Why Did Small Business FinTech Lending Dry Up During the COVID-19 Crisis?

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ABSTRACT

We document how FinTech lending was affected by the first major crisis in its short history. Using detailed data about loan applications, offers, and take-up from a major small business FinTech credit platform, we find that while the number of loan applications increased sharply in early March 2020, the supply of credit collapsed as lenders dropped from the platform, so that the likelihood of applicants receiving loan offers fell precipitously. The funding model of FinTech lenders helps explain the drying up of the loan supply as lenders became financially constrained and lost their ability to fund new loans.

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1. Introduction

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). Before the COVID-19 crisis, FinTech lending had become an increasingly important source of funds for younger and riskier small businesses (Barkley and Schweitzer, 2020). Since the business model of FinTech lenders differs sharply from the business model of banks, FinTech lenders may respond to a crisis differentially. There are a few critical attributes of the business model of FinTech lenders that could lead to a different evolution of lending from banks. First, small business FinTech lending is transactional and does not use collateral (Gopal and Schnabl, 2020; Beaumont, Tang, and Vansteenberhe, 2020), but the soft information collected through relationship lending and the use of collateral may be especially valuable during a crisis, so that FinTech lenders may be at a disadvantage relative to banks during such a period (Berger and Udell, 2006; Liberti and Petersen, 2019). These characteristics of FinTech lending make lending decisions particularly sensitive to uncertainty about revenue. Second, as banks rely on their deposit franchise and typically receive large inflows of deposits during a crisis, they can fund credit line drawdowns and new loans (Gatev, Schuermann, and Strahan, 2009). In contrast, FinTech lenders are not depository institutions and rely on funding sources that can dry up during a crisis. These funding sources, such as debt, loan sales, or equity, require continuous interaction with investors and therefore depend on their interest and risk appetite. Finally, FinTech lenders disburse the loans they make as cash, meaning they need to have the cash on hand. Conversely, when banks make loans, they fund deposit accounts, so that funds remain with the bank initially.

To date, despite the considerable attention from academics, practitioners, and regulators that have focused on FinTech in recent years,[1] there is only limited understanding of the strengths and weaknesses of the FinTech small business lending model and of the extent to which small business FinTech lending can

[1] For reviews of the literature and surveys of FinTech activity in general, see Philippon (2016), CGFS (2017), IMF (2019), Stulz (2019), and Thakor (2019). 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.

substitute for bank lending. This issue is important for understanding the role of FinTech lending and the provision of funds to small businesses as large banks have reduced their supply of funds to these businesses in recent years (Chen, Hanson, and Stein, 2017).

In this paper, we examine the behavior of small business FinTech lenders during March 2020, which corresponds to the financial crisis period of the COVID-19 pandemic. For simplicity, we call this period the COVID-19 crisis. This was the first significant crisis that the young industry faced. It was also when small businesses experienced a high demand for liquidity as revenues declined suddenly. We use unique data from a FinTech small business platform (the platform hereafter) that connects small businesses with dozens of online lenders. We have data on loan applications, loan offers, and the terms of loans actually made. Since we observe applications, offers, and loans, we can study the demand for loans separately from the supply of loans. Our results confirm that the supply of FinTech small business lending fell sharply during the COVID-19 crisis and indicate that the funding model of FinTechs, which caused FinTechs to become financially constrained, was an important cause of the dry-up.

It appears that during the COVID-19 crisis, there was a massive disparity between the potential need for short-term financing by small businesses and actual online lending. As the crisis unfolded, many businesses experienced a sudden drop in revenues but still had to fund fixed charges (Fahlenbrach, Raggetz, and Stulz, 2021). This situation was especially problematic for small businesses as the typical small business had cash on hand to cover only a month or two of expenses (Bartik, Bertrand, Cullen, Glaeser, Luca, and Stanton, 2020). Not surprisingly, many small businesses became inactive—by April 2020, the number of active business owners had declined by 22% relative to what it was before the crisis (Fairlie, 2020). In striking contrast to the increased demand for liquidity, aggregate statistics show that actual FinTech lending declined precipitously. 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.[2] Furthermore, an industry

[2] 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.

report concludes that out of 16 small business FinTech lenders originating loans before the COVID-19 shock in 2020, only six were still operating in the third quarter of 2020.[3] In contrast, bank lending to small businesses did not experience a noticeable decrease.[4]

During March 2020, the actual loan volume on the platform declined sharply from its pre-crisis levels. 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. By observing applications, offers, and loan take up, we can study the demand for FinTech loans separately from the supply and trace individual lenders' behavior. Our results imply that the activity of FinTech lenders can be disrupted during a crisis because of financial constraints originating from their business model, which relies on accessing the market frequently for funding.

Our analysis is organized 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. Furthermore, loan applicants in March 2020 were of higher credit quality, were larger in terms of sales and employees, and appeared to be in a better position financially, at least by historical measures. These facts are consistent with many businesses applying for online loans seeking immediate liquidity as their revenue was falling sharply or seeking to hoard liquidity in the face of a looming crisis. Towards the end of March 2020, the number of applications fell as potential borrowers contemplated using the Paycheck Protection Program (PPP) of the CARES Act. The CARES Act was signed into law by President Trump on March 27, 2020.

In the second part of the paper, we turn to 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—

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

fell sharply starting with the second week of March. Conditional on observable pre-COVID-19 characteristics, the likelihood of an applicant receiving a loan offer declined by more than 50%.

The decrease in the loan supply to small businesses is unique to FinTech lenders. It has no equivalent for banks.[5] 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 riskiness of borrowers for FinTech lenders for at least four reasons. First, they lend to riskier borrowers that banks tend not to lend to. The creditworthiness of these borrowers would be more affected by an increase in economic uncertainty than the creditworthiness of safer borrowers. Second, FinTech lenders are more reliant on revenue for repayment of loans, so that they do not benefit from the risk-reducing impact of collateral that may not be as affected by the COVID-19 shock than revenue. Third, the potential greater reliance on models of FinTech lenders could be a liability when uncertainty increases because the models were not calibrated to a crisis of the type of the COVID-19 crisis. Fourth, the absence of soft up-to-date information means that FinTech lenders may be at greater risk of adverse selection during a crisis that could potentially eliminate their income within days. For instance, a local banker might have better information about how a business might fare during a lockdown than a FinTech.

With the second hypothesized channel, the *financial constraints channel*, FinTech lenders stopped making new loans because they became financially constrained in that they no longer had the funds to make new loans, nor could they raise new funds from lenders or investors on acceptable terms. Loans on FinTech platforms are mostly funded in two ways, and both could lead to financial constraints when an economic shock hits. Some FinTech lenders lend capital that they raised 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 after to investors (called "loan sales" or "originate to distribute"). Regardless of

[5] See for example the report by the Richmond Federal Reserve Bank documenting the loan volume to small businesses during March 2020 from banks. https://www.richmondfed.org/publications/research/economic_brief/2021/eb_21-05

the method of sale—either directly or through securitization—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. Either financing model implies that an unexpected increase in the default risk of existing loans results in a decrease in the value of existing loans and impairs lenders' ability to make new loans unless they raise new equity or debt. Furthermore, the riskiest loans tend to have frequent interest payments, so that if the borrowers are subject to a shock, income falls quickly for the lender. Lenders can quickly fail to meet covenants for lending facilities when loans on their balance sheets 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 dissuade lenders from making these loans in the first place. Additional frictions exists in the securitization market, as defaults on existing loans in a trust can lead to rapid amortization, which effectively eliminates the trust as an instrument for funding new loans as loan repayments have to be disbursed rather than used for new loans. Further, lenders are required to hold some risk or provide excess collateral; in the case of increased uncertainty, the cost of capital associated with holding this risk would be elevated. In other words, the "originate to distribute" model became materially more expensive to operate as risk increased and loans defaulted at a higher rate. Eventually, the market for the sale of loans through securitization or through direct sales to investors closed altogether.

The evolution of lending behavior in the data shows that the *financial constraints channel* played an important role, while the *uncertainty channel* is likely to have had a minor one. The uncertainty channel works at the loan level, so that some loans become too risky to make. Hence, it predicts that lenders would tighten their loan offer terms and tilt their lending more towards less risky borrowers. Furthermore, lenders should be particularly leery from lending to borrowers potentially more exposed to COVID-19 risk. Our empirical analysis shows mixed and relatively weak support for this channel. Specifically, we find that the terms on offered loans did not materially change despite the heightened risk. The supply of loans did decrease more for the restaurant industry—which was highly impacted by lockdowns—than for other industries, and there is also some evidence that the supply of loans fell more for borrowers in states 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.

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 drop out entirely during the month. Strikingly, the typical pattern is that a lender kept making loans at the same level as in February until the level of lending suddenly dropped to a trivial amount or zero. Such an evolution seems to reflect lenders' financial constraints.

We also investigate which type of lenders dropped out first. Johnson (2021) shows that the FinTech lenders have preferred habitats that can be characterized by the FICO scores of the borrowers with whom they transact. The financial constraint channel implies that lenders specializing in making riskier loans, i.e., 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 relationship 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.

One might argue that the uncertainty channel could also explain the finding that riskier lenders dropped out first. This is because the creditworthiness of riskier borrowers is likely to fall faster and more when uncertainty increases for transactional lenders who do not have access to a collateral technology. In Merton (1974), the impact of an increase in volatility of assets on the creditworthiness of a borrower increases as the borrower is more levered. However, a direct test enables us to distinguish between the financial constraint and the uncertainty hypothesis using the Khwaja and Mian (2008) identification approach. We investigate the outcome of loan applications from the same applicant to different lenders. Absent financial constraints, we would expect an applicant to be more likely to receive an offer from a lender who makes offers to riskier borrowers. Conversely, if financial constraints affect lenders that make riskier loans more, we 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 that were turned down by riskier lenders, which we see as further evidence that the fall in loan supply is lender-specific rather than borrower-specific. Riskier lenders could have become more reluctant to lend for other reasons than financial constraints. For instance, riskier lenders might have become more risk-averse for reasons unrelated to financial constraints. We cannot exclude such an explanation without having data on the financial situation of lenders during March 2020. Unfortunately, public information is hard to come by for most lenders because they are private firms.

In the third part of the paper, we focus on lenders for which there is publicly-available information. We use public information where some firms explicitly discuss dropping out or having a lending pause. More importantly, we show that asset prices tied to marketplace lending collapsed during March. For example, a lender called Kabbage had a securitization issued under Rule 144a before the crisis. The price of its B-Note dropped from 100 prior to the onset of the crisis to less than 10 in early April and then bounced back to almost 100 in July. We also discuss On Deck Capital Inc., the only U.S. publicly traded FinTech lender that specialized in small business loans at the time. In March, it experienced a sharp stock price drop that did not reverse even though the overall stock market recovered its losses; eventually, the lender was bought by another firm. On Deck is one of several small business FinTech lenders that did not survive as independent entities following the COVID-19 crisis.

Overall, our results indicate that the COVID-19 shock reduced the supply of credit by FinTech small business lenders sharply. However, the decrease in the supply of credit cannot be explained by the exposure of potential borrowers to the COVID-19 shock alone. Instead, the primary channel that appears at play is the lender financial constraints channel: the supply of FinTech credit dried up because lenders became financially constrained. We show that the pattern we document is not unique to small business lending. Using data on personal loans issued by FinTechs, we show a similar drop in loans during March 2020. Although our empirical analysis is limited to this segment of the market, the reason for the supply dry-up is common to FinTech lenders across the board. The reliance on external funding, particularly the "originate-to-distribute" model, makes FinTech lenders susceptible to fluctuations in their investors' interest and risk appetite.

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

Second, 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 was dramatic. Though PPP appears to have led some FinTech lenders to stop making unsecured loans, PPP provided credit when the supply of credit to the riskiest firms from FinTech lenders had essentially dried up. Balyuk, Prabhala, and Puri (2021) and Li and Strahan (2021) show that bank relationships were helpful to PPP applicants through banks. However, FinTech lenders became important distributors of PPP loans as they were used to dealing with and were accessible to a clientele that had no banking relationships (Erel and Liebersohn, 2020). PPP lending through FinTech lenders, however, came with high rates of fraud (Griffin, Kruger, and Mahajan, 2021).

Though we are not aware of a study of the impact of COVID-19 on small business FinTech lending, Bao and Huang (2021) explore the 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 the loan performance of banks.

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

2. FinTech lending and lending platforms

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

2.1. FinTech lending

In this paper, FinTech lenders are defined as non-deposit taking institutions that make loans online either directly or through an online platform. Berg, Fuster, and Puri (2021) conclude that "An increase in convenience and speed appears to have been more central to FinTech lending's growth than improved screening or monitoring". Instead of relying on deposits to fund loans, they 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, financial reporting and disclosures, as well as other federal or state rules. Banks are also limited by regulatory guidance in their ability to make loans to low FICO borrowers.[6] 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.

The role of FinTech lending as a source of financing for small businesses has increased dramatically over the last decade. Gopal and Schnabl (2020) estimate that the volume in loan originations to small 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.[7] However, this figure underestimates the potential impact of FinTech lending as the average dollar size of FinTech loans is substantially smaller than those made by banks and finance companies.[8] 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

[6]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.
[7] The S&P Global Market Intelligence U.S. FinTech Market Report 2021 estimates that SME focused FinTech originations totaled roughly $13 billion.
[8] See, for instance, https://www.valuepenguin.com/average-small-business-loan-amount.

5 years which amounts to millions of loans. Importantly, evidence suggests that these loans are typically being used by businesses that have the most difficulty obtaining finance elsewhere.[9]

The legal structure through which these lenders originate loans typically follows one of two models. The first is to obtain licenses from each state as a non-depository financial institution and make loans directly to businesses. The second approach is to partner with an industrial bank that has a national charter to lend across the country.[10] 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.[11]

FinTech lenders typically follow one of two models—originate-to-distribute or balance sheet lending. Lenders who originate to distribute earn a fee for the screening and origination of the loan. This model is common in consumer lending and is used as well for small business lending. In recent years before the COVID-19 shock, as discussed more later, an increasing number of securitizations were completed that allowed lenders to move assets off their balance sheets and secure additional funds. 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.[12] 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). Instead of seeing an inflow of deposits in a crisis, FinTech lenders are more likely to be confronted by 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

[9] See for example Barkley and Schweitzer (2020) as well as statistics released by the Federal Reserve in the Small Business Credit Survey (2020).
[10] Industrial banks are also known as Industrial Loan Corporations or ILCs (see Barth and Sun, 2018).
[11] For example On Deck capital makes loans in partnership with Celtic Bank, an ILC chartered in Utah. Loans made through Celtic Bank to an individual in Texas are not required to be capped by the usury laws in Texas. See https://www.wsj.com/articles/FinTech-firms-look-to-enter-banking-via-century-old-tactic-1518085801.
[12] Mills (2019) provides greater detail about the business models and identifies the differences in business models among small business FinTech lenders.

for the amount of a loan 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.

Much of the research on FinTech credit focuses on lenders and platforms that cater to consumers. However, some of the literature also addresses the provision of credit to small businesses. The existing literature on FinTech small business credit shows that some FinTech lenders use big data analytics in their credit decisions (Mills, 2019), although other lenders appear to use simple decision-making rules (Johnson, 2021). Existing evidence for consumer lending also suggests the use of simple decision-making rules (Ben-David, Johnson, Lee, and Yao, 2022). Huang (2021) develops a model where FinTech lenders set a screening standard even though they have access to big data analytics because their lending decisions are determined by competition with banks.

In contrast to many bank borrowers, FinTech borrowers have no business relationships with lenders. FinTech lenders typically do not offer products that would enable them to develop a relationship with borrowers. As a result of this lack of relationships, FinTech lenders do not have access to soft information that is often important in bank loan decisions. The literature shows that soft information is not as important for large banks than small banks (Liberti and Petersen, 2019). FinTech lenders also do not have a collateral lending technology. To make loans with collateral, a lender has to have the ability to monitor the collateral and dispose of it if the lender defaults. It follows from this that FinTech lenders are much more dependent on the cash flow of borrowers than bank lenders who typically require collateral. These differences between FinTech lenders and bank lenders are important when the economy as a whole becomes more risky. The value of FinTech loans will be more sensitive to the uncertainty about cash than bank loans because banks can also rely on cash flow (see Stulz and Johnson, 1985, for 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. Merchant cash advances, sometimes referred to as short-term loans, are those made based on the frequency and timing of the borrower's cash flows. Equal payments are typically drawn from the borrower's bank account at a daily or weekly frequency. Lines of credit from these lenders allow borrowers to draw down credit up to some limit and are similar to merchant cash advances in the frequency of payments after a draw. Term loans are typically longer maturity loans with less frequent payments and lower interest rates resembling a more traditional bank loan. However, unlike banks or finance companies, all these loan products are almost exclusively unsecured, but they typically have a personal guarantee from the business owner.[13] Business owners waive the limited liability of the company through a personal guarantee which allows the lender to seek recourse through collection agencies, court proceedings, or by placing liens on business or personal assets.

FinTech lenders have differentiated themselves by speeding up and simplifying the application and funding processes. The most often cited challenges that small businesses face working with traditional banks are the long wait times and the difficult application process.[14] 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. The speed, convenience, and probability of receiving funding appear to be the primary reasons that small businesses apply to online lenders relative to banks.[15]

2.2. The role of marketplace platforms

Marketplace platforms are FinTech firms that connect potential borrowers with lenders. Two basic models of marketplace platform lending exist for consumers and businesses. The first is often referred to as peer-to-peer lending (or P2P platforms). These platforms accept applications for financing, evaluate and price risk, and then invite retail or institutional investors to fund the loans at the prices set by the platform. The peer-to-peer name has become somewhat a misnomer in the U.S. as institutional investors have become the primary investors and retail or peer investors have been pushed out. Before the COVID-19 crisis, the

[13] Gopal and Schnabl (2020) note the key differences between finance companies and FinTechs with the primary difference being the collateral that is pledged.
[14] https://www.fedsmallbusiness.org/medialibrary/FedSmallBusiness/files/2020/2020-sbcs-employer-firms-report.
[15] 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.

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. The data used in this paper come from a platform using this second model of marketplace lending and it will be referred to through the remainder of the paper as "the platform".

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

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

In a matter of hours or days, applicants may receive offers from one or multiple lenders. Prior to the pandemic about 58% of applicants with completed applications were approved by at least one lender, so more than a third of applicants did not receive any offers.[16] 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 at the borrower's bank account via direct payment. The platform receives commissions from each lender set as a percentage of the loan amount for a completed transaction.

2.3. Data used in this study

The primary data source for this paper come from a marketplace platform that connects small business with dozens of online lenders. We observe all applications made on the platform, solicitations for offers from the platform to various lenders, loan offers received from lenders, and loan deals when they occur. 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 among a drop-down list that includes two-digit NAICS classifications with some notable exceptions discussed in later sections. In cases where the industry is undisclosed or does not neatly fit into industry classifications we use the label of "uncategorized".[17]

We augment this 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 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 county when available. For industry-specific exposure measures we identify high exposure industries using the Small Business Pulse Survey which asked "overall how has the COVID-19 pandemic

[16] 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.
[17] Missing industry classification occurs in roughly 15% of applications.

affected your business?" in the initial survey from April 26-May 2, 2020.[18] To determine exposure we assign industries that are above the median in responding that they experienced a "large negative impact".

Finally, we use data that include daily loan originations from seven of the largest online personal loan lenders made available through a fintech aggregator.[19] 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 occurs. Unlike the small business data, however, we do not observe applications or lender identifiers which limits the analysis. We apply only one filter to this data as we aggregate loan volume by origination date and that is to replace origination volumes on the last day of the month with the average volume from the prior week. Roughly 45% of loans in the data 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 investigating the loan demand and the loan supply separately, we present statistics about the lending volume for small business loans made on the platform both before March 2020 and during March 2020. We first report the five previous business days moving average for the three months ending in March 2019 and March 2020. For comparison, we report similar data for personal fintech loans.

Figure 1, Panels (a) and (b) show similar patterns for lending volumes of small business loans originated on the marketplace platform. Panel (a) shows moving averages for the number of loans. The number of loans in 2020 exceeds the number of loans in 2019 until the middle of March. The number of loans in 2020 increases in March before falling precipitously almost to zero. Though the number of loans becomes trivially small in April once PPP is in effect, the number of loans falls sharply before PPP is proposed and almost all of the decrease takes place before the stimulus package is approved by Congress. Figure 1, Panel

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

(b), shows similar results for the amount of loans funded. Again, the amount funded plummets and becomes a fraction of what it was in 2019.

To check whether the sharp drop in loan origination activity was unique to our platform, we present the aggregate volume of personal loans originated using a dataset which aggregates lending statistics from seven of the largest lenders in the space and covers over 70% of loans originated in the U.S. In Figure 1, Panels (c) and (d) show the evolution of personal loan volumes from January to March 2019 and 2020. Panel (c) plots the five business day moving averages for the number of loans funded while Panel (d) shows the aggregate amounts. The volume of funded personal loans is much higher in 2020 than in 2019 aside for the large dip in volume during March 2020. Average volumes were 49% higher in January and February of 2020 relative to the volumes in the same months the year prior. Yet, in the last week of March, the number of funded loans was 17.5% *lower*.[20] Hence, these plots affirm that the decline in FinTech loan origination was not unique to our platform, but was experienced also by other large FinTech lenders.

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

4. COVID and the demand for FinTech small business loans

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

[20] Including the loans with time stamps on the last day of the month has no material effect on the overall magnitude by which lending drops. For example, when looking at monthly loan volumes, the year over year decreases in April and May are 82% and 88% respectively.

Table 1 shows the characteristics of loan applicants conditional on having completed the entire application process.[21] 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 653. This average score reflects, depending on the classification chosen, a subprime score or a near-prime credit score.[22] Applying small businesses on average have annual sales of $805,272 and are 55 months old. The average number of employees for applicants is 7.4. The average bank balance is $19,460. In the prior three months, they have on average 1.4 days with negative bank balances and $77,141 and $77,137 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, and applicants are more established, larger, and with a better FICO score than applicants a year earlier. Average sales are 36% higher. The average age of the business of the applicants is 6% 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 672. Bank balances are 43% higher. In sum, the applicants are overall more creditworthy based on the attributes reported in the table.

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 half of March to the second half of March. As the crisis worsens during March 2020, the volume of applications increases

[21] A previous version of the paper looked at all applicants including those that had not submitted all relevant documentation. Qualitatively, the results are the same whether we use started applications or completed applications, but we believe completed applications are a better representation of true demand.

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

and their credit quality as measured by historical characteristics improves. The number of applicants in the second half of March is higher than in the first half of March by 62%. Surprisingly, the creditworthiness of the applicants based on historical characteristics is higher on average in the second half of March than in the first half. Average sales and bank balances are significantly higher in the second half of March than in the first half.

The data in Table 1 suggests that the decline in lending is unlikely to be due to a drop in demand. To understand better the evolution of demand, we show in Figure 2 plots for the daily number of applicants and the daily total amount of financing sought on business days for March 2019 and March 2020. In each plot, we show the amounts for 2019 and for 2020. In Panel (a), we see that the number of applicants is higher throughout March 2020 than in March 2019. After March 9, 2020, the number of applicants increases sharply and almost doubles over one week. The number of applicants subsequently decreases, but it is higher on every day of the month in 2020 than it was in 2019. The evolution of the total amount of financing sought shown in Panel (b) is similar.

Figure 2 suggests that the demand for FinTech loans drops as aid to small businesses through a stimulus package becomes more likely. The White House first proposed $500 billion worth of aid to small businesses on March 17, which corresponds to a sharp drop in the demand for loans.[23] On March 20, the senate rejected the stimulus program, which is followed by an increase in the demand for loans. The demand for loans falls after it becomes certain that the stimulus package will become law on March 23. However, despite the prospect of the stimulus program, the number of applicants stays higher than in 2019.

The historical credit quality of applicants at the onset of the COVID-19 crisis may not be a good predictor of loan performance because it does not reflect the anticipated impact of the COVID-19 shock on their business. For instance, a borrower who owns a restaurant could appear creditworthy based on information available when the loan application is made, but this restaurant owner may be expecting to

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[23] 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/.

have to close the restaurant the next day. Hence, even though demand increases and the creditworthiness of borrowers increases based on the historical characteristics we observe, it is important to investigate the exposure of the applicants to the COVID-19 shock based on their industry and location. In the remainder of this section, we explore the evolution of the demand in greater detail.

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

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

Lastly, in Panel (c) of Figure 3, we show abnormal demand by industry. Industry is self-reported by the applicant among a drop-down list that includes two-digit NAICS classifications with some notable exceptions. In some circumstances the drop-down menu includes industries that are more granular than the two-digit classifications. Examples include restaurants being separate from travel, both of which would fall under "Accommodation and Food Services", and automotive being separate from "Other Services". We use the most granular level of industry available to us. In Figure 3 we show abnormal demand among the top 10 industries in terms of volume. The figure shows that demand moves in tandem across industries. In particular, during the time that demand is particularly elevated, abnormal demand is elevated across all industries. There is little evidence of a demand shift towards the industries most vulnerable to the COVID-19 shock. According to the Census Pulse Business Survey, restaurants and arts and entertainment were the industries that experienced the largest negative impact and, while arts and entertainment have the highest abnormal demand, restaurants have relatively low abnormal demand. Oddly, the finance industry experiences the second highest abnormal demand. During the period of peak demand, the restaurant and construction industries have the highest demand, but they also have the highest demand before the period of peak demand. The "Other" category includes those businesses that classify themselves as "other services", but due to self-reporting, could include businesses for which the applicant was unsure of the appropriate categorization.

We now turn to a more formal analysis. We first assess whether the demand is abnormally high during some portion of March 2020. We show the results in Table 2. For our analysis, we proceed as follows. We regress the daily number of applicants 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 11-17 by 250 applications and the week following sees a similar daily increase of 197 applications. In Column (2), we estimate the same model for 2019. Not surprisingly, none of the weeks during that month experience a significantly different level of demand. Lastly, in Column (3), we estimate the regression for 2019 and 2020. We add an indicator variable for 2020. We find the same result as in Column (1), namely that the demand for the weeks of March 11-17 and March 18-24 is significantly higher than in the omitted week, but the demand for the first and last weeks of March is not. The other coefficients are not significant. It is noteworthy that the week indicator variables explain little of the daily variation in demand in 2019, but they explain much more of the daily variation in 2020.

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

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

Table 3 shows that the supply falls in the second week of March 2020 and decreases steadily through the rest of the month. In the last week, the probability that an applicant receives an offer is 41 percentage points lower than at the beginning of March. At the beginning of March, the unconditional probability of acceptance is 54.2% meaning that by the end of the month the unconditional probability of acceptance is 13.2%. In Column (2), we re-estimate the regression with applicant controls. The applicant controls are 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 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 increases in March, so that the acceptance rate is higher unconditionally than when controlling for the creditworthiness of the applicant. The next two columns repeat the regressions of Columns (1) and (2) but use the sample period from January to March. By the second week of March, the probability of acceptance is already down by 22.9 percentage points. Column (5) shows the regression estimated for January to March 2019 and no indicator variable for March has a significant coefficient. Finally, Column (6) uses the sample of January to March 2019 and 2020. The regression includes week indicator variables, an indicator variable for 2020, applicant controls, and industry fixed effects. In the last week of March, applicants are 52.7 percentage points less likely to receive an offer relative to applicants with similar characteristics prior to the onset of the pandemic.

5.2. Loan supply and applicant industry risk

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

In Table 4 we propose a simple way to examine the possibility that the supply is impacted by the increasing risk of applicants. The table shows regression results of our indicator variable for whether an applicant receives an offer on indicator variables for the industry, controls, an indicator variable for the period starting on March 12, 2020, which is when the World Health Organization (WHO) declared a pandemic emergency, and an interaction of the industry indicator variable with the post-March 12 indicator variable. Our industries are North American Industry Classification System (NAICS) sectors that match to the industries surveyed in the Small Business Pulse Survey by the Census, 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 of the industry and of the post-March 12 indicator. The restaurant industry is the only industry with a significantly negative interaction irrespective of the sample period. It is also the industry in the initial Census's Small Business Pulse Survey from April 26-May 2, 2020 that reports the largest fraction of businesses saying that they are strongly negatively affected by COVID-19. When we use the longest sample period, the interaction has a coefficient of 19, so that supply to the restaurant industry is abnormally low by 19 percentage points compared to other industries. Surprisingly, however, arts and entertainment has a marginally significant positive coefficient on the interaction with the longest sample period and is also one of the industries most negatively impacted by the pandemic according to the Pulse Survey.

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 level affect the supply of loans. We estimate regressions where the dependent variable is the indicator variable for whether an applicant receives an offer. We use a difference-in-differences framework where the treatment effect is the imposition of a state lockdown. We also use the percentage of the population staying at home as the treatment. The data is obtained from SafeGraph which uses cell phone data to track mobility. For the U.S. as a whole, the percentage staying home reported by SafeGraph evolves from 23.8% on March 1 to 39.9% on March 31. We report the estimates in Table 5. In the first three columns, we estimate the regression for March and have no controls but application date fixed effects. In Column (1), we have an indicator variable for whether a state is in lockdown. The coefficient on the indicator variable for whether a state is in lockdown is marginally significant statistically, but economically small. In Column (2), we have a variable corresponding to the percent of the population working from home at the county level. The coefficient on percent of the population working from home is negative but not statistically different from zero. Lastly, in Column (3), we use a seven-day average for the percentage of the population working from home. The result is similar to Column (2). In the next three columns, we add applicant controls, county fixed effects, and industry fixed effects. Now, the coefficients on state lockdowns and population working from home are negative but statistically insignificant as seen in Columns (4), (5), and (6). Lastly, in Columns (7) to (9), we re-estimate the regressions of Columns (4) to (6), but include January-March 2019 in the sample. In these regressions, the state lockdown indicator is statistically significant at the 5% level with a negative coefficient and the county-level measures continue to be negative and insignificant. For perspective on the magnitudes, an increase in the likelihood of staying at home of 16.1 percentage points, which is the average increase for the U.S. during March, reduces the likelihood of an offer by 5.3 percentage points using the coefficient in Column (9).

So far, we have seen that the supply falls sharply. The drop is significantly worse in the restaurant industry but largely unaffected by the location of the firm. 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 (untabulated), the weekly indicator variables exhibit little change, so that our COVID-19 exposure variables do not by themselves explain the drop in supply.

5.4. Loan offer terms in March 2020

We now explore the other dimension of supply, which is the terms of loans. Applicants could receive an offer, but the rate might be higher than they anticipated, which could reduce the take-up rate of offers. We report the results in Table 6. In Panel A of Table 6, we estimate regressions for offer terms similar to the regressions for the supply of loans in Table 3. We regress offer terms on an indicator for the week of the offer, the applicant's FICO, age of the business, log sales of the business, cash flows, liquidity measures, industry fixed effects, and lender fixed effects. We also estimate the regressions without lender fixed effects and the overall conclusions are similar. Columns (1) and (2) show results when the dependent variable is the Annual Percentage Rate (APR). In Column (1), the week indicators are never significant at the 5% level. Since that regression only uses data from March 2020, the interpretation is that the APR does not change within March. As expected, the APR falls as FICO increases, as the age of the business increases, as sales increase, and as the number of days with negative balances decreases. In Column (2), we use data from January to March 2020. We find that APR is significantly lower in the first week of March relative to the omitted week, which is the first week of January. In Columns (3) and (4), the dependent variable is the maturity of loans. None of the week indicator variables are significant though it does appear that there is a trend to extend shorter maturity loans as the month progresses. Finally, in Columns (5) and (6), the dependent variable is the loan amount. As expected, the maturity and size of the loan increase with FICO, age of the business, and log sales. Column (5) shows that the loan amount falls during the month. In Column (6), the loan amount decreases in magnitude throughout the month but no week indicator is statistically significant. In summary, there is no evidence that interest rates increase, as one would expect with tighter credit conditions, but there is some rather weak evidence that maturities and loan amounts fall.

In Panel B, we regress each offer's Annual Percentage Rate (APR) on the COVID-19 exposure variables used in Table 5 as well as firm controls. The sample is from January to March 2020 and only differs from the previous panel in that we only include applicants for whom county information is available. We use in Column (1) an indicator variable for whether the state is in lockdown. The coefficient on whether the state is in lockdown is not significant. In Column (2), we include in the regression the percentage of the population staying at home. Again, this variable does not have a significant coefficient. The 7-day average of that variable does not have a significant coefficient in Column (3). We explore next in the table whether the maturity is lowered or the loan amount is lowered as the applicant comes from a county more affected by COVID-19. We find no evidence of an impact of COVID-19 exposure on the maturity of the loan offered or on the amount of the loan offered.

We analyze whether the exposure of the industry of a business to COVID-19 affects the terms of the loan in Panel C. Our variables that proxy for COVID-19 exposure are an indicator variable for the period of March after the WHO declares a pandemic emergency and an indicator variable for high exposure industries. High exposure industries are identified using the Small Business Pulse Survey which asks "overall how has the COVID-19 pandemic affected your business?" in the initial survey from April 26-May 2, 2020.[24] To determine exposure we assign industries that are above the median in responding that they experienced a "large negative impact".[25] We then interact these two variables. The sample is again from January to March 2020 and is restricted to firms from industries that match with those in the survey. We find that, controlling for firm characteristics, the indicator variable for the period after the declaration of emergency is insignificant for APR, positive for maturity, and negative for loan amount. The interaction between the temporal indicator variable and the exposure indicator variable is not significant for any of the loan terms when controlling for firm characteristics. Hence, if lenders made any attempt to adjust loan terms due to increased risk, it was done by reducing the size of loans and not through increased rates or by adjusting offers for particularly high-risk industries.

The conclusion of this section is that the supply of loans falls sharply. However, loans do not become more expensive. The effect of COVID-19 exposure when measured by lockdowns on the supply of credit is weak. The effect for the restaurant industry is stronger and the effect of the percentage of the population

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

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

staying at home is marginal. Hence, COVID-19 exposure does appear to explain part of the drop in the supply, but much of the drop in supply is unexplained. In the next section, we analyze the role of the uncertainty channel and of the financial constraint channel in explaining the dry-up in supply.

6. Why did the supply fall?

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

In this section, we consider possible explanations for this pattern. In the first part of the section, we explore the economics of FinTech lenders to show how the COVID-19 shock affected FinTech lenders' supply of loans through a financial constraint channel and an uncertainty channel. In the second part of the section, we provide evidence showing that FinTech lenders dropped from the platform. Lastly, we provide direct evidence that lender-specific factors played a significant role in the decrease in supply. These lender specific factors, as well as the way lenders drop out of the platform, are consistent with lenders becoming financially constrained. In Section 7, we provide lender-level evidence that further supports the interpretation that financial constraints played a significant role in the decrease in supply.

6.1. The economics of FinTech small business lenders

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

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

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

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

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 high enough by lenders, these applicants are simply rejected. Hence, with this scenario, we expect demand to increase from the riskiest borrowers, but these borrowers would not receive loans. The borrowers who receive loans would not be riskier and their rates would be largely unaffected. The greater risk of borrowers explains the drop in supply. However, the greater risk of borrowers is magnified by the fact that credit models were not built using data from an event like the COVID-19 shock, so the reliability of these models becomes questionable when such a shock occurs. We call the uncertainty channel the impact of the COVID-19 shock on the supply of loans through its effect on the risk of borrowers and the model risk of lenders that is not due to lenders becoming financially constrained.

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

A complicating factor in this analysis is that eventually the CARES Act was signed into law by President Trump and PPP was implemented. As the adoption of the CARES Act became highly likely, the lenders could expect the demand for their loans to fall as potential borrowers would anticipate switching to PPP loans. They could also see that lending through the PPP program would be more profitable for them than to keep making the loans they were making as the market for these loans would mostly disappear for a while. However, lending through the PPP program would require reconfiguring their systems and hence might require them to stop lending to do so. It was not entirely clear prior to the disbursal of PPP funds whether these lenders would be included as certified distributors and many were not cleared to do so until after banks had already begun to fulfill the demand.[26] In the last week of March, we would expect lenders to drop out as they anticipate being involved in PPP.

6.2. The uncertainty channel and the financial constraint channel

The supply of loans could fall because lenders gradually reject more applications. With the uncertainty channel, we expect fewer loans to be made as more applicants are rejected, so that progressively a lender makes fewer and fewer loans, and the loans to become more expensive and smaller for given borrower historical characteristics to account for the increase in uncertainty. To the extent that a higher FICO score means that a borrower is more resilient to the COVID-19 shock everything else equal, we would expect lenders to become less likely to make loans to low FICO borrowers. We already saw in Section 5 that the evolution of loan terms is not consistent with lenders progressively adjusting loan terms to reflect greater uncertainty. With the financial constraint channel, we expect a lender to stop lending when it becomes constrained. Of course, these channels are not necessarily mutually exclusive.

6.2.1. Evolution of supply in March 2020

We find that lenders did not progressively reduce their lending as predicted by the uncertainty hypothesis but instead they dropped out suddenly during the month. A lender has a fairly steady acceptance

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[26] 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/.

rate, but suddenly that acceptance rate goes to almost zero or zero. Panel (a) of Figure 5 gives an example of a fairly typical evolution. After the collapse in the acceptance rate, the number of applications went to zero because the platform was no longer sending applications to this particular lender as the lender had dropped out. Panel (b) of Figure 5 shows the decrease in the number of active lenders. The decrease is steady through the last three weeks of March. This evidence is supportive of the role of the financial constraint channel. The *Wall Street Journal* reported on lenders dropping out from a platform in March 28 stating that "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."[27]

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

1) March 17, one lender,
2) March 19, four lenders,
3) March 20, one lender,
4) March 21, one lender,
5) March 23, one lender,
6) March 25, two lenders,
7) March 24, three lenders.

An alternative approach is to focus on lenders making almost no offers. When we use that measure, lenders generally dropped out almost a week earlier. Irrespective of the definition we use, we find lenders dropping out, which is consistent with a role for financial constraints in explaining the drop in supply.

The financial constraints explanation of the drop in supply applies to the lender irrespective of where the lender lends. Hence, it would be problematic for the financial constraints explanation if lenders stop lending on the platform but keep lending separately from the platform. In this case, the lenders would stop lending on the platform for reasons related to the platform rather than to financial constraints. We are not

[27] "People need loans as coronavirus spreads. Lenders are making them tougher to get," by AnnaMaria Andriotis and Peter Rudegeair, *Wall Street Journal*, March 28, 2020.

aware of reasons why lenders would drop from the platform but keep lending away from the platform. Nevertheless, we investigated this 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 used 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 found direct evidence on their website that they stopped lending. In some additional cases, the website disappeared. In many other cases, it is not possible to reach a conclusion based on the evolution of the website. By April, many companies advertise PPP loans rather than loans they would make directly. More generally, looking at lenders on the platform as well as other lenders, we found that in many cases the lenders made important business model shifts that brought them away from FinTech lending per se and transformed them into utilities for banks. For instance, the CEO of Fundation explained in a podcast that what apparently enabled them to survive was their business of making small business loans for banks.[28]

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

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

Our evidence is that supply dropped because lenders dropped out. It does not appear that their offer rate slowly fell, so that they eventually ended with no offers. Instead, it seems that it was almost business as usual until fairly close to their exit. Such a pattern is inconsistent with the view that lenders exited because it became harder for lenders to find acceptable borrowers because of an increase in risk. It is a pattern that one would expect with the financial constraint channel. However, we cannot exclude the possibility that lenders concluded suddenly that uncertainty was too high to make loans and hence shut down their lending. In particular, they could have concluded that their lending models were no longer capturing risk adequately, so that they stopped lending because they found that the loans they accepted were too risky for reasons not captured by their models. Some market participants discussed this risk.[29] While both of these explanations likely played a role in lender supply cuts as we discuss further in Section 7, we first test whether potentially profitable loan opportunities were passed up by the lenders most likely to have experienced a shortfall in funding. Such evidence would be supportive of the role of the financial constraint channel.

6.2.2. Did riskier lenders pass up viable lending opportunities?

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

[29] For instance, the CEO of Fundera stated that “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 AnnaMaria Andriotis and Peter Rudegeair, *Wall Street Journal*, March 28, 2020.

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 have made it past the initial screening. The data allow us to identify not only when an offer is made, but also when these credit solicitations are rejected by lenders. This provides an avenue for identifying the likelihood that an offer will be extended to a particular applicant based on the characteristics of the *lender*. In particular, we can use application fixed effects to test how the lender's borrower risk preferences influences 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 by examining lender responses for the same applicant. On average each application is sent to 5.5 lenders so that there are substantially more observations in these regressions. As before, we define a lender's habitat as the median FICO on the transacted loans in 2019. We test whether this habitat influences the probability of extending an offer by regressing an offer indicator on lender habitats and applicant fixed effects. Unsurprisingly, prior to the pandemic crisis riskier lenders (those with lower median FICO loans) are relatively more likely to extend an offer as seen in Column (1) of Table 7, Panel A. 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. Summing the coefficients of median FICO with its 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 does not adequately describe a lender's habitat, we run the same tests using the median interest rate on closed loans for each lender in 2019. This serves as a market-based summary variable for the riskiness of the loans made by the lender and is not necessarily correlated with the median FICO of its borrowers. The results using this measure are reported in Panel B of Table 7 and the interpretation is nearly identical to the previous results, though perhaps slightly stronger as median APR has no impact on offer likelihood during the month of March.

The evidence presented in this section supports the view that riskier lenders were simply unwilling to or unable to make loans that safer lenders deemed profitable. There is no good economic argument for why lenders who were willing to make loans to the riskier borrowers would suddenly change their business model in response to the COVID-19 because of a change in preferences rather than because of being constrained to do so. Instead, we would expect lenders to make offers with a higher APR, lower amounts, and lower maturity. However, we already showed in Section 5 this was not the case. In the next section, we show evidence for lenders with public information that the crisis made lenders financially constrained.

7. Evidence from the securitization market and individual lenders

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

7.1. Securitization markets during March 2020

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

The securitization market between March and June 2020 provided only limited funding to FinTech lenders. In general, securitizations use tranching, so that they have a large highly rated tranche and then riskier tranches. The top-rated tranche of the securitizations that were underwritten before March 2020 did not have top ratings from any rating agency at issuance. One exception is the On Deck securitization in April 2019, which was rated by Kroll and received an AAA rating for its safest tranche. The largest securitization was the Kabbage securitization in 2019. It issued notes for $700 million. The top-rated notes had a rating of AA by Kroll at issuance. In March 2020, Kroll put 10 small business ABS deals on downgrade watch due to COVID-19.[30] Subsequently, by June, six transactions had entered rapid amortization.[31] A rapid amortization occurs when the loans in the trust fail to meet a quality threshold. At that point, repayments are disbursed to investors and loans are no longer purchased by the trust. In sum, these developments for securitizations are inconsistent with the securitization market being open for those issuers.

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

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

lending during the March crisis. The rebound in prices is dramatic. It seems inconsistent with markets still expecting a high default rate in the summer.

7.2. The experience of individual FinTech lenders

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

7.2.1. 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. Figure 8 shows the evolution of its stock price. The stock price dropped from $3.52 at the start of March 2020 to $1.54 at the end of the month. During March, the stock price was $0.65 on March 18. It rebounded sharply after it became clear that the CARES Act would be adopted. The company filed an 8-K form on March 23, 2020. In that form, it said that it recently experienced both an increase in loan applications and slower collections. The increase in loan applications is consistent with the results we present in Section 3.

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

In its earnings call for Q1, 2020, on April 30, On Deck explained that the surge in loan applications in March represented "a higher degree of risk" so that they "proactively tightened credit policies and slowed originations dramatically. We suspended new originations to certain industries, limited draws on certain customer lines of credit, tightened underwriting standards."[32] It then reported that it was working with lenders to amend certain debt facilities. It discussed suspending new term loan and credit line originations to support the PPP program. The CFO stated in the call that "Our liquidity and funding position became our top priority as the COVID crisis emerged. We quickly took actions to bolster our available cash, fully drawing on our corporate line, and managing both origination and operating cost outflows."

In its 10-Q filing for Q2, 2020, OnDeck recounts changes in the funding of two wholly owned subsidiaries, Loan Assets of On Deck LLC and Receivable Assets of On Deck LLC. The Loan Assets subsidiary had a revolving debt facility that was renegotiated during the quarter. The renegotiation suspended portfolio performance tests and no borrowing base deficiency was deemed to occur from April 27, 2020, to July 16, 2020. In exchange, the lenders imposed restrictions on actions On Deck could take and were no longer obligated to advance funds. The revolving facility for Receivable Assets was renegotiated as well and so were various funding trusts. In all cases, On Deck received some forbearance in exchange for restrictions on its actions and suspension of the agreements to provide new funding for new loans.

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

[32] Q1 2020 OnDeck Capital Inc. Earnings Call, April 30, 2020, Thompson Reuters.

7.2.2. Kabbage

The CEO of Kabbage posted a statement on April 2, 2020, that Kabbage had paused lending on March 29 to convert its systems to process loans through PPP. However, before that, there was much discussion that Kabbage had cut and/or suspended credit lines. It had also furloughed a "significant number" of its 500 U.S. employees. According to Bloomberg, Kabbage said that it took these actions to conserve cash to be able to continue operate.[33] Kabbage relied on securitization as we have discussed. Its securitization structures were such that it was responsible for some of the losses on the loans included in securitization trusts. The president of Kabbage was quoted in the Financial Times saying "We securitize our receivables and we are on the hook for loan performance, which is suffering because of delinquencies, because our customers have no revenue, because they are closed".[34] As reported by the *Financial Times*, Kabbage eventually processed more loans for the PPP program than it had lent in the previous year: $3.5 billion PPP loans by May 8, 2020, versus $2.8 billion loans in 2019.[35]

7.2.3. LendingClub

LendingClub, as discussed in Section 2, is built on the peer-to-peer lending model. As the business model evolved, the investors in the loans became financial institutions and professional investors rather than individuals. Most of the loans from LendingClub are loans to individuals rather than businesses, but some of the loans of LendingClub are loans to small businesses. The company itself also acquires loans. In the fourth quarter of 2019, LendingClub originated loans for $3.1 billion. In the first quarter of 2020, the origination volume dropped to $2.56 billion. The origination volume dropped by 18.2% even though March is only one of three months in the quarter. In the "Current Economic and Business Environment" section of its 10-Q form, LendingClub stated:

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

> "There has been a reduction in investor demand on our platform reflecting market dislocation for unsecured personal loans driven in part by wider credit spreads and increased liquidity constraints. Similarly, the Company has temporarily ceased purchasing loans to preserve capital due to the lack of investor demand for our Structured Program transactions and whole loan sales. The reduction in investor demand on our platform has had a direct impact on the reduction in loan origination and transaction fees earned by the Company from our issuing banks."[36]

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

7.3. Banks

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

[36] 10-Q filings for the quarter ending on March 31, 2020, p. 59.

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

For banks, the survey only shows acceptance rates for banks that lend on the biz2credit platform. The Federal Reserve Bank of Kansas City (FRBKC) publishes a survey of small business lending by banks.[37] This survey queries banks generally. That survey reports different approval rates from those of the biz2credit index. The FRBKC survey has much higher acceptance rates for banks and, further, finds an unchanged approval rate for the first quarter of 2020. That survey further shows an increase in small business lending during the first quarter of 2020 compared to the same quarter in 2019. The same survey reports that about 20% of respondents experienced an increase in credit line usage. The survey has mixed evidence on overall loan demand as on net small banks reported a decrease in loan demand but the other banks report an increase. From this survey evidence, it is clear that the experience of banks differs from the

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

experience of the platform from which we obtain our data. As discussed earlier, such a difference may not be surprising given that banks have a different funding model and make loans to less risky borrowers (banks often have a minimum FICO threshold for loans that excludes subprime borrowers; see Ben-David, Johnson, Lee, and Yao, 2022).

8. Conclusion

In this paper, we examine the evolution of FinTech small business lending during the COVID-19 crisis period of March 2020 using unique data from a lending platform that allows us to examine separately the demand and the supply for loans. We find that the demand increased in response to the COVID-19 shock and the applicants for loans became more creditworthy using historical characteristics. However, paradoxically, at a time when FinTechs' advantage in responding to demand rapidly compared to banks would have been most valuable, they were not able to respond as the supply fell. Surprisingly, while the supply fell, the terms of the loans were mostly unaffected by the COVID-19 shock. We provide further 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 investigate two explanations for the drop in supply. One explanation is the increase in uncertainty resulting from the COVID-19 shock. The other explanation is that FinTech lenders became financially constrained. We find strong evidence that the supply fell because of lender factors rather than because of borrower factors. We show that the supply fell because lenders dropped out. The typical lender kept lending during March with an acceptance rate that stayed relatively stable. Suddenly, that acceptance rate collapsed and the lender dropped out. It seems difficult to rationalize a decrease in supply taking place this way simply by an increase in risk resulting from the COVID-19 shock that affected borrowers. This is because the decrease in supply is to a large extent the result of lender exits.

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

A plausible 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 be financially constrained first. As a result, they would drop out first and, being financially constrained, would reject the opportunity to make safer loans. We find support for this hypothesis. We show that the lenders with the riskiest borrowers dropped out first. Using a Khwaja and Mian (2008) identification, we find that the borrowers with the riskiest lenders became less likely to accept loans compared to borrowers with safer lenders who were less likely to be financially constrained. We also show that the prices of securitization notes fell sharply but then bounced back. The dramatic evolution of securitization prices seems to support an explanation where lenders stopped lending at least in part because they were concerned about running out of funding. Public statements by lenders support this interpretation. The alternative explanation is that the riskier lenders somehow became more risk-averse compared to the safer lenders for reasons unrelated to their financial situation. Such an explanation could make sense if riskier lenders use a different lending technology whose reliability is more affected by the COVID-19 shock, but we have seen no evidence consistent with this view.

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

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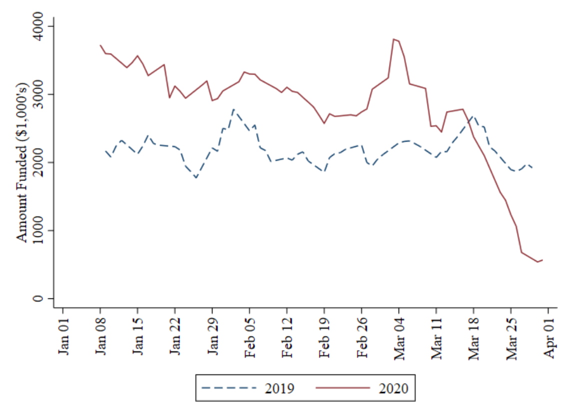
Figure 1. FinTech loan volume-Small business and personal loans

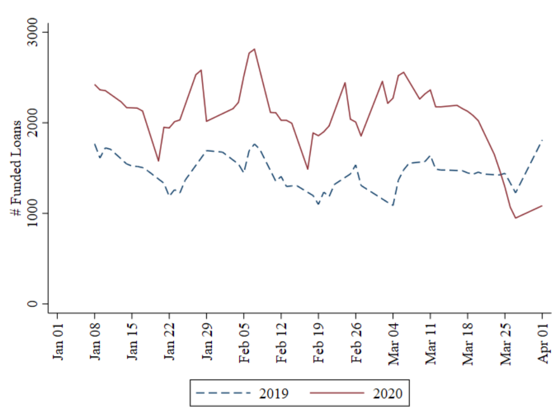
These figures depict the evolution of funded loans in the first three months of 2020 for both small business loans (SB) and personal loans originated by fintech lenders. Panels (a) and (b) use data from marketplace platform that connects small businesses with the major online lenders. Panel (a) plots a five- 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 of the major fintech platforms. Panel (c) shows the five- 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)

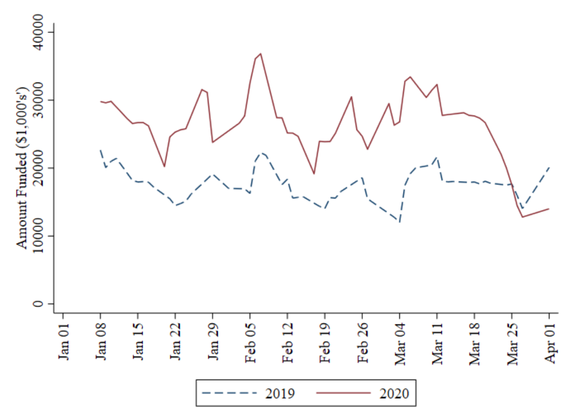


Figure 2. Small business loan demand

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

(a) Number of applicants

(b) Total amount requested (Millions)

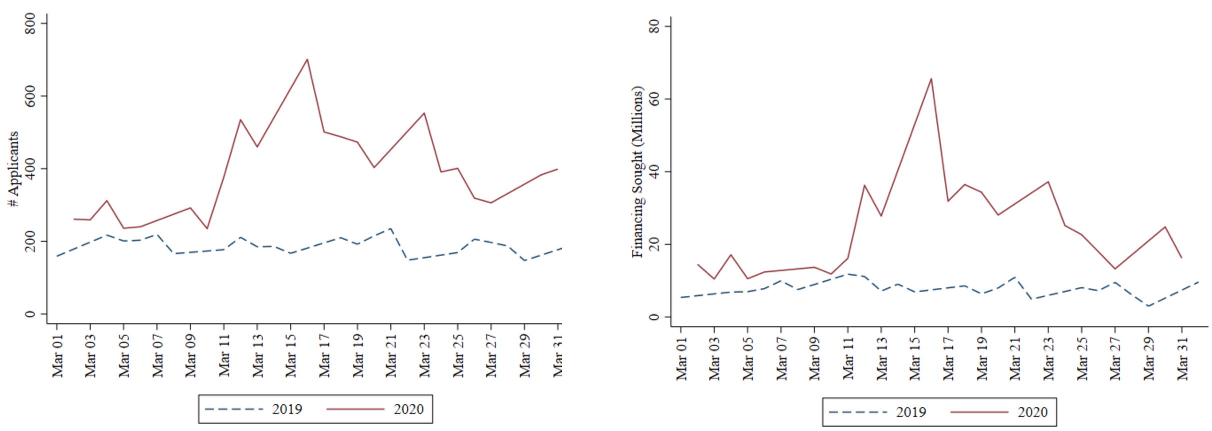
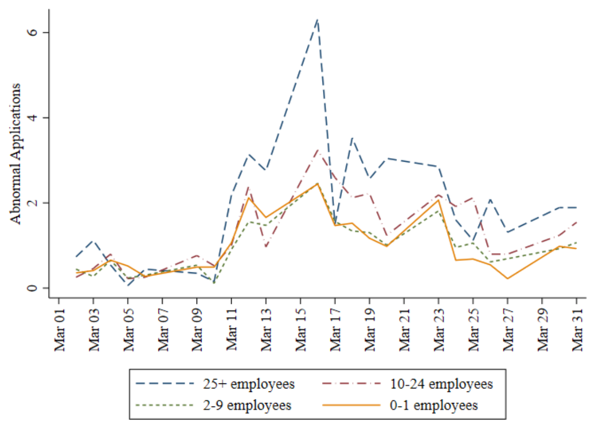


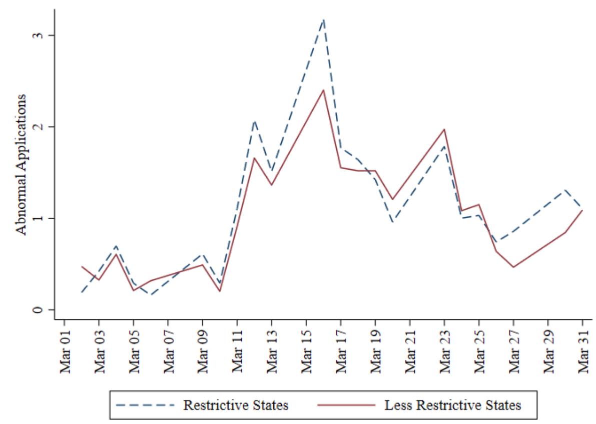
Figure 3. Abnormal demand for small business FinTech loans

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

(a) Firm size



(b) State restrictiveness



(c) Industry

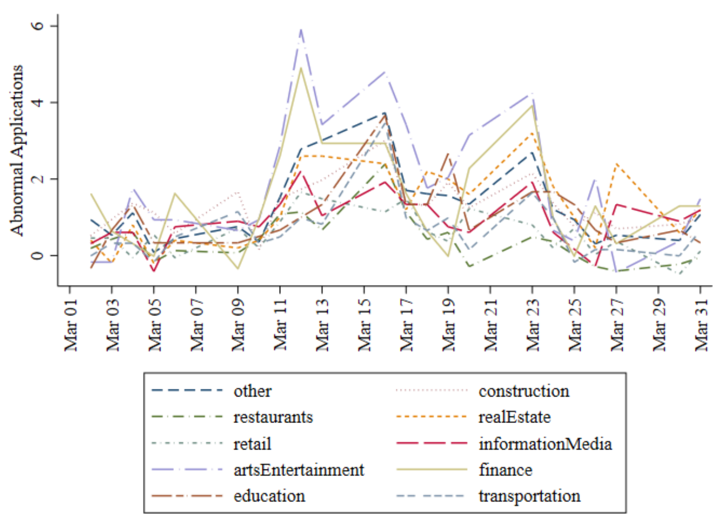
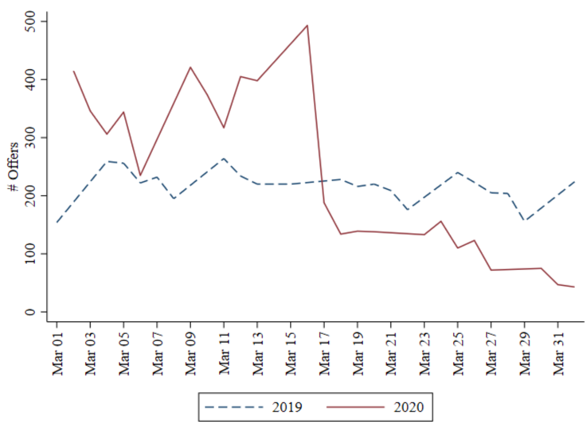


Figure 4. Loan supply

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

(a) Number of offers



(b) Number of offers per applicant

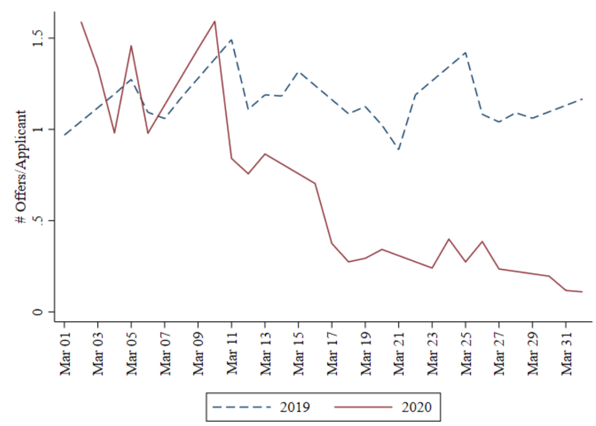
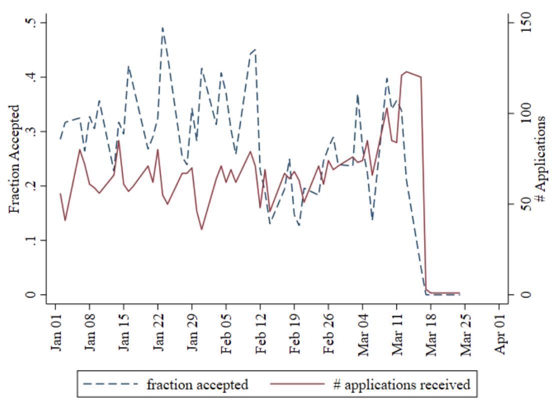


Figure 5. Lender dropouts

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

(a) Lender dropout example



(b) Active lenders (moving average)

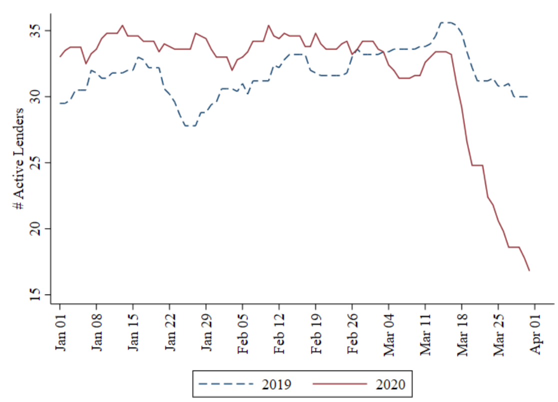


Figure 6. Lender dropouts by average lender risk

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

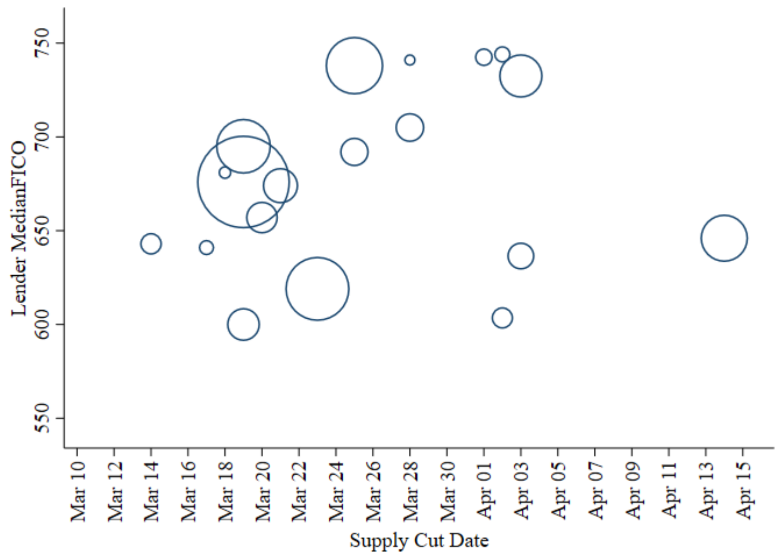
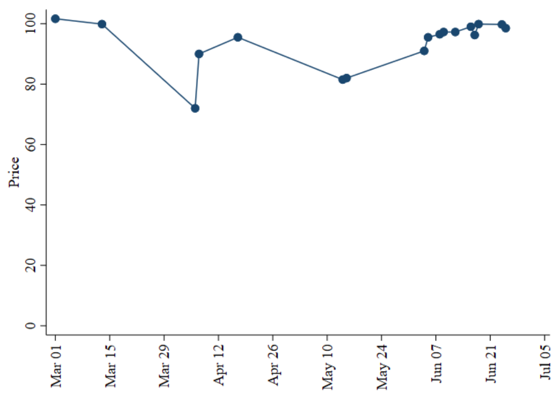


Figure 7. Securitization prices

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

(a) A-Note securitization prices (Kabbage)



(b) B-Note securitization prices (Kabbage)

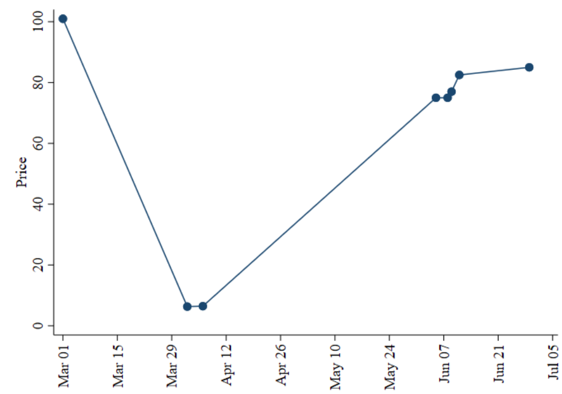


Figure 8. On Deck Capital stock price evolution

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

Table 1. Applicant comparative statistics

This table compares applicant characteristics between those that applied prior to the COVID-19 shock and those after. Panel A compares applicants in March 2019 with those in March 2020 while Panel B compares those in the first part of March with those in the latter part. 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 negative balance, average monthly number and amount 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 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 home all day in the county from the prior week. Difference 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	652.8	73.0	671.7	79.5	18.9***	11.71
Annual Sales	805,272	1,064,472	1,099,588	1,316,319	294,315***	11.83
Age(Months)	54.94	50.15	58.28	44.52	3.34**	3.28
# Employees	7.38	10.92	8.42	12.49	1.04***	4.15
Avg Bank Balance	19,460	39,408	27,860	50,641	8,400***	8.95
# Days Negative Balance	1.42	2.93	1.12	2.73	-0.30***	-4.84
# Monthly Credits	26.95	27.01	28.36	27.76	1.41*	2.33
Monthly Credit Amount	77,141	127,822	96,317	150,186	19,176***	6.52
# Monthly Debits	90.6	68.21	89.63	69.38	-0.97	-0.69
Monthly Debit Amount	77,137	128,309	97,142	151,607	20,005***	6.76
Seasonal Business	0.06	0.23	0.05	0.21	-0.01*	-2.18
I(Offer)	0.56	0.50	0.30	0.46	-0.26***	-24.53
APR	96.53	58.84	80.28	52.98	-16.25***	-8.70
Maturity	11.64	12.13	16.82	22.79	5.18***	8.81
Loan Amount	44,356	46,341	59,151	59,411	14,795***	8.60
I(State Lockdown)	-	-	0.25	0.43	-	-
% Population Home	-	-	0.30	0.09	-	-
% Population Home (7-day avg)	-	-	0.29	0.08	-	-
Observations	3,220		6,575		9,795	

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	659.7	79.0	679.1	78.9	19.3***	9.56
Annual Sales	967,771	1,252,145	1,180,561	1,348,008	212,790***	6.45
Age(Months)	54.04	42.19	60.89	45.71	6.85***	6.23
# Employees	7.70	11.93	8.86	12.8	1.15***	3.66
Avg Bank Balance	23,199	45,088	30,723	53,573	7,524***	6.04
# Days Negative Balance	1.40	3.12	0.95	2.45	-0.44***	-6.08
# Monthly Debits	92.21	69.88	88.05	69.03	-4.16*	-2.40
Monthly Debit Amount	89,356	146,634	101,924	154,406	12,567***	3.25
Seasonal Business	0.05	0.23	0.04	0.19	-0.01**	-2.69
I(Offer)	0.46	0.50	0.21	0.40	-0.26***	-21.77
APR	91.22	55.29	65.12	45.47	-26.10***	-11.18
Maturity	13.88	17.61	20.87	27.93	7.00***	6.29
Loan Amount	51,727	53,996	69,399	64,811	17,672***	6.37
I(State Lockdown)	0.00	0.00	0.41	0.49	0.41***	52.57
% Population Home	0.22	0.03	0.36	0.06	0.15***	114.44
% Population Home (7-day avg)	0.23	0.02	0.33	0.07	0.10***	71.26
Observations	2,502		4,073		6,575	

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 up 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. * p<.1; ** p<.05; *** p<.01.

Dependent variable	Number of Applicants		
	(1)	(2)	(3)
Mar 4-10 (2020)	-2.00		-36.60
	(42.77)		(53.25)
Mar 11-17 (2020)	249.80***		216.60***
	(66.62)		(73.64)
Mar 18-24 (2020)	196.60***		163.40***
	(49.47)		(60.05)
Mar 25-31 (2020)	87.25*		61.60
	(45.60)		(56.15)
Mar 5-11 (2019)		34.60	34.60
		(31.72)	(31.72)
Mar 12-18 (2019)		33.20	33.20
		(31.38)	(31.38)
Mar 19-25 (2019)		33.20	33.20
		(34.03)	(34.03)
Mar 26-Apr 1 (2019)		25.65	25.65
		(32.77)	(32.77)
Constant	265.00***	158.60***	158.60***
	(39.55)	(30.24)	(30.24)
Sample Period	Jan-Mar 2020	Jan-Mar 2019	Jan-Mar 2019-2020
R-squared	0.65	0.34	0.76
N	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 include the FICO score of the owner, log of firm age, log of sales, average bank balance, number of days with negative balance, average monthly number and amount of credits and debits, and fixed effects for industry. To save space only the coefficients on indicators for weeks in March are included, but all week indicators are included in regressions where the sample period extends prior to March. In Columns (1) and (2), the sample is limited to applications received in March 2020. The sample used in Columns (2)-(4) include January and February 2020. The sample use 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. Robust standard errors are reported. * p<.1; ** p<.05; *** p<.01.

Dependent variable	I(Offer)*100					
	(1)	(2)	(3)	(4)	(5)	(6)
Mar 4-10 (2020)	-3.96**	-4.77***	-8.38***	-8.20***		-9.64***
	(1.66)	(1.53)	(1.61)	(1.77)		(3.09)
Mar 11-17 (2020)	-18.43***	-22.39***	-22.85***	-26.22***		-30.48***
	(3.16)	(3.83)	(3.10)	(3.99)		(4.93)
Mar 18-24 (2020)	-33.30***	-37.75***	-37.72***	-41.60***		-41.68***
	(1.19)	(0.93)	(1.13)	(1.30)		(2.43)
Mar 25-31 (2020)	-41.05***	-47.07***	-45.48***	-50.92***		-52.72***
	(1.89)	(2.20)	(1.83)	(2.29)		(3.04)
Mar 5-11 (2019)					1.05	1.36
					(2.54)	(2.51)
Mar 12-18 (2019)					3.81	4.00
					(2.95)	(2.89)
Mar 19-25 (2019)					-0.34	-0.20
					(2.09)	(2.06)
Mar 26-Apr 1 (2019)					1.44	1.42
					(2.01)	(1.99)
Sample Period	Mar 2020	Mar 2020	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2019	Jan-Mar 2019-2020
Controls		X		X	X	X
Industry FE		X		X	X	X
R-squared	0.09	0.16	0.12	0.21	0.13	0.18
N	6,575	6,575	15,342	15,342	8,198	23,540

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

This table examines which industries were most impacted by the reduction in the supply of credit in the latter half of March. The dependent variable is an indicator variable that takes value 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 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. Robust standard errors are reported. * p<.1; ** p<.05; *** p<.01.

Dependent variable	I(Offer)*100		
	(1)	(2)	(3)
AgricultureForestry * I(Post 3/12)	0.82	10.35	4.38
	(10.09)	(7.71)	(7.29)
ArtsEntertainment * I(Post 3/12)	6.16	12.60**	9.72*
	(8.99)	(5.32)	(4.98)
Automotive * I(Post 3/12)	8.91	6.69	5.93
	(10.92)	(5.24)	(4.70)
Construction * I(Post 3/12)	-1.34	0.04	-1.08
	(5.60)	(2.79)	(2.55)
Education * I(Post 3/12)	-5.15	-2.04	-1.37
	(12.35)	(6.93)	(6.48)
Finance * I(Post 3/12)	7.22	6.99	5.46
	(6.77)	(5.16)	(4.70)
FreightTrucking * I(Post 3/12)	-4.72	-1.74	-2.24
	(7.23)	(5.33)	(5.07)
Healthcare * I(Post 3/12)	6.18	8.52*	6.20
	(9.54)	(4.70)	(4.29)
InformationMedia * I(Post 3/12)	6.95	3.75	2.91
	(5.43)	(4.55)	(4.24)
LegalServices * I(Post 3/12)	-0.75	8.42	12.07
	(14.47)	(8.55)	(8.05)
Manufacturing * I(Post 3/12)	1.07	5.54	3.94
	(6.94)	(3.74)	(3.47)
RealEstate * I(Post 3/12)	-3.17	-4.22	-5.23
	(6.05)	(4.19)	(4.06)
Restaurants * I(Post 3/12)	-21.27***	-18.08***	-18.97***
	(4.57)	(3.59)	(3.43)
Retail * I(Post 3/12)	-2.15	-3.69	-3.49
	(6.12)	(3.80)	(3.48)
Transportation * I(Post 3/12)	-0.27	-0.57	-1.38
	(7.84)	(3.71)	(3.48)
Wholesale * I(Post 3/12)	-28.06**	12.25	14.30
	(11.07)	(12.44)	(11.79)
Sample Period	March 2020	Jan-Mar 2020	Jan-Mar 2019-2020
Controls	X	X	X
R-squared	0.15	0.20	0.18
N	6,575	15,342	23,540

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

This table shows the effect of geographic exposures to the pandemic on the likelihood that a firm receives an offer. The dependent variable is an indicator equal to 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 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 negative balance, average monthly number and amount of credits and debits, and industry indicators. Standard errors are clustered by application date and county. Robust standard errors are reported. * p<.1; ** p<.05; *** p<.01.

Dependent variable	I(Offer)*100								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
I(State Lockdown)	-3.97**			-1.51			-3.94**		
	(1.61)			(2.68)			(1.82)		
% Population Home		-8.23			-18.45			-19.21	
		(9.93)			(28.21)			(17.15)	
% Population Home (7-day avg)			-21.30			-41.57			-33.37
			(16.59)			(35.59)			(23.29)
FICO				0.07***	0.07***	0.07***	0.08***	0.08***	0.08***
				(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ln(Age)				3.78***	3.77***	3.76***	2.34***	2.35***	2.34***
				(1.00)	(1.02)	(1.02)	(0.66)	(0.66)	(0.66)
ln(Sales)				3.11***	3.12***	3.13***	3.82***	3.81***	3.81***
				(0.83)	(0.83)	(0.83)	(0.55)	(0.55)	(0.55)
Avg Bank Balance				-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
# Days Negative Balance				-2.88***	-2.88***	-2.88***	-3.67***	-3.67***	-3.67***
				(0.27)	(0.27)	(0.28)	(0.17)	(0.17)	(0.17)
# Monthly Credits				0.12***	0.12***	0.12***	0.12***	0.12***	0.12***
				(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Monthly Credit Amount				-0.00	-0.00	-0.00	-0.00**	-0.00**	-0.00**
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
# Monthly Debits				-0.00	-0.00	-0.00	0.01	0.01	0.01
				(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Monthly Debit Amount				0.00	0.00	0.00	0.00**	0.00**	0.00**
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
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	X	X	X	X	X	X	X	X	X
Industry FE				X	X	X	X	X	X
County FE				X	X	X	X	X	X
R-squared	0.09	0.09	0.09	0.26	0.26	0.26	0.27	0.27	0.27
N	4,760	4,760	4,760	4,760	4,760	4,760	11,548	11,548	11,548

Table 6. Offer terms and exposure to COVID-19

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

Panel A: Changes in loan offer terms in March 2020

Dependent Variable	APR		Maturity		ln(Loan Amount)	
	(1)	(2)	(3)	(4)	(5)	(6)
Mar 4-10 (2020)	-3.99*	-3.00***	0.11*	0.06	0.07***	0.02
	(2.16)	(1.03)	(0.06)	(0.08)	(0.02)	(0.02)
Mar 11-17 (2020)	-2.21	-1.76	0.08	0.07	0.04	-0.00
	(2.52)	(1.31)	(0.14)	(0.08)	(0.03)	(0.03)
Mar 18-24 (2020)	-1.09	-0.06	0.09	0.14	0.03	-0.03
	(3.21)	(1.41)	(0.31)	(0.35)	(0.07)	(0.06)
Mar 25-31 (2020)	-1.12	0.29	-0.28	-0.20	-0.07	-0.12
	(3.78)	(1.94)	(0.44)	(0.40)	(0.11)	(0.10)
FICO	-0.06***	-0.07***	0.01***	0.01***	0.00***	0.00***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
ln(Age)	-4.46***	-4.15***	0.51***	0.53***	0.06**	0.05***
	(1.03)	(0.94)	(0.17)	(0.16)	(0.02)	(0.02)
ln(Sales)	-1.51*	-1.91*	0.20**	0.12*	0.44***	0.48***
	(0.85)	(1.11)	(0.08)	(0.06)	(0.03)	(0.03)
Avg Bank Balance	0.00	0.00*	-0.00	-0.00	0.00***	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
# Days Negative Balance	1.43*	1.41***	-0.09**	-0.07**	-0.01	-0.01
	(0.78)	(0.44)	(0.04)	(0.03)	(0.01)	(0.01)
# Monthly Credits	-0.04**	-0.02	0.01	0.00	0.00**	0.00
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Monthly Credit Amount	0.00	-0.00	0.00	0.00	0.00*	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
# Monthly Debits	-0.00	-0.00	-0.00*	-0.00	0.00***	0.00***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Monthly Debit Amount	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(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	X	X	X	X	X	X
Lender FE	X	X	X	X	X	X
R-squared	0.84	0.83	0.99	0.96	0.69	0.69
N	3,572	14,590	3,572	14,590	3,572	14,590

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

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

Panel B									
Dependent variable	APR			Maturity			ln(Loan Amount)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
I(State Lockdown)	2.67			-0.86			0.11		
	(2.61)			(0.52)			(0.07)		
% Population Home		5.96			0.38			-0.33	
		(10.87)			(1.24)			(0.39)	
% Population Home (7-day avg)			24.62			0.01			-0.91
			(18.98)			(2.64)			(0.68)
FICO	-0.07***	-0.07***	-0.07***	0.01***	0.01***	0.01***	0.00***	0.00***	0.00***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln(Age)	-4.52***	-4.54***	-4.53***	0.47***	0.48***	0.48***	0.06***	0.06***	0.06***
	(1.01)	(1.01)	(1.01)	(0.14)	(0.14)	(0.14)	(0.01)	(0.01)	(0.01)
ln(Sales)	-1.73	-1.73	-1.73	0.09	0.09	0.09	0.47***	0.47***	0.47***
	(1.16)	(1.16)	(1.16)	(0.07)	(0.07)	(0.07)	(0.03)	(0.03)	(0.03)
Avg Bank Balance	0.00	0.00	0.00	-0.00	-0.00	-0.00	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
# Days Negative Balance	1.70***	1.71***	1.71***	-0.07**	-0.07**	-0.07**	-0.02*	-0.02*	-0.02*
	(0.58)	(0.58)	(0.58)	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)
# Monthly Credits	-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)
Monthly Credit Amount	0.00	0.00	0.00	0.00	0.00	0.00	0.00*	0.00*	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
# Monthly Debits	-0.01	-0.01	-0.01	-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)
Monthly Debit Amount	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(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	X	X	X	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X	X	X	X
Lender FE	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
R-squared	0.85	0.85	0.85	0.98	0.98	0.98	0.74	0.74	0.74
N	8,617	8,617	8,617	8,617	8,617	8,617	8,617	8,617	8,617

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)	-1.05	1.41	0.21*	-0.00	0.09*	-0.12**
	(1.54)	(1.59)	(0.12)	(0.15)	(0.05)	(0.05)
I(HighIndExposure)	-0.99*	-1.06**	0.18	0.12	-0.15***	-0.01
	(0.57)	(0.44)	(0.14)	(0.11)	(0.04)	(0.02)
I(HighIndExposure) * I(Post 3/12)	-0.05	0.56	0.33	0.24	0.10**	0.07
	(1.26)	(1.15)	(0.23)	(0.25)	(0.04)	(0.04)
FICO		-0.07***		0.01***		0.00***
		(0.01)		(0.00)		(0.00)
ln(Age)		-4.96***		0.64***		0.08***
		(1.19)		(0.20)		(0.02)
ln(Sales)		-1.66		0.15		0.49***
		(1.30)		(0.11)		(0.03)
Avg Bank Balance		0.00		-0.00		0.00***
		(0.00)		(0.00)		(0.00)
# Days Negative Balance		1.66***		-0.11**		-0.02
		(0.59)		(0.04)		(0.01)
# Monthly Credits		-0.05**		0.01***		0.00***
		(0.02)		(0.00)		(0.00)
Monthly Credit Amount		0.00		0.00		0.00
		(0.00)		(0.00)		(0.00)
# Monthly Debits		-0.00		-0.00*		0.00***
		(0.01)		(0.00)		(0.00)
Monthly Debit Amount		-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
Lender FE	X	X	X	X	X	X
R-squared	0.82	0.83	0.97	0.97	0.39	0.70
N	6,524	6,524	6,524	6,524	6,524	6,524

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)* equal to 1 if the application was submitted on or after March 12 identifies the applicants that were "treated" to the pandemic shock. This treated indicator is interacted with measures of lender risk. Standard errors are clustered at the lender level. Robust standard errors are reported. * p<.1; ** p<.05; *** p<.01.

Panel A: Lender risk appetite measured using median FICO

Dependent variable	I(Offer)*100			
	(1)	(2)	(3)	(4)
MedianFICO	-0.24***	-0.10**	-0.22***	-0.20***
	(0.06)	(0.04)	(0.05)	(0.05)
MedianFICO * I(Post 3/12)			0.20***	0.18***
			(0.06)	(0.05)
I(Post 3/12)			-135.39***	-123.53***
			(40.60)	(36.84)
Sample Period	Jan-Feb 2020	Mar 2020	Jan-Mar 2020	Jan-Mar 2019-2020
Applicant FE	X	X	X	X
R-squared	0.29	0.31	0.29	0.30
N	58,256	26,490	84,961	131,925

Panel B: Lender risk appetite measured using median APR

Dependent variable	I(Offer)*100			
	(1)	(2)	(3)	(4)
MedianAPR	0.16***	0.04	0.15***	0.15***
	(0.05)	(0.03)	(0.05)	(0.04)
MedianAPR * I(Post 3/12)			-0.18***	-0.18***
			(0.03)	(0.03)
I(Post 3/12)			15.52***	12.84***
			(4.15)	(4.25)
Sample Period	Jan-Feb 2020	Mar 2020	Jan-Mar 2020	Jan-Mar 2019-2020
Applicant FE	X	X	X	X
R-squared	0.29	0.31	0.29	0.30
N	58,256	26,490	84,961	131,925

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 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 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.