau's initial April 26–May 2, 2020 Small Business Pulse Survey with the largest fraction of businesses strongly negatively affected by the pandemic. When we use the longest sample period, the interaction has a coefficient of -18.2, meaning that the supply of loans to the restaurant industry is abnormally low by 18.2 percentage points compared to before March 12.

5.3. Loan supply and applicant location-related risk

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 or county levels affect the supply of loans. We estimate regressions where the dependent variable is an 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 lockdown. We also use the percentage of the population staying at home as the granularity of this measure is at the county level. The data are 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 increased 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 but include application-date fixed effects. In Column (1), the coefficient on the indicator variable for whether a state is in lockdown (*I(State lockdown)*) is statistically significant and indicates that the imposition of a lockdown reduces the probability of receiving an offer by 5.24 percentage points. In Column (2), the coefficient on the indicator variable for the percentage of the population working from home *(% Population home*) is -18.06 and statistically significant at the 5% level. Lastly, in Column (3), we use a 7-day average for the percentage of the population working from home *(% Population home (7-day avg)*). The coefficient is -31.62 and is significant at the 10% level. The economic significance of the coefficients is such that these variables explain relatively little of the decrease in the probability of receiving a loan offer. Specifically, a one standard deviation increase in the percent of the population at home and its 7-day average leads to a lower offer probability of 1.62 and 2.43 percentage points, respectively. In the next three columns, we add applicant controls, county fixed effects, and industry fixed effects. The coefficients on state lockdowns and population working from home remain negative but are statistically insignificant except for when the population working from home is averaged over seven days. Lastly, in Columns (7) to (9), we re-estimate the regressions of Columns (4) to (6) but include January–March 2019 in the sample. In these regressions, the state lockdown indicator is statistically significant at the 1% level with a negative coefficient similar to the coefficient in Column (1), but the county-level measures are negative and insignificant.

So far, we have seen that the supply of loans fell sharply. The drop was significantly worse in the restaurant industry and following the imposition of a lockdown. However, the overall impact of COVID-19 exposure, as measured by lockdowns, seems rather limited. When we re-estimate the regressions of Table 3 with the addition of the lockdown and working-from-home variables (Internet Appendix, Table 1A), the weekly indicator variables exhibit little change, meaning that our COVID-19 exposure variables do not by themselves explain the drop in supply.

5.4. Loan offer terms in March 2020

Another important aspect in understanding how the credit supply changes in March 202 is to examine how the terms of the loans evolve. We examine how loan terms vary for the same lender for an applicant within the same industry and the same historical characteristics. We report the results in Table 6. In Panel A, we estimate regressions for offer terms similar to the regressions for the supply of loans in Table 3. We regress offer terms on an indicator for the week of the offer, the control variables used previously, industry fixed effects, and lender fixed effects. We also estimate the regressions without lender fixed effects, and the overall conclusions are similar. The odd columns use the sample period of March 2020 and the even columns use the sample period of January to March 2020. Column (1) shows results when the dependent variable is the annual percentage rate (APR) and the sample period is March 2020. The indicator variable for the last week of March is positive and significant. The APR is higher in that week by an amount slightly greater than four percentage points, representing a 4.9% increase from the average APR at the beginning of March. As expected, the APR falls as the FICO score increases, as the age of the business increases, and as sales increase. In Column (2), we use data from January to March 2020. The results are similar to those in Column (1), except the coefficient on the number of days with negative balance is positive and significant and the log of sales is insignificant. In Columns (3) and (4), the dependent variable is the maturity of loans. None of the week indicator variables are significant except the one in the first week in Column (3) that is negative and significant at the 5% level. Finally, in Columns (5) and (6), the dependent variable is the log of the loan amount. Neither Column (5) nor Column (6) has a significantly negative coefficient on a week indicator.

In Panel B, we regress each offer's terms on the location COVID-19 exposure variables used in Table 5 as well as firm controls. We have application date, industry, lender, and county fixed effects. The sample is from January to March 2020, though the results are the same if the sample is only March 2020. The variables of interest are the variables that measure COVID-19 exposure locally. No variable has a significant coefficient. We find no evidence of an impact of location COVID-19 exposure on the APR, the maturity, or the amount of the loan offered.

In Panel C of Table 6, we analyze whether an industry's exposure to COVID-19 affects the terms of the loans businesses are offered. We use two variables to proxy for COVID-19 exposure: an indicator variable for the period of March starting when the WHO declares a pandemic emergency and an indicator variable for high-exposure industries.[21] We then interact these two variables. The sample is again from January to March 2020 and included in all regressions are lender fixed effects. We find no evidence that the APR is different after March 12 for the sample as a whole and no evidence that it increases for the most exposed industries after that date. Maturity increases for the most exposed industries after March 12 when we do not include control variables, but there is no effect when we do. Finally, the loan amount increases after March 12 for the whole sample when we do not include control variables. There is no consistent evidence that lenders adjusted the terms of their offers to account for COVID-19 exposure.

6. Why did the supply fall?

In this section, we offer potential hypotheses for the drop in the credit supply in March 2020, discuss their ability to explain the data, and conduct further tests. In Section 6.1, we show how the COVID-19 shock could affect the lenders' supply of loans through a financial constraint channel and an uncertainty channel. In Section 6.2, we provide evidence showing that FinTech lenders dropped from the platform. In Section 6.3, we provide direct evidence that lender-specific factors played a significant role in the decrease in supply. Lastly, in Section 6.4., we investigate the role of several additional explanations for the decrease in supply and show that it is unlikely that the evidence we view as supportive of the role of financial constraints in the decrease in supply can be attributed to these additional explanations.

[21] See https://portal.census.gov/pulse/data/. High-exposure industries are identified using responses to the initial April 26–May 2, 2020 Small Business Pulse Survey, which asked, "Overall, how has the COVID-19 pandemic affected your business?" We assign industries that are above the median in responding that they experienced a "large negative impact." 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 the 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.

6.1. The economics of FinTech small business lenders and the drop in supply

As a result of a shock like COVID-19, FinTech lenders may decrease the supply of loans because borrowers have become riskier (the uncertainty channel), because they do not have the resources to make loans because of lack of funding (the financial constraint channel), or for other reasons. We discuss these two channels successively in this Section and we discuss possible other reasons in Section 6.4.

6.1.1. The uncertainty channel

The uncertainty channel posits that the supply of loans fell because the COVID-19 shock made lending to some borrowers too risky. To understand how the uncertainty channel operates, it is best to consider a situation where the financial constraint channel does not operate. We consider an all-equity FinTech lender that has access to frictionless financial markets where it can invest its cash and issue equity. Its lending is purely transactional so that not making loans has no reputation or franchise costs. Such a lender makes new loans if they have a positive NPV. Everything else equal, an increase in loan demand would increase the number of loans the lender makes. However, the lender has to worry about the impact of the COVID-19 shock on the risk of loans. Loan applicants may look creditworthy based on historical characteristics, but the risk of loans depends on the impact of the COVID-19 shock on the borrower's business. The uncertainty created by the COVID-19 shock increases the risk of loans, but does so differentially. The risk of loans is increased further by the fact that applicants know more about the impact of the COVID-19 shock on their business than lenders.

Suppose now that a financially unconstrained lender has a mix of applicants. Some applicants are mostly 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 too high by lenders, they are simply rejected. Otherwise, they would receive more expensive loans than justified by their historical credit data because these data do not reflect the increase in risk caused by COVID-19. The greater risk of applicants explains a decrease in the supply of loans, but this drop in supply is not across the board. We would expect the supply to be cut for lenders for whom historical characteristics are least likely to reflect the risk of the loan because of COVID-19 exposure. We define the *uncertainty channel* as the impact of the COVID-19 shock on the supply of loans through its effect on the risk of applicants. We would expect this impact to become worse through March, so supply at the lender level would become progressively more restricted and loan terms would become progressively more expensive.

With the uncertainty channel, we would expect the supply to drop for those applicants that are more exposed to the COVID-19 shock but not others. Because the applicants more exposed to the COVID-19 shock are riskier, we would expect to see an effect of COVID-19 exposure on loan terms. Lending would shift towards safer applicants, which are those with better historical creditworthiness and less exposed to COVID-19.

6.1.2. The financial constraint channel

The financial constraint channel posits that the supply of loans dropped because lenders ran out of funding on acceptable terms. With the uncertainty channel, lenders can make loans but do not want to make some of them because they are negative NPV projects due to the heightened risk. With the financial constraint channel, lenders would make loans but cannot make them because they are resource-constrained. To understand this channel, consider a FinTech lender that funds loans with a debt facility. This lender has debt liabilities. With the COVID-19 shock, the value of the loans used as collateral for the debt facility falls. The lender becomes more highly levered. If the increase in leverage is high enough, the lender develops 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 would mostly benefit debtholders. For a levered firm in this situation, no new loans may be positive NPV projects for the equity holders even if some new loans would be positive NPV projects if it were an all-equity firm. Covenants on the loan facilities used by the lender may worsen its financial constraints. For instance, in some cases, covenants may limit funding if the weekly delinquency rate increases 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. The lender would then have to find alternative sources of funding to make new loans. Given the shock to the net worth of the lender, 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*.

With the financial constraint channel, a lender that becomes constrained can no longer fund new loans. It may choose to stop making new loans before it runs out of funding since it requires resources to pay its expenses. However, a constrained lender cannot choose to substitute less risky loans for more risky loans as it needs funds to make such loans. It follows that we expect constrained lenders to drop out and stop lending.

6.2. Empirical investigation of the uncertainty and the financial constraint channels

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; thus, a lender makes progressively fewer and fewer loans. With the financial constraint channel, we expect a lender to stop lending when it becomes constrained.

6.2.1. Evolution of supply in March 2020

With the uncertainty hypothesis, we would expect that safer applicants would see their likelihood of getting a loan fall less in March 2020 than riskier applicants. We estimate a logit model of the probability that an applicant receives a loan based on observable characteristics using data from January 2020.[22] We then use this model to compute the probability that an applicant receives a loan offer in February and March

[22] The model is constructed as follows. The dependent variable is an indicator equal to 1 if the applicant receives at least one offer. The independent variables are applicant characteristics including 5-point FICO bin indicators, industry indicators, the log of firm age, the log of revenues, average bank balance over the prior three months, the number of days with a negative bank balance, the monthly number of credits, the monthly credit amount, the number of monthly debits, and the monthly debit amount.

if lending proceeded as it had in January. We separate applicants into two groups: those likely to receive a loan, namely those with a probability of receiving a loan greater than 50%, and those unlikely to receive a loan. We compute the average daily frequency of receiving a loan for each group for January and February. We then compute the frequency of loan offers each day for each group in March. In Figure 4, we show the percentage drop in the frequency of receiving offers for each group relative to the average frequency during the first two months of the year. We find a steady decline in the frequency in March relative to the average frequency in January-February for both groups and the decline is similar. This means that applicants likely to receive a loan experienced a decrease in the probability of receiving a loan relative to the probability of receiving one earlier in the year similar to the decrease experienced by applicants unlikely to receive a loan. Such evidence is hard to reconcile with the uncertainty hypothesis.

Turning to the lender level, 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. Many went from having a steady acceptance rate to an acceptance rate of zero or almost zero. Panel (a) of Figure 5 gives an example of a fairly typical evolution of the supply of a lender. 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. The *Wall Street Journal* reported on lenders dropping out from a platform in March 28, stating, “About half a dozen lenders that have found borrowers through Fundera Inc., an online marketplace for small business loans, have paused new extensions of credit.”[23] Finally, Panel (c) of Figure 5 shows the number of offers made daily by the 25 most active lenders in 2020. The lenders are ranked by volume of offers in 2020 in ascending order. The figure shows that many lenders drop out in March and that our supply results are not due to one or two of the largest lenders becoming inactive. From this figure one can also observe the timeline of lender dropouts with one lender becoming

[23] “People need loans as coronavirus spreads. Lenders are making them tougher to get,” by Anna Maria Andriotis and Peter Rudegeair, *Wall Street Journal*, March 28, 2020.

inactive as early as March 14 and many others becoming inactive soon after March 17. In summary, we find lenders dropping out which is consistent with a role for financial constraints in explaining the drop in supply.

We would expect lenders making riskier loans to experience a greater weakening of their balance sheet and to become financially constrained faster than other lenders. Johnson (2021) shows that lenders differ greatly with respect to the median FICO score of their borrowers. Lenders with a lower median FICO score are lenders that make riskier loans. We define a lender's loan type using the median FICO score for loans that were transacted in 2019 and in Figure 6 plot lenders' exits over time in relation to their loan type. 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, we see a significant relation between when a lender dropped out and the median FICO score of that lender's loans. However, three lenders with a low-median-FICO-score habitat did not drop out in March. If we extend the analysis to April, the significant relation does not hold because of these three lenders, though it is relevant to note that all three of these lenders significantly reduce their lending by March 25. The largest outlier at April 15, for example, extended approximately 40 loans a day during 2020, but in the last week of March most days were below 5.

Our evidence indicates that the supply dried up because lenders dropped out. It does not appear that their offer rate slowly fell so that they eventually ended with no offers. Instead, lenders seem to have conducted almost business as usual until close to their exit. Such a pattern is inconsistent with the view that lenders exited because it became harder to find acceptable borrowers due to an increase in risk. This pattern, instead, is in line with the financial constraint channel.

6.2.2. Did riskier lenders pass up viable lending opportunities?

The two possible channels for lender supply cuts have different predictions about how lenders will respond to credit solicitations from a particular applicant. If supply falls because lenders perceive risk as being too high, 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. In contrast, if financial constraints are the primary source for lender supply cuts, we anticipate that the lenders most susceptible to funding shortfalls would be the first to forgo 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 liquidity as delinquencies increase and funders balk. 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 make 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. Thus, we can identify 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 borrower risk preferences influence the probability of extending an offer by controlling perfectly for applicant characteristics. Therefore, unlike previous regressions where we look at whether an applicant receives an offer from *any* lender, in these tests we include each solicitation for credit from the platform to the lenders. Our approach effectively uses the Khwaja and Mian (2008) identification strategy by examining lender responses for the same applicant. On average, each application is sent to 5.5 lenders, so these regressions include substantially more observations. As before, we define a lender's habitat as the median FICO score of 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 and applicant fixed effects.

In Table 7, Column (1), we estimate the regression on the sample period of January and February 2020. Unsurprisingly, prior to the pandemic crisis, riskier lenders (those with lower median FICO loans) are relatively more likely to extend an offer. 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 whether we use the sample period of January to March 2020 as in Column (3) or the sample period of January to March 2019 and 2020 as in Column (4). Summing the coefficients of median FICO with the crisis interaction yields an effect that is indistinguishable from 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.

To address the possibility that the median FICO score of borrowers does not adequately describe a lender's risk preferences, we run the same tests using the median interest rate on closed loans for each lender in 2019. This measure 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 score of its borrowers. The results using this measure are reported in Panel B of Table 7. 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.

6.3. Alternative explanations

In this section, we discuss several possible explanations and explain why they do not appear to be so convincing as to call in question the role of the financial constraint channel.

6.3.1. Operational constraints

As we saw, demand increased sharply in early March. Such an increase meant that the platform and lenders had to process more applications than they used to. They might have had difficulties coping with the higher volume of activity. As a result, they might have responded to fewer applications in a timely manner. We have data on the speed with which lenders responded to applications and with the speed with which they closed loans. Surprisingly, there is no evidence that they either took more time to respond to applications or that it took more time for loans to close. In particular, we find that the median number of days to respond to an application is one throughout. We also find that the mean number of days is lower in March than earlier in the year or than March of the previous year. It follows from this that operational difficulties cannot explain the drop in supply.

6.3.2. Lenders dropping from the platform but still lending

Another possible concern is that lenders decided that it was no longer worthwhile to lend through the platform but that they continued to lend outside the platform. Such lenders would not be financially constrained. We are not aware of reasons why this behavior might have occurred, but we investigate the possibility. The difficulty with assessing whether lenders stopped lending separately from the platform is that most lenders are private firms that do not report their lending activities publicly. We use the web's Wayback Machine to track the evolution of the websites of the 30 most-active lenders on the platform. For nine of the lenders, we find direct evidence on their websites that they stopped lending. In some additional cases, the lender's website disappeared. In the remaining cases, it is not possible to reach a conclusion based on the evolution of the website. By April, many companies direct traffic to PPP loans rather than direct loans. More generally, looking at lenders on the platform as well as other lenders, we find that many lenders made important business model shifts away from FinTech lending per se and transformed themselves into utilities for banks. For instance, the CEO of Fundation explained in a podcast that what enabled the business to survive was making small business loans for banks.[24]

6.3.3. Paycheck Protection Program (PPP)

A complicating factor in the 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, lenders may have expected the demand for their loans to fall as potential borrowers would anticipate switching to PPP loans. Some could also conclude that lending through the PPP program would be more profitable for them than continuing to make their conventional loans, as demand for such 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

[24] See https://fundation.com/small-business-lending-in-the-age-of-covid-fundation-ceo-sam-graziano/

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.[25] In the last week of March, we would expect lenders to drop out if they anticipated being involved in PPP. We find that only four of the lenders on the platform switched to making PPP loans. Since so many lenders dropped out before the last week and since participation of the lenders in the PPP program seems low, the PPP program does not seem to be a credible explanation for what we observe.

6.3.4. Model risk

A lender might have suddenly decided that uncertainty was too high to make any loans. The behavior of such a lender cannot be distinguished from the behavior of a lender who cannot make loans because of financial constraints. It is possible that some lenders might have decided that their lending models were no longer adequately capturing risk, so they stopped lending because they found that the loans they accepted were too risky for reasons not captured by their models. Some market participants discussed this risk.[26] Our evidence that less risky lenders were willing to offer loans to borrowers when more risky lenders were not willing to do so is hard to reconcile with this hypothesis. It suggests that more conservative lenders were less worried about the risk increase than less conservative lenders.

7. Evidence from the securitization market and individual lenders

This section presents evidence drawn from public information about the collapse of the credit supply by small business FinTech lenders in March 2020. Some of the lenders we discuss did not participate in the platform from which we obtain the data used in the earlier sections of this paper, but some did. We begin this analysis by examining the evolution of securitization markets during March 2020. We then provide

[25] 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/.

[26] For instance, the CEO of Fundera stated, “There is no model that can predict today if I lend $1, will I get paid back?” See “People need loans as coronavirus spreads. Lenders are making them tougher to get,” by Anna Maria Andriotis and Peter Rudegeair, *Wall Street Journal*, March 28, 2020.

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

By March 2020, several FinTech lenders were financing 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 if the 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 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, issuing 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 asset-backed-security (ABS) deals on downgrade-watch due to COVID-19.[27] Subsequently, by June, six transactions had entered rapid amortization,[28] which 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. These developments suggest that securitizations largely stopped being a source of funding for the lenders with securitization programs.

The secondary market for securitization notes offers another perspective on the withdrawal of investors. Many securitizations are private transactions, so prices are not available. However, the Kabbage securitization is a 144a issuance, so prices are available on TRACE. Perhaps not surprisingly, almost no trades took place during the crisis period. The tranches were issued at 100 in 2019. Figure 7 shows prices

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

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 or 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 to marketplace lending during the March crisis. The rebound in prices is dramatic and 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. Others provided some information about their lending and the issues they faced. Public companies have the most available information, but only one U.S. public company specialized in small business FinTech lending at the time, On Deck Capital.

7.2.1. 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 and in a financing subsidiary. It used debt facilities and securitization to finance loans. Its stock price dropped from $3.52 at the start of March 2020 to $1.54 at the end of the month, hitting a low of $0.65 on March 18. On Deck's stock rebounded sharply after it became clear that the CARES Act would be adopted. The company filed an 8-K form on March 23, 2020, stating that it had recently experienced both an increase in loan applications and slower collections. This 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, 22% of loans were non-paying. For comparison, at the end of the fourth quarter of 2019, 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 were 1–14 days past due. These are the loans that bore the brunt of the COVID-19 shock in March 2020.

In its April 30 earnings call for Q1, 2020, On Deck explained that the surge in loan applications in March represented “a higher degree of risk” so the firm “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.”[29] 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 during the call, “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.”

OnDeck was purchased by Enova, a publicly traded diversified FinTech firm, for $1.38 a share in July 2020. Strikingly, before 2020, OnDeck had a peak market capitalization of $1.6 billion, but it had lost much value before COVID-19. Enova purchased OnDeck for $90 million.

7.2.2. Kabbage

The CEO of Kabbage posted a statement on April 2, 2020, indicating that the firm 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 to operate.[30] 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* as 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.”[31] As reported by the *Financial Times*,

[29] Q1 2020 OnDeck Capital Inc. Earnings Call, April 30, 2020, Thompson Reuters.
[30] “Softbank-backed lender Kabbage cuts off businesses as cash needs mount,” by Zeke Faux and Jennifer Surane, *Bloomberg*, April 1, 2020.
[31] “Online lender stops making loans to small U.S. businesses,” by Robert Amstrong, April 1, 2020.

Kabbage eventually processed more loans for the PPP program than it had lent in the previous year: $3.5 billion in PPP loans by May 8, 2020, versus $2.8 billion in loans in 2019.[32]

7.3. Banks

Banks do not appear to have cut back on lending to small businesses in the same way that FinTech lenders did. Evidence supporting the idea that FinTech lenders decreased small business lending more sharply than banks comes from a survey by biz2credit, a lending platform that distributes a small business lending index. This index reports acceptance rates of applications made through the platform to various types of lenders. The index is computed 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 higher 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 an alternative lender category. This category's acceptance rate dropped from 57.3% to 30.4%. This evidence suggests an overall decrease in the acceptance rate for small business loans, but less so for small banks.

Because the survey only shows acceptance rates for banks that lend on the biz2credit platform, we rely on a second, broader survey conducted by the Federal Reserve Bank of Kansas City (FRBKC) on small business lending by banks.[33] The FRBKC 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

[32] "Kabbage rebounds after accessing U.S. loan programme," by Miles Kruppa and Robert Amstrong, *Financial Times*, May 18, 2020.
[33] See Federal Reserve Bank of Kansas City Small Business Lending Survey, June 24, 2020.

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 FRBKC survey also reports that about 20% of respondents experienced an increase in credit-line usage. The survey provides mixed evidence on overall loan demand: on net, small banks reported a decrease in loan demand but larger banks reported an increase.

8. Conclusion

In this study, 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 separately examine the demand for and supply of loans. We find that demand increased in response to the COVID-19 shock and that the average loan applicant became more creditworthy based on historical characteristics. However, paradoxically, at a time when FinTech lenders' advantage over banks in responding to demand rapidly would have been most valuable, they were not able to respond as the supply fell. Surprisingly, while the supply decreased, the terms of the loans were mostly unaffected by the COVID-19 shock. We provide evidence that the phenomenon we document and try to explain is not unique to FinTech small business lending as originations of online individual loans fell as well.

We focus our investigation on two potential explanations for the drop in supply: a) the increase in uncertainty resulting from the COVID-19 shock, and b) FinTech lenders became financially constrained. We find strong evidence that the supply fell more because of lender factors rather than because of applicant factors. We show that the supply of loans dried up because lenders dropped out. The typical lender kept lending in 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 simply due to an increase in risk resulting from the COVID-19 shock that affected applicants. This is because the decrease in supply is to a large extent the result of lender exits.

If the reason for the drop in supply is that applicants become riskier, we would expect lenders to decrease the supply of loans to the riskier applicants and to adjust terms for other applicants. We find no consistent evidence of a change in lending terms. We also show that the COVID-19 exposure of applicants played a relatively small role in the drop in supply.

The main explanation for lender exits is that 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 become 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. Using a Khwaja and Mian (2008) identification approach, we find that the riskiest lenders became less likely to extend offers to a particular applicant compared to safer lenders, who were less likely to be financially constrained.

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. This model also makes loans available quickly and conveniently. However, because these are transactional loans and borrowers do not have a relationship with the lender, the lender has to rely on hard information to make loans. During the COVID-19 shock, such information became less useful. Further, FinTech small business lending relies on loan sales and debt facilities collateralized by loans to fund additional loans. Such a funding model becomes problematic when existing loans lose value and default more.

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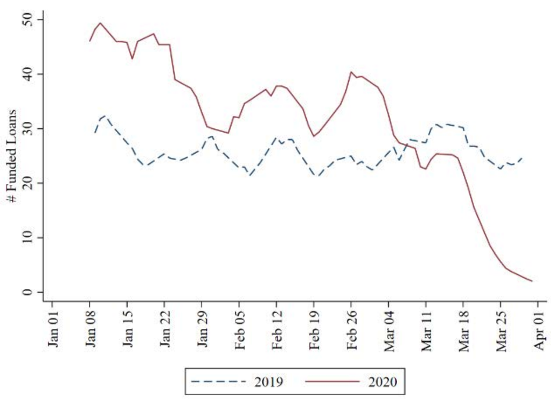
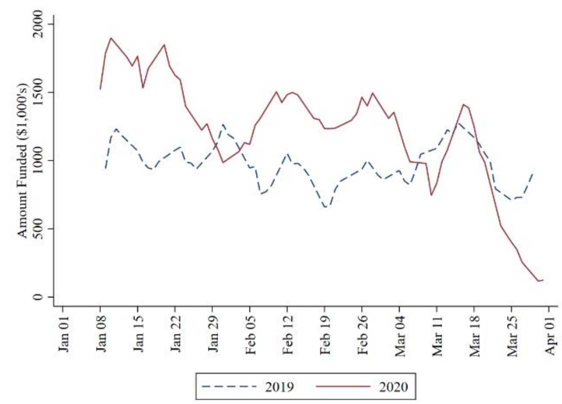
Figure 1. FinTech loan volume: Small business loans and personal loans

This figure depicts the evolution of funded loans in the first three months of 2020 for both small business loans (SB, Panels (a) and (b)) and personal loans (Panels (c) and (d)) originated by FinTech lenders. Panels (a) and (b) use data from a marketplace platform that connects small businesses with the major online lenders. Panel (a) plots the 5-business-day moving average of the number of funded loans on the platform in 2020 relative to 2019. Panel (b) plots a similar moving average but for total amount funded. Panels (c) and (d) use data from an aggregator of personal loans with coverage on all major FinTech platforms. Panel (c) shows the 5- business-day moving average of the number of funded loans, and Panel (d) shows the aggregate amount funded.

(a) Number of funded loans (SB)



(b) Total amount funded (SB)



(c) Number of funded loans (Personal)

(d) Total amount funded (Personal)

Figure 2. Small business loan demand

The figure shows 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 March. Weekends are excluded.

(a) Number of applicants

(b) Total amount requested ($ millions)

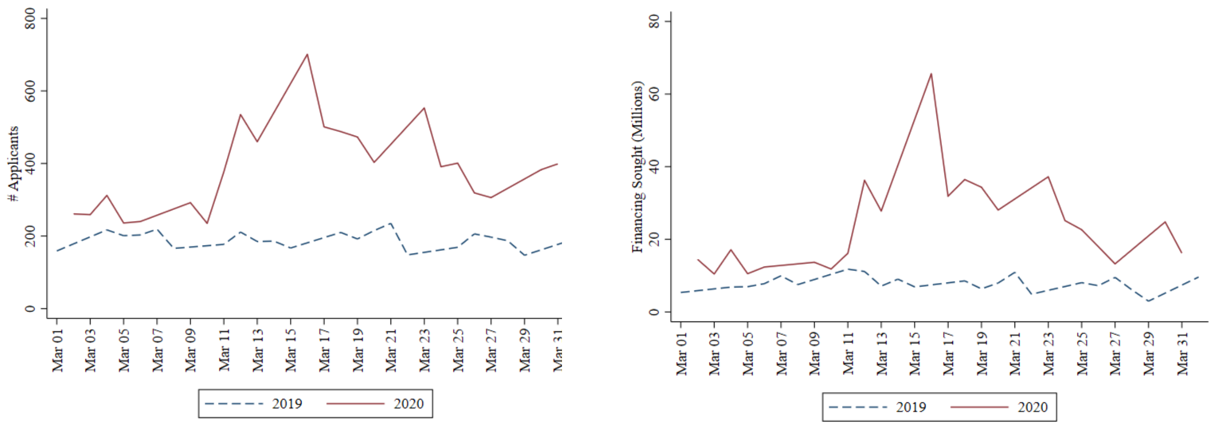
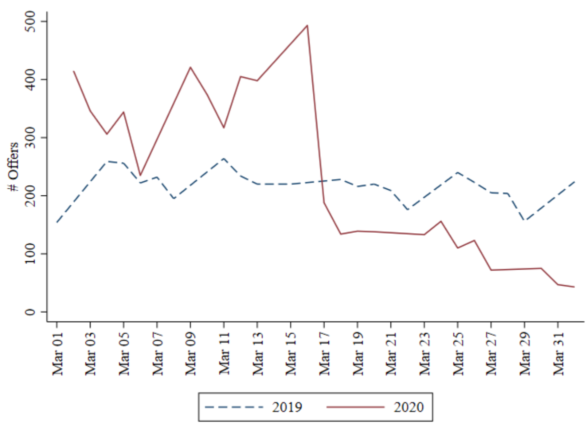


Figure 3. Loan supply

This figure shows how supply changes during the crisis. Applicants receive anywhere from zero to more than 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 4. Offers by Offer Likelihood

This figure shows the relative drop in offer likelihood in March 2020 separately for applicants with high and low likelihood of receiving an offer. Applicants with high (low) offer probability are those with greater (less) than 50% likelihood of receiving an offer. Plotted below is the average daily frequency of loan offers divided by the average daily frequency for January and February separately for each of these groups. Offer likelihood is determined using a logit model that is trained out-of-sample in January 2020. The dependent variable is an indicator equal to 1 if the applicant receives at least one offer. The independent variables are applicant characteristics including 5-point FICO bin indicators, industry indicators, the log of firm age, the log of revenues, average bank balance over the prior three months, the number of days with a negative bank balance, the monthly number of credits, the monthly credit amount, the number of monthly debits, and the monthly debit amount.

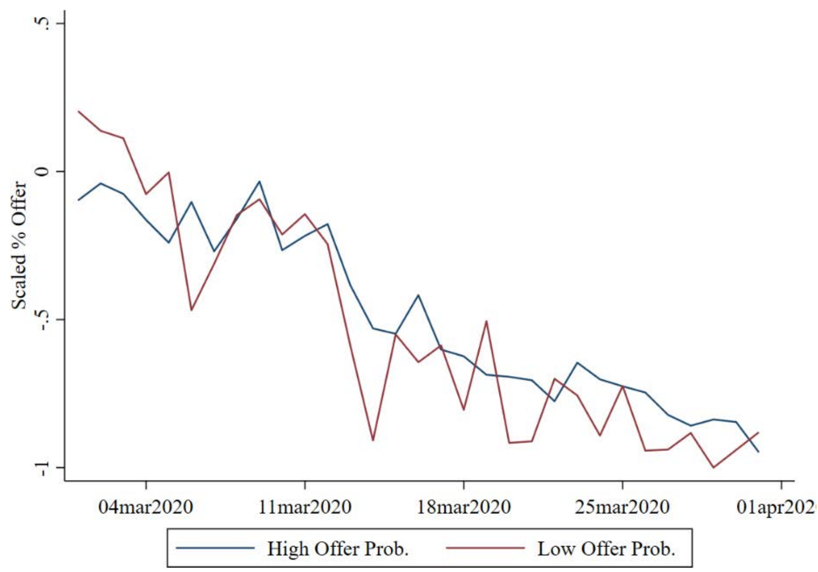
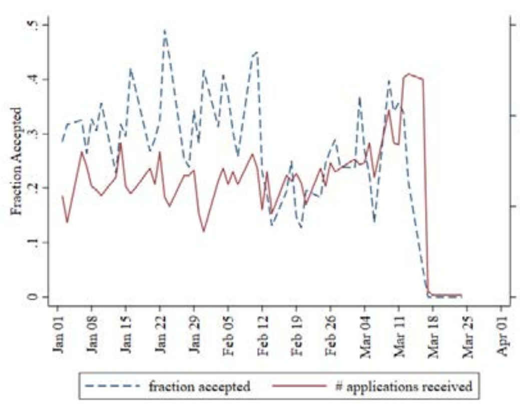


Figure 5. Lender dropouts

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. 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. Panel (c) shows the number of offers extended by individual lenders and the date of the application. Lenders included in this figure are the 25 lenders with the highest volume in 2020. Lenders are sorted by loan offer volume in 2020 and displayed in ascending order on the y-axis.

(a) Lender dropout example



(b) Active lenders (moving average)

(c) Offers by lender and application date

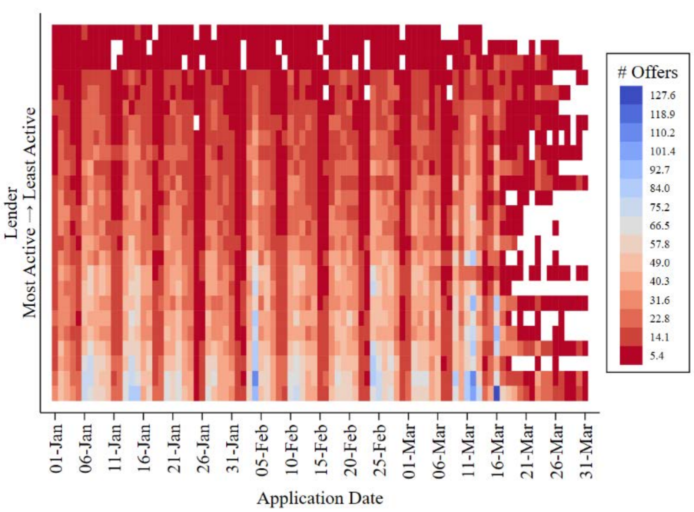


Figure 6. Lender dropouts by average lender risk

This figure shows the relation 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 FICO score of the median borrower with whom the lender transacted in the previous year. This can be viewed as a proxy for a lender's risk appetite. Lender circles are weighted by the number of transacted loans in the previous year.

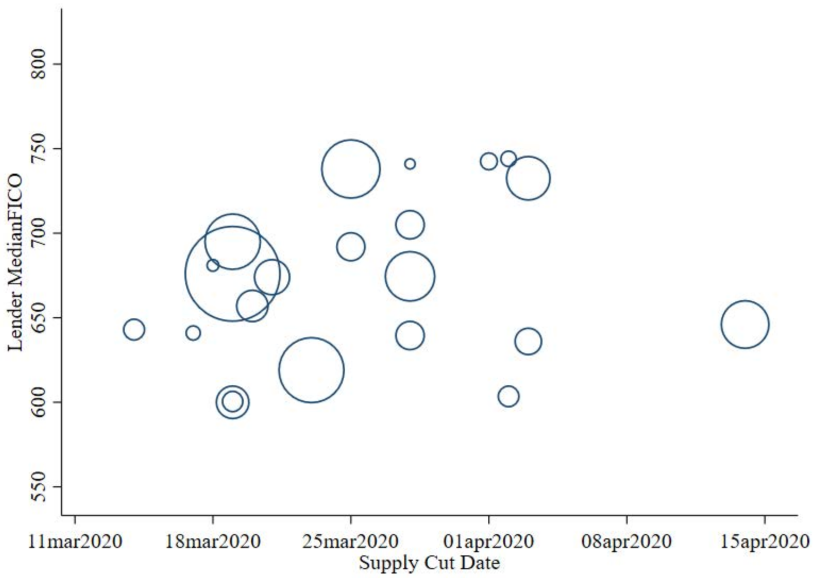
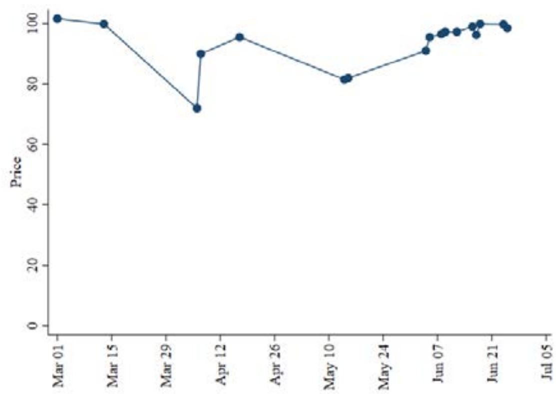


Figure 7. Securitization prices

This figure shows 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, and 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)

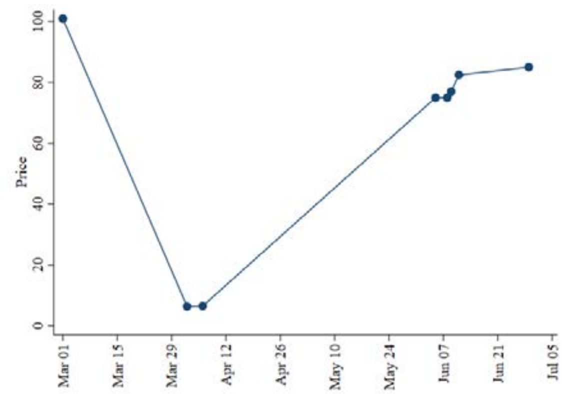


Table 1. Applicant comparative statistics

This table compares the characteristics of applicants who applied for loans prior to the COVID-19 shock and those who applied 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. *FICO* is the credit score of the business owner. Sales, firm age, and number of employees are reported by the firm at the time of application. Bank account information like average bank balance, number of days with a negative balance, and average monthly number and amounts of credits and debits are average monthly values taken from the prior-3-months' bank statements. *Seasonal business* is an indicator equal to one if the business defines itself as seasonal. *I(Offer)* is an indicator for whether the applicant received an offer from any lender within 30 days of the application. *APR*, *Maturity*, and *Loan Amount* are, respectively, the average annual percentage rate, maturity (in months), and loan amount on offers received by the applicant. *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 avg)* is the average fraction of the population that was home all day in the county from the prior week. The differences in means and *t*-statistics are reported in the last two columns.

Panel A: Comparing applicants between 2019 and 2020

	March 2019		March 2020		Difference	
Variable	Mean	St. Dev	Mean	St. Dev	b	t
FICO	652.2	72.6	671.3	79.7	19.17***	12.08
Annual Sales	784,138	1,043,705	1,051,744	1,281,691	267,605***	11.26
Age(Months)	53.58	49.98	58.03	45.09	4.45***	4.32
# Employees	7.25	11	8.35	12.39	1.10***	4.46
Avg Bank Balance	18,065	36,142	26,620	48,653	8,554.***	10.01
# Days Negative Balance	1.47	3.03	1.13	2.75	-0.34***	-5.39
# Monthly Credits	26.32	26.42	28.4	27.13	2.08***	3.67
Monthly Credit Amount	73,280	118,768	91,881	141,737	18,600***	6.95
# Monthly Debits	89.24	67.07	89.15	69.3	-0.09	-0.07
Monthly Debit Amount	73,063	119,355	92,641	142,800	19,578***	7.28
Seasonal Business	0.06	0.23	0.04	0.21	-0.01**	-2.77
I(Offer)	0.47	0.50	0.27	0.44	-0.20***	-19.65
APR	95.08	58.37	80.66	52.51	-14.42***	-7.38
Maturity	11.36	11.53	16.60	23.19	5.24***	8.74
Loan Amount	43,470	44,072	57,866	57,544	14,395***	8.39
I(State Lockdown)	-	-	0.26	0.44	-	-
% Population Home	-	-	0.31	0.09	-	-
% Population Home (7-day avg)	-	-	0.29	0.08	-	-
Observations	3,157		7,470		10,627	

Table 1. Applicant comparative statistics (Cont.)

Panel B: Comparing applicants within March 2020

	March 1-14, 2020		March 15-31, 2020		Difference	
Variable	Mean	St. Dev	Mean	St. Dev	b	t
FICO	656.5	78.2	679.6	79.4	23.06***	12.15
Annual Sales	905,186	1,199,631	1,133,124	1,318,167	227,937***	7.59
Age(Months)	52.93	42.47	60.87	46.25	7.94***	7.50
# Employees	7.47	11.61	8.84	12.79	1.37***	4.66
Avg Bank Balance	21,045	41,650	29,716	51,883	8,670***	7.88
# Days Negative Balance	1.40	3.11	0.98	2.51	-0.42***	-6.00
# Monthly Credits	26.92	25.58	29.22	27.92	2.30***	3.60
Monthly Credit Amount	81,132	132,959	97,849	146,056	16,717***	5.02
# Monthly Debits	91.2	69.54	88.01	69.16	-3.19	-1.90
Monthly Debit Amount	81,631	133,551	98,755	147,345	17,123***	5.11
Seasonal Business	0.05	0.22	0.04	0.2	-0.01	-1.78
I(Offer)	0.44	0.50	0.18	0.38	-0.26***	-23.42
APR	92.76	55.35	64.28	43.34	-28.48***	-12.62
Maturity	13.37	17.06	21.02	29.02	7.65***	6.84
Loan Amount	48,841	50,974	70,207	63,454	21,366***	8.10
I(State Lockdown)	0.00	0.00	0.40	0.49	0.40***	56.48
% Population Home	0.22	0.04	0.37	0.06	0.15***	109.56
% Population Home (7-day avg)	0.23	0.02	0.33	0.07	0.10***	73.71
Observations	2,667		4,803		7,470	

Table 2. Demand for loans in March 2020

This table examines the effect of the pandemic on the demand for loans. For each business day starting January 1 and ending March 31, the number of applicants to the platform are summed and regressed on an indicator for the week of the year. In Column (1), the sample period is January to March of 2020. Column (2) examines January to March of 2019. In each of these specifications, the first week of the year (January 1–7) is omitted. In Column (3), both years are included, along with an indicator variable for the year 2020 (unreported). In the last specification, the first weeks in both 2019 and 2020 are omitted. Robust standard errors are reported in parentheses. * p<.1; ** p<.05; *** p<.01.

Dependent variable	Number of Applicants		
	(1)	(2)	(3)
Mar 2-8 (2020)	43.60		-6.35
	(47.49)		(60.68)
Mar 9-15 (2020)	161.80**		127.85
	(71.40)		(80.37)
Mar 16-22 (2020)	295.20***		246.45***
	(67.95)		(78.41)
Mar 23-29 (2020)	176.00***		146.05*
	(63.63)		(74.02)
Mar 4-10 (2019)		49.95	49.95
		(37.89)	(38.07)
Mar 11-17 (2019)		33.95	33.95
		(37.39)	(37.57)
Mar 18-24 (2019)		48.75	48.75
		(39.51)	(39.71)
Mar 25-Mar 31 (2019)		29.95	29.95
		(38.16)	(38.34)
Constant	218.00***	151.25***	151.25***
	(45.46)	(36.67)	(36.85)
Sample Period	Jan-Mar 2020	Jan-Mar 2019	Jan-Mar 2019-2020
R^2	0.612	0.268	0.739
Observations	64	64	128

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 100 if the applicant receives at least one offer. Firm controls are included in all but Columns (1) and (3). These controls are the FICO score of the owner, log of firm age, log of sales, average bank balance, the number of days with a negative balance, the average monthly number and amount of credits and debits, and industry fixed effects. 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. In Columns (1) and (2), the sample is limited to applications received in March 2020. The sample used in Columns (3)–(4) includes January and February 2020. The sample used in Column (5) is limited to January–March of 2019. The sample used in Column (6) includes January–March for both years. Standard errors are clustered by application date and reported in parentheses. * p<.1; ** p<.05; *** p<.01.

Dependent variable	I(Offer)*100					
	(1)	(2)	(3)	(4)	(5)	(6)
Mar 2-8 (2020)			-3.85	-2.71		-17.46***
			(2.75)	(3.02)		(5.36)
Mar 9-15 (2020)	-9.65***	-11.42***	-13.50***	-14.43***		-31.63***
	(3.42)	(3.59)	(3.76)	(4.17)		(6.47)
Mar 16-22 (2020)	-25.72***	-30.45***	-29.57***	-33.75***		-47.97***
	(3.38)	(3.05)	(3.73)	(3.71)		(5.85)
Mar 23-29 (2020)	-33.67***	-38.87***	-37.52***	-41.93***		-58.30***
	(2.22)	(2.43)	(2.74)	(3.16)		(5.50)
Mar 4-10 (2019)					14.42***	14.71***
					(4.43)	(4.45)
Mar 11-17 (2019)					16.77***	17.09***
					(4.97)	(5.00)
Mar 18-24 (2019)					13.98***	14.07***
					(4.53)	(4.57)
Mar 25-Mar 31 (2019)					16.10***	16.19***
					(4.50)	(4.55)
Sample Period	Mar 2020	Mar 2020	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2019	Jan-Mar 2019-2020
Controls	No	Yes	No	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes	Yes
R^2	0.09	0.16	0.12	0.20	0.12	0.17
Observations	7,470	7,470	16,171	16,171	7,817	23,990

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 a value of 100 if an application received an offer. *I(Post 3/12)* is an indicator variable equal to one if the application was submitted on or after March 12. This indicator is interacted with firm characteristics, including FICO score of the owner, log of firm age, log of sales, average bank balance, number of days with a negative balance, average monthly number and amount of credits and debits, and fixed effects for industry. For ease in reporting, the table includes only the coefficients on the 16 largest industries by applications 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 and are reported in parentheses. * p<.1; ** p<.05; *** p<.01.

Dependent variable	I(Offer)*100		
	(1)	(2)	(3)
AgricultureForestry * I(Post 3/12)	8.38	8.98	4.40
	(7.20)	(7.35)	(6.75)
ArtsEntertainment * I(Post 3/12)	6.05	8.55**	7.65**
	(5.97)	(4.15)	(3.72)
Automotive * I(Post 3/12)	1.55	-0.85	-0.64
	(10.08)	(5.03)	(4.65)
Construction * I(Post 3/12)	-3.80	-3.35	-3.25
	(6.02)	(3.10)	(2.84)
Education * I(Post 3/12)	-2.31	-4.00	-2.55
	(11.23)	(6.28)	(5.90)
Finance * I(Post 3/12)	12.23*	7.80	5.42
	(6.33)	(4.78)	(4.25)
FreightTrucking * I(Post 3/12)	-6.09	-3.77	-3.73
	(7.43)	(5.50)	(5.25)
Healthcare * I(Post 3/12)	6.06	7.75*	5.43
	(9.29)	(4.63)	(4.27)
InformationMedia * I(Post 3/12)	2.54	-1.09	-0.76
	(5.24)	(3.72)	(3.56)
LegalServices * I(Post 3/12)	1.25	4.64	8.96
	(13.42)	(7.82)	(7.18)
Manufacturing * I(Post 3/12)	-5.19	-2.52	-1.69
	(6.97)	(3.77)	(3.49)
RealEstate * I(Post 3/12)	0.77	-1.49	-3.31
	(5.32)	(4.32)	(4.04)
Restaurants * I(Post 3/12)	-20.33***	-18.34***	-18.20***
	(5.89)	(3.04)	(2.69)
Retail * I(Post 3/12)	2.86	1.42	1.70
	(6.70)	(4.19)	(3.87)
Transportation * I(Post 3/12)	-1.74	-1.18	-2.56
	(7.01)	(3.56)	(3.37)
Wholesale * I(Post 3/12)	-8.48	-1.84	-0.22
	(6.26)	(5.59)	(5.06)
Sample Period	March 2020	Jan-Mar 2020	Jan-Mar 2019-2020
Controls	Yes	Yes	Yes
R^2	0.14	0.20	0.16
Observations	7,470	16,171	23,990

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

This table shows the effect of geographic exposure to the pandemic on the likelihood that a firm receives a loan offer. The dependent variable is an indicator equal to 100 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 avg)* is the average fraction of the population that was home all day in the county from the prior week. Firm controls included are FICO score of the owner, log of firm age, log of sales, average bank balance, number of days with a negative balance, average monthly number and amount of credits and debits, and industry indicators. FICO is scaled by 100 while bank balances and debit (credit) number and amounts are scaled by 1,000. Standard errors are clustered by application date and county and are reported in parentheses. * p<.1; ** p<.05; *** p<.01.

Dependent variable	I(Offer)*100								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
I(State Lockdown)	-5.24***			-3.44			-5.90***		
	(1.76)			(2.31)			(1.63)		
% Population Home		-18.06**			-35.52			-22.66	
		(8.51)			(26.61)			(18.45)	
% Population Home (7-day avg)			-31.62*			-70.64*			-43.16
			(18.07)			(35.45)			(26.48)
FICO				7.65***	7.60***	7.65***	8.28***	8.27***	8.29***
				(1.30)	(1.31)	(1.30)	(0.82)	(0.82)	(0.82)
ln(Age)				3.45***	3.44***	3.40***	2.60***	2.62***	2.60***
				(0.75)	(0.77)	(0.76)	(0.62)	(0.62)	(0.61)
ln(Sales)				2.71***	2.70***	2.71***	3.83***	3.81***	3.81***
				(0.77)	(0.77)	(0.77)	(0.54)	(0.54)	(0.54)
Avg Bank Balance				-0.02	-0.02	-0.02	-0.01	-0.01	-0.01
				(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
# Days Negative Balance				-2.65***	-2.65***	-2.64***	-3.43***	-3.43***	-3.43***
				(0.28)	(0.28)	(0.29)	(0.19)	(0.19)	(0.19)
# Monthly Credits				107.76***	107.26***	107.39***	116.30***	116.35***	116.42***
				(26.80)	(26.78)	(26.62)	(19.82)	(19.74)	(19.74)
Monthly Credit Amount				-0.02	-0.01	-0.02	-0.04	-0.04	-0.04
				(0.05)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)
# Monthly Debits				2.46	2.49	2.45	12.72*	12.95*	12.96*
				(11.50)	(11.46)	(11.51)	(6.61)	(6.61)	(6.63)
Monthly Debit Amount				0.01	0.01	0.01	0.03	0.03	0.03
				(0.05)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)
Sample Period	Mar 2020	Mar 2020	Mar 2020	Mar 2020	Mar 2020	Mar 2020	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2020
App Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.11	0.11	0.11	0.27	0.27	0.27	0.29	0.29	0.29
Observations	5,069	5,069	5,069	5,069	5,069	5,069	11,538	11,538	11,538

Table 6. Offer terms and exposure to COVID-19

This table shows the effect of time, geographical, and industry exposure 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 March 2020, controlling for firm characteristics and holding constant the lender. Panel B examines the effect of COVID-19 exposure on loan 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 avg)* is the average fraction of the population that was 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?" Industries that were above median in responding that they experienced a "large negative impact" are identified with the dummy *I(HighIndExposure)*. FICO is scaled by 100 while bank balances and debit (credit) number and amounts are scaled by 1,000. Standard errors are clustered by application date and lender and are reported in parentheses. * p<.1; ** p<.05; *** p<.01.v

Panel A: Changes in loan offer terms in March 2020

Dependent variable	APR		Maturity		ln(Loan Amount)	
	(1)	(2)	(3)	(4)	(5)	(6)
Mar 2-8 (2020)		-1.30		-0.14		-0.04
		(1.73)		(0.16)		(0.03)
Mar 9-15 (2020)	0.40	-1.02	-0.09	-0.23	0.04	0.01
	(1.19)	(1.29)	(0.14)	(0.19)	(0.04)	(0.04)
Mar 16-22 (2020)	2.58	1.13	0.10	0.02	-0.04	-0.06
	(2.00)	(1.31)	(0.36)	(0.21)	(0.06)	(0.05)
Mar 23-29 (2020)	4.55*	4.02*	-0.68**	-0.61	0.03	0.01
	(2.67)	(1.98)	(0.28)	(0.41)	(0.13)	(0.14)
FICO	-5.83***	-6.75***	0.68***	0.62***	0.15***	0.15***
	(1.50)	(1.45)	(0.17)	(0.13)	(0.03)	(0.02)
ln(Age)	-4.32***	-4.34***	0.44**	0.59***	0.09***	0.08***
	(1.35)	(0.99)	(0.19)	(0.18)	(0.03)	(0.02)
ln(Sales)	-1.29**	-1.05	0.10	0.05	0.27***	0.30***
	(0.62)	(0.70)	(0.07)	(0.05)	(0.07)	(0.05)
Avg Bank Balance	0.01	0.02**	-0.00	-0.00	0.00*	0.00***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
# Days Negative Balance	0.72	1.25***	-0.08	-0.09***	0.00	-0.01
	(1.00)	(0.39)	(0.06)	(0.03)	(0.02)	(0.01)
# Monthly Credits	-15.48	-36.15**	5.85	6.64**	0.56	1.18***
	(18.86)	(16.46)	(3.83)	(2.86)	(0.91)	(0.43)
Monthly Credit Amount	-0.02	-0.02	0.00	0.01**	0.00***	0.00***
	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
# Monthly Debits	2.31	4.15	-1.18	-0.22	0.81***	0.76***
	(8.84)	(5.78)	(1.05)	(0.78)	(0.20)	(0.15)
Monthly Debit Amount	0.01	0.01	-0.00	-0.00**	-0.00***	-0.00
	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Sample Period	Mar 2020	Jan-Mar 2020	Mar 2020	Jan-Mar 2020	Mar 2020	Jan-Mar 2020
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.82	0.81	0.98	0.95	0.65	0.65
Observations	2,400	8,192	2,400	8,192	2,400	8,192

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

Panel B: Offer terms and geographical exposure to COVID-19

Dependent variable	APR			Maturity			ln(Loan Amount)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
I(State Lockdown)	0.49			-0.75			0.11		
	(3.54)			(0.53)			(0.13)		
% Population Home		14.99			-0.80			-0.19	
		(22.81)			(2.20)			(0.51)	
% Population Home (7-day avg)			27.48			-2.43			-0.90
			(25.23)			(4.00)			(0.83)
FICO	-6.57***	-6.57***	-6.58***	0.59***	0.59***	0.59***	0.15***	0.15***	0.15***
	(1.51)	(1.51)	(1.51)	(0.14)	(0.14)	(0.14)	(0.02)	(0.02)	(0.02)
ln(Age)	-4.81***	-4.81***	-4.80***	0.60***	0.60***	0.60***	0.09***	0.09***	0.09***
	(1.13)	(1.14)	(1.13)	(0.19)	(0.19)	(0.19)	(0.02)	(0.02)	(0.02)
ln(Sales)	-1.40*	-1.39*	-1.39*	0.02	0.02	0.02	0.31***	0.31***	0.31***
	(0.71)	(0.71)	(0.71)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
Avg Bank Balance	0.02*	0.02*	0.02*	-0.00	-0.00	-0.00	0.00**	0.00**	0.00**
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
# Days Negative Balance	1.29***	1.29***	1.29***	-0.09***	-0.09**	-0.09***	-0.01	-0.01	-0.01
	(0.45)	(0.45)	(0.45)	(0.03)	(0.04)	(0.03)	(0.01)	(0.01)	(0.01)
# Monthly Credits	-47.81**	-47.33**	-46.94**	7.58**	7.61**	7.55**	1.49***	1.48***	1.45***
	(19.01)	(18.88)	(18.99)	(3.01)	(3.13)	(3.03)	(0.49)	(0.49)	(0.49)
Monthly Credit Amount	-0.03**	-0.03**	-0.03**	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
# Monthly Debits	1.81	1.81	1.81	-0.35	-0.38	-0.38	0.67***	0.67***	0.67***
	(7.02)	(7.13)	(7.30)	(0.73)	(0.76)	(0.73)	(0.20)	(0.20)	(0.20)
Monthly Debit Amount	0.02	0.02	0.02	-0.00**	-0.00**	-0.00**	-0.00*	-0.00*	-0.00*
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sample Period	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2020
App Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.83	0.83	0.83	0.95	0.95	0.95	0.71	0.71	0.71
Observations	8,192	8,192	8,192	8,192	8,192	8,192	8,192	8,192	8,192

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

Panel C: Offer terms and industry exposure to COVID-19

Dependent variable	APR		Maturity		ln(Loan Amount)	
	(1)	(2)	(3)	(4)	(5)	(6)
I(Post 3/12)	-0.57	1.22	0.09	-0.06	0.16***	-0.04
	(2.01)	(1.88)	(0.12)	(0.14)	(0.04)	(0.05)
I(HighIndExposure)	-1.88**	-2.22***	0.33**	0.31**	-0.12***	-0.00
	(0.79)	(0.77)	(0.15)	(0.13)	(0.04)	(0.02)
I(HighIndExposure) * I(Post 3/12)	-1.95	-0.34	0.37*	0.16	-0.00	0.00
	(1.55)	(1.44)	(0.19)	(0.17)	(0.04)	(0.04)
FICO		-6.63***		0.60***		0.14***
		(1.49)		(0.13)		(0.02)
ln(Age)		-4.37***		0.62***		0.08***
		(0.99)		(0.18)		(0.03)
ln(Sales)		-0.96		0.04		0.30***
		(0.73)		(0.06)		(0.05)
Avg Bank Balance		0.02*		-0.00		0.00***
		(0.01)		(0.00)		(0.00)
# Days Negative Balance		1.26***		-0.11***		-0.01
		(0.37)		(0.03)		(0.01)
# Monthly Credits		-62.52***		10.04***		1.48***
		(19.47)		(3.45)		(0.41)
Monthly Credit Amount		-0.03*		0.01***		0.00***
		(0.01)		(0.00)		(0.00)
# Monthly Debits		9.03		-1.25		0.62***
		(6.25)		(1.01)		(0.16)
Monthly Debit Amount		0.01		-0.00***		-0.00
		(0.01)		(0.00)		(0.00)
Sample Period	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2020
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.79	0.80	0.95	0.95	0.37	0.65
Observations	8,192	8,192	8,192	8,192	8,192	8,192

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)*100,* is equal to 100 if 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). The indicator variable *I(Post 3/12)* is equal to one 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. Standard errors are clustered at the lender level and are reported in parentheses. * p<.1; ** p<.05; *** p<.01.

Panel A: Lender risk profile measured using median borrower FICO

Dependent variable	I(Offer)*100			
	(1)	(2)	(3)	(4)
MedianFICO	-0.32***	-0.15**	-0.30***	-0.29***
	(0.07)	(0.07)	(0.07)	(0.06)
MedianFICO * I(Post 3/12)			0.29**	0.28**
			(0.12)	(0.12)
I(Post 3/12)			-207.47**	-198.53**
			(81.13)	(78.02)
Sample Period	Jan-Feb 2020	Mar 2020	Jan-Mar 2020	Jan-Mar 2019-2020
Applicant FE	Yes	Yes	Yes	Yes
R^2	0.25	0.20	0.24	0.24
Observations	30,619	11,414	42,035	59,951

Panel B: Lender risk profile measured using median borrower APR

Dependent variable	I(Offer)*100			
	(1)	(2)	(3)	(4)
MedianAPR	0.24***	0.08	0.22***	0.22***
	(0.06)	(0.05)	(0.06)	(0.05)
MedianAPR * I(Post 3/12)			-0.31***	-0.31***
			(0.07)	(0.07)
I(Post 3/12)			11.55	12.36
			(17.64)	(16.05)
Sample Period	Jan-Feb 2020	Mar 2020	Jan-Mar 2020	Jan-Mar 2019-2020
Applicant FE	Yes	Yes	Yes	Yes
R^2	0.26	0.20	0.24	0.24
Observations	30,619	11,414	42,035	59,951

Appendix A. Variable Definitions

Variable	Definition
FICO	Business owner's personal credit score created by the Fair Isaac Corporation.
ln(Age)	The natural logarithm of (1+age of the firm in months).
ln(Sales)	The natural logarithm of (1+annual sales of the firm).
Avg Bank Balance	The average daily balance in the business's (or owner's) bank account measured using bank statements from the prior three months.
# Days Negative Balance	The number of days in the previous three months with negative balances in the business's (or owner's) bank account.
# Monthly Credits	The average number of credits in the bank account of the owner/businesss each month over the prior three months.
Monthly Credit Amount	The total amount of credits received each month and averaged over the prior three months.
# Monthly Debits	The average number of credits in the bank account of the owner/businesss each month over the prior three months.
Monthly Debit Amount	The total amount of debits received each month and averaged over the prior three months.
I(State Lockdown)	An indicator variable equal to one if the applicant's state has been ordered on lockdown at the time of application.
% Population Home	The fraction of individuals in the county that are home all day on the date the application was submitted. This is calculated using data from SafeGraph which tracks the movement of individuals through cell phones.
%Population Home (7-day avg)	The average of the % Population Home over the prior 7 days.
I(Offer)	An indicator variable equal to one if the applicant received a loan offer within 30 days of the application date.
APR	The interest rate on the loan offer expressed as the Annual Percentage Rate.
Maturity	The loan offer maturity expressed in months.
ln(Loan Amount)	The natural logarithm of (offered loan amount).
MedianFICO	The median FICO on transacted deals for a given lender during 2019.
MedianAPR	The median APR on transacted deals for a given lender during 2019.
I(HighIndExposure)	An indicator equal to one if the applicant comes from an industry that was above the median in responding that they experienced a “large negative impact” in the Small Business Pulse Survey when asked “overall how has the COVID-19 pandemic affected your business?”.
I(Post 3/12)	An indicator equal to one if the application is received after the World Health Organization declared COVID-19 a global pandemic on March 11, 2020.

Internet Appendix

Table 1A. Loan supply, geographic exposure to COVID-19, and weekly indicators

This table is identical to Table 5 with one key exception. Application date fixed effects are removed in order to estimate the coefficient on weekly indicator variables. The weekly indicator variables can then be compared with those in Table 3 to see the relative importance of COVID exposure variables on offer likelihood. The dependent variable is an indicator equal to 100 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 avg)* is the average fraction of the population that was home all day in the county from the prior week. Firm controls included are FICO score of the owner, log of firm age, log of sales, average bank balance, number of days with a negative balance, average monthly number and amount of credits and debits, and industry indicators. Standard errors are clustered by application date and county and are reported in parentheses. * p<.1; ** p<.05; *** p<.01.

Dependent variable	I(Offer)*100								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mar 2-8 (2020)							-8.94***	-9.29***	-11.61***
							(1.48)	(1.63)	(1.84)
Mar 9-15 (2020)	-8.27***	-7.13***	-9.31***	-10.31***	-8.15***	-11.81***	-19.35***	-19.08***	-23.09***
	(2.37)	(2.36)	(2.42)	(2.72)	(2.72)	(2.80)	(2.76)	(2.67)	(2.89)
Mar 16-22 (2020)	-25.16***	-19.29***	-22.69***	-31.03***	-20.14***	-25.84***	-39.62***	-37.71***	-39.43***
	(3.25)	(4.05)	(3.24)	(3.11)	(4.27)	(3.05)	(2.84)	(3.62)	(2.41)
Mar 23-29 (2020)	-32.07***	-27.22***	-25.12***	-38.78***	-26.56***	-22.95***	-46.28***	-47.23***	-40.98***
	(2.51)	(3.58)	(4.30)	(2.91)	(4.46)	(5.54)	(2.46)	(3.68)	(4.22)
I(State Lockdown)	-7.16***			-6.64**			-8.16***		
	(2.13)			(2.90)			(2.12)		
% Population Home		-51.11***			-86.29***			-24.84	
		(13.01)			(17.63)			(16.52)	
% Population Home (7-day avg)			-76.77***			-129.63***			-86.62***
			(23.04)			(30.97)			(26.42)
Sample Period	Mar 2020	Mar 2020	Mar 2020	Mar 2020	Mar 2020	Mar 2020	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2020
Applicant Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
App Date FE	No	No	No	No	No	No	No	No	No
Industry FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.10	0.10	0.10	0.26	0.26	0.26	0.28	0.28	0.28
Observations	5,069	5,069	5,069	5,069	5,069	5,069	11,538	11,538	11,538