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MODELS BEHAVING BADLY: THE LIMITS OF DATA-DRIVEN LENDING

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ABSTRACT

Data-driven lending relies on the calibration of models using training periods. We find that this type of lending is not resilient in the presence of economic conditions that are materially different from those experienced during the training period. Using data from a small business fintech lending platform, we document that the small business credit supply collapsed during the COVID-19 crisis of March 2020 even though the demand for loans doubled relative to pre-pandemic levels. As the month progressed, most lenders significantly reduced or halted their lending activities, likely due to the heightened risk of model miscalibration under the new economic conditions.

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1. Introduction

Lenders can use hard and soft information in loan underwriting. Hard information can be documented and verified, such as applicants' FICO scores or their bank statements. Soft information is gathered over the course of the lender-borrower relationship. Such information may include the firmness of a borrower's handshake, her punctuality in meetings, and so on (Stein 2002; Liberti and Petersen 2019). Banks, especially smaller ones, use a combination of hard and soft information for many types of loans. In contrast, fintech lenders rely strictly on data-driven lending as they underwrite loans using hard information fed into statistical models, which recommend approval decisions and price loans based on applicants' risk.¹ The models allow fintech lenders to efficiently evaluate a large number of applications from geographically dispersed applicants and provide quick approval decisions to borrowers. As a result, fintech lending has been particularly attractive for small businesses without developed banking relationships seeking immediate financing to bridge temporary cash shortages.

For all its advantages, data-driven lending has a dark side as well, which is common to the use of data technologies generally (Bonelli 2023). Data-driven lending relies on models that have to be trained, but they can only be trained on past data. As a result, the models work well for loans when their performance is expected to relate to their attributes in the same way as the performance of loans related to loan attributes during the training period. Otherwise, when the past is not representative of the future, the models will still come up with an estimate of the probability of default of the loan (or some other metric), but this estimate may be extremely inaccurate. A lender using the estimate may then think it is making a positive NPV loan when in fact it is an extremely

¹ Some fintech use non-traditional data for the purpose of evaluating the credit quality of a borrower (e.g., Di Maggio, Ratnadiwakara, and Carmichael, 2022; Gambacorta, Huang, Qiu, and Wang, 2024). The lenders we consider do not appear to do so in March 2020.

poor loan. In the language of risk management, data-driven lenders are exposed to model risk – the risk that the model they use is not fit for its purpose (Derman 1996). In this case, the risk is that a model has become unreliable. Crises are periods when models are likely to become unreliable because the economic environment is typically sharply different from the economic environment of the training periods used to calibrate models. Once lenders become concerned that their models may have become unreliable, they have to change their models to adapt them to the new environment and, if they cannot do so quickly and reliably, have to stop lending.

In this paper, we use the COVID-19 crisis to examine the resilience of data-driven lending when the economic environment changes dramatically in a very short period of time. The COVID-19 crisis offers a particularly attractive setup to assess the dark side of data-driven lending because it brought about an economic environment that had not been experienced in the modern US economy. To conduct our analysis, we study small business unsecured lending through a fintech platform in March 2020 (prior to the rollout of federal PPP loans which largely replaced private small business loans) that connects small businesses applying for loans with dozens of the most prominent online lenders. Small business unsecured lending offers an ideal testing ground because the credit models used by lenders were not designed to account for the unique features of the pandemic. For example, they were not predictive of whether a business could operate in the near future or be closed because of a lockdown or other public health restrictions. We present evidence that is consistent with data-driven lenders reacting to the risk that their models had become unreliable by shutting down all or most of their lending. We conclude that, among plausible explanations for the collapse in lending, model risk is the only explanation that appears to fit all the facts concerning the evolution of small business fintech lending during March 2020.

The platform data we use contains loan applications, approval decisions, and offer terms at the daily frequency. The daily data is especially suitable to analyze how lenders adjusted to the evolution of the COVID-19 crisis because they were responding extremely rapidly to applicants (in most cases within a day). We begin by documenting a large increase in demand for fintech loans followed by a sharp contraction in supply. Loan applications rose sharply in the first two weeks of March 2020, and at their peak, they were more than twice as high compared to the prepandemic period. When using traditional credit metrics, the credit quality of applicants rose. Compared to the same period in 2019, loan applicants in March 2020 had higher average FICO scores by nearly twenty points, and their annual sales were higher by 33%. This demand surge is consistent with survey evidence that many small businesses quickly became financially constrained and had to look for emergency funding (Bartik et al. 2020). At the beginning of March 2020, the fintech credit supply (measured as loan offers) appeared to increase in lockstep with the rising demand. However, after roughly the first two weeks of March, the number of offers dramatically collapsed while the number of active lenders on the platform fell rapidly. By the end of March, the number of fintech loan offers on the platform was less than a tenth of the peak number during the month.

Next we investigate the extent to which the collapse in the supply of small business fintech lending can be traced to the dark side of data-driven lending. During March 2020, the models used by fintech lenders were developed on data that did not include events remotely resembling the events lenders were observing. These models were not designed to incorporate the impact of a pandemic that could force a borrower to close overnight what until then had been a healthy business. As one observer put it, "the impact of COVID-19 on model performance has been monumental, with both characteristics and outcomes largely distorted due to changes in behaviors,

unprecedented government support, and key economic indicators reaching levels outside of anything seen previously..." (Warhurst 2022). When lenders rely on models that use exclusively hard data to make loan decisions, they fly blind when dealing with circumstances for which their models were not designed. Another way to put it is that in such circumstances, like large language models asked to answer questions that they know nothing about, their models hallucinate (Danielsson 2024). This issue is well-understood among risk managers as a type of model risk issue where a model that worked well before stops working when the world changes too drastically (Derman 1996, Derman 2011).

Our explanation for the behavior of small business fintech lenders in March 2020 is that they stuck to their models, lending as if it were 2019, until they decided they could no longer do so and largely stopped lending. By then, they could no longer expect that they were making positive net present value (NPV) loans when their models told them to approve more loans. Lenders publicly discussed this model risk issue at the time. For instance, Jared Hecht, the CEO of Fundera, a fintech lending platform, told the *Wall Street Journal* that "Lenders have zero idea how to assess risk in this environment. (...) There is no model that can predict today if I lend \$1, will I get paid back?"²

Our null hypothesis is that lenders make their approval and pricing decisions consistent with modern credit analysis based on Merton (1974), and their screening and pricing decisions reasonably adapt to the evolving economic environment. Because the typical small business loan made by fintech lenders has no collateral but often a personal guarantee, lenders widely rely on the applicant's FICO score as the main metric for applicants' creditworthiness. With the COVID-19 crisis, had loan pricing models been able to take into account the unexpected impact of the pandemic on applicants, they would have assumed greater volatility of future earnings and lower

² "People need loans as Coronavirus spreads. Lenders are making them tougher to get" by Anna Maria Andriotis and Peter Rudegear, *Wall Street Journal*, March 28, 2020.

expected future earnings for a given FICO score, and the extent to which they would have done so would have depended on the exposure of applicants to the COVID-19 shock. Hence, lenders would have increased the loans' annual percentage rate (APR), decreased their maturity, and decreased their amounts relative to normal times had their models accounted for the impact of the pandemic on applicants. They would have rejected applications from the lowest FICO score applicants, as these applicants would have become too unlikely to repay loans. The extent to which their decisions would have differed from normal times would have been greater for applicants more exposed to the COVID-19 shock. For instance, applicants with a business that depended heavily on personal interactions or in a state about to have a lockdown would have been viewed as riskier than previously.

We find little evidence that lenders adjusted their decisions concerning which loans to make and what terms to offer to take into account the applicant-specific impact of the COVID-19 shock. The fall in the probability that an applicant would have received a loan offer in March cannot be explained by the evolving COVID-19 exposure of applicants. Further, we show that the terms of loans offered to applicants were only marginally affected by the applicants' exposure to the COVID-19 shock. Finally, there is no evidence that lenders shifted credit from riskier low-FICO score applicants to high-FICO score applicants.

Our evidence indicates that the aggregate credit supply on the platform shrank dramatically over the course of March 2020. The dramatic decline did not occur because lenders scaled down their operations or became more cautious in their lending. Rather, most lenders simply stopped lending suddenly. As the month progressed, there were fewer and fewer lenders in the market. Looking at the behavior of the lenders in event time, where the event is the week they dropped out, we find that small business fintech lenders lent like it was 2019 in March 2020 while they kept lending. Specifically, lenders continued to make offers as predicted based on their decision making before the COVID-19 crisis until the week they dropped out. Moreover, the terms they offered did not change much, if at all. When we reverse engineer the lenders' models for offered interest rates using 2019 data, we find that the rates that lenders offer during March 2020 are not materially different from the predicted rates. In other words, lenders appear to have priced loans as if it were still 2019 and the COVID-19 crisis was not ongoing until they dropped out. Strikingly, using the reverse-engineered models estimated using 2019 data, they would have recommended increasing the rate of offers towards the end of March, as more small businesses with high FICO scores submitted their loan applications. The dissonance between the model recommendations and the grim economic outlook may have driven home to the lenders the fact that their models did not account properly for the changing economic conditions.

Because almost all fintech lenders are private firms, we do not have balance sheet and earnings data to evaluate directly the most plausible alternative to explain the behavior of lenders, namely that they became so financially constrained that they were no longer able to lend. However, this alternative is related to the model risk explanation for the lending collapse for three reasons. First, data-driven lending can make it more likely a lender becomes financially constrained because the lender does not have as much flexibility to take into account unusual economic conditions in its decisions. Second, as long as the models are followed, the lenders likely overstate the creditworthiness of applicants under the unusual economic conditions, so that the lender will perform more poorly. Third, the funders of the lenders may conclude on their own that the lenders cannot make correct lending decisions given their models and, hence, stop funding them. However, for financial constraints to explain our results, they would need to be unexpected, sudden, and dramatic, but hit lenders at different times. In other words, they would have to be such that lenders

keep lending as in 2019 but then suddenly stop lending. We would expect lenders to have been pro-active with respect to the risk of becoming financially constrained, so that they would decrease their lending and make safer loans. We do not see such behavior.

Our results from small business fintech lending suggest that the lack of resilience we observe is endemic to data-driven lending in general. During the COVID-19 crisis, the dark side of datadriven lending extended beyond small business fintech lending to other types of data-driven lending. For instance, our analysis of personal fintech loan originations reveals that this market also experienced a significant decline in March 2020. We discuss other instances where the supply of data-driven loans has dried up. Specifically, banks that had lending programs where they used only hard data before the GFC also ran into difficulties with that type of lending. Other financial institutions besides fintech lenders have used data-driven lending over time and have had difficulties. Model risk associated with data-driven lending has played a prominent role in explanations for the global financial crisis (Gorton 2008; Rajan, Seru, and Vig 2015).

In contrast, our explanation for the drop in fintech uncollateralized lending does not apply to small business lending by bank lenders that use both hard and soft data. The banks most active in small business lending rely both on soft information and hard data (Berger and Black 2011), their loans are collateralized, and their decisions may be affected by the relationship they have with potential applicants (Petersen and Rajan 1994). Lastly, bank lenders have incentives to keep lending to relationship borrowers who are financially constrained in a crisis (Bolton, Freixas, Gambacorta, and Mistrulli, 2016). With the soft information available to them, small business bank lenders were in a much better position to assess the impact of COVID-19 on applicants than fintech lenders were. Further, using collateral also made loans less dependent on business income (Stulz

and Johnson 1985). Using publicly-available data, we show that small bank lending did not drop in March 2020.

Our paper contributes to multiple strands of the literature. First, we add to the growing literature on the implications of the use of data technologies. These implications have been explored for credit markets, financial analysts, asset management, and stock price information dissemination (see Bonelli 2023, for references). The credit market literature has focused on how data-driven lending is affected by racial and income disparities (e.g., Blattner and Nelson 2022 and Blattner, Nelson, and Spiess 2024), on how data-driven lending affects potential lending discrimination (e.g., Bartlett et al. 2022), and on how the use of non-standard data makes it possible for individuals to borrow that otherwise would not be able to (e.g., Di Maggio, Ratnadiwakara and Carmichael 2022). An earlier literature focuses on the use of credit-scoring by banks. We are the first studying the resilience of uncollateralized data-driven lending to shocks not experienced during the training period.

Second, we contribute to the literature on fintech lending to small firms. Gopal and Schnabl (2022) show that the increase in lending by nonbanks substituted for a reduction in lending to small businesses by banks after the global financial crisis of 2007-2009. Barkley and Schweizer (2021) find that fintech credit has become an important source of loans for small businesses. Balyuk, Berger, and Hackney (2020) argue that fintech lenders make loans using technologies similar to those of large banks, namely using hard instead of soft information (Berger and Black 2011). We add to this literature by showing how fintech lending demand and supply respond to an unprecedented systemic shock.³

³ Abedifar, Doustali, and Ongena (2023) examine how Lending Club lending responds to natural disasters. Their sample includes the 33 worst natural disasters that occurred between 2013 and 2017. They find lending to be resilient. The model risk issues that apply to lending in March 2020 do not apply to lending in response of natural disasters in that there is a large amount of data about the implications of natural disasters.

Third, we contribute to the literature on the impact of the COVID-19 shock. As shown by Bartik et al. (2020), Fairlie (2020), Gourinchas et al. (2020), and others, the COVID-19 shock had a dramatic impact on small businesses in March 2020. We show that the decrease in credit supply for the riskiest businesses that did not have access to bank lending was dramatic. Though we believe this is the first study of the impact of COVID-19 on small business fintech lending during March 2020,⁴ Bao and Huang (2022) explore the effects of COVID-19 on fintech personal loans in China. They find that fintech lenders expanded lending more than banks. Still, subsequently, they experienced poor loan performance even though, historically, the loan performance for fintech lenders was similar to that of banks.

2. Fintech lending and lending platforms

This section describes the small business fintech lending model and provides institutional details about the fintech small business lending platform for which we have lending data. We begin by defining who fintech lenders are and how they differ from other lending institutions. We discuss the strengths and weaknesses of their business model relative to that of banks and their importance relative to banks and other finance companies. We then describe how the platform connects these lenders with potential borrowers.

2.1 Fintech lending

In this study, fintech lenders are non-deposit-taking institutions that make loans online, either directly or through an online platform. Like banks, fintech lenders offer a variety of loan products,

⁴ Subsequently, fintech lenders became important distributors of PPP loans because they were used to dealing with and were accessible to a clientele that had no banking relationships (Erel and Liebersohn 2020; Howell et al. 2024), but this lending through fintech lenders appears to have had high rates of fraud (Griffin, Kruger, and Mahajan 2023).

including merchant cash advances, lines of credit, term loans, and business credit cards.⁵ However, unlike banks or finance companies, they generally do not have a collateral technology, they make unsecured loans, and do not rely on business relationships with their borrowers.⁶ As a result, the creditworthiness of fintech loans are much more dependent on borrowers' cash flow than bank lenders, who typically require collateral. Instead, for fintech loans, business owners waive the company's limited liability and provide personal guarantees to lenders, allowing them to seek recourse through collection agencies and court proceedings or by placing liens on personal assets. Fintech lenders have a simplified application process, and many lenders boast of their ability to make decisions within minutes and for funds to hit the owner's bank account within 24 hours. This convenience and speed are central drivers of fintech lending growth (Berg, Fuster, and Puri 2022).⁷

Fintech lending became an increasingly important source of financing for small businesses in the years preceding the COVID-19 crisis. Gopal and Schnabl (2022) estimate that the volume of loan originations to small businesses from banks and non-fintech finance companies was roughly \$243 billion in 2016. Assuming similar magnitudes in 2019, fintech loan originations of \$13 billion comprise 5% of loans in volume.⁸ The average dollar size of fintech loans is substantially smaller than that of loans made by banks and finance companies.⁹ Consequently, while the total lending volume may be relatively small, the number of businesses using fintech loans is large. A survey by the Federal Reserve found that 1 in 5 businesses had used an online lender in the 5 years

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

⁵ Merchant cash advances, sometimes referred to as short-term loans, are made based on the frequency and timing of the borrower's cash flows. Equal payments are typically drawn from the borrower's bank account at a daily or weekly frequency. Lines of credit from these lenders allow borrowers to draw down credit up to some limit and are often similar to merchant cash advances in the frequency of payments after a draw. Term loans are typically longer maturity loans with less frequent payments and lower interest rates, resembling a more traditional bank loan.

⁶ Banks specializing in small business lending generally rely on soft information that they gain through relationships with borrowers and on a collateral technology (Berger and Black 2011; Liberti and Petersen 2019).

⁷ 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.

⁸ The S&P Global Market Intelligence U.S. Fintech Market Report 2021 estimates that SME-focused fintech originations totaled roughly \$13 billion.

⁹ See, for instance, <u>https://www.valuepenguin.com/average-small-business-loan-amount.</u>

preceding the COVID-19 crisis, which amounts to millions of loans. Importantly, evidence suggests that these loans are typically used by businesses with the most difficulty obtaining financing elsewhere.¹⁰

2.2 The role of marketplace platforms

Online marketplace platforms are an innovation that centralizes the application process to reduce search costs for both lenders and borrowers. These platforms make no attempt to price risk, but instead disseminate applications to multiple lenders and assist borrowers in finding the best offer. The largest and most well-known marketplace platforms of this type are LendingTree, Fundera, and Lendio, with the latter two focusing solely on small business lending. Our data come from one such marketplace lending platform (hereafter, "the platform"). Our best estimate is that in 2019, approximately 8% of fintech small business lending in the United States took place through the platform.

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

The platform has relationships with dozens of the most established fintech lenders. Typically, an application is forwarded to only a handful of lenders based on specific predetermined attributes.

¹⁰ See for example Barkley and Schweitzer (2021) as well as statistics released by the Federal Reserve in the Small Business Credit Survey (2020).

For example, many lenders have hard cutoffs related to firm age, owner's credit score, annual revenues, or industry (Johnson 2021). The platform also uses its own data analysts to decide where to send applications based on the likelihood of acceptance and the financing needs of the applicant.

Applicants may receive offers from one or multiple lenders in hours or days. Before the pandemic, about 58% of applicants with completed applications were approved by at least one lender, meaning more than 40% of applicants did not receive any offers.¹¹ Each offer includes the cost of the loan, maturity, offer amount, payment amount, payment frequency, and loan type.

2.3 Data used in this study

The primary data source for this study is a marketplace platform that connects small businesses with dozens of online lenders. We observe all applications made on the platform, solicitations for offers from the platform to lenders, loan offers received from lenders, and loan deals. Completed applications include firm characteristics like age, sales, industry, and number of employees and variables derived from submitted bank statements from the prior three months. Applicants' industry is self-reported by the applicant from a drop-down list that includes two-digit NAICS classifications with exceptions for some industries that are disclosed more granularly. If the industry is undisclosed or does not neatly fit into industry classifications, we use the label "other."¹² In short, we observe all the hard information that is passed to lenders from which they make lending decisions. Internet Appendix Table A1 summarizes the applicant data we use in the study. In March 2020, we have 7,285 applications. For much of the analysis, the data is collapsed at the applicant level so that we can assess whether the applicant received loan offers and the

¹¹ 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.

¹² Missing industry classification occurs in roughly 15% of applications. The results are robust to dropping firms where industry is not well classified.

average terms on these offers. Later, when we do analysis that includes lender specific models or lender fixed effects, the analysis proceeds at the applicant-lender level as the application is forwarded to many lenders.

We augment these data with geographic 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 measure the pandemic's local impact by summing the number of devices at home all day in a county and dividing that by the total number of devices in the county. We then match applicants to these exposure measures using the applicant's county when available. For our main industry-specific exposure measure, we identify high exposure industries by calculating the stock returns of firms that belong to the various industries classified in the platform over the first twelve days of March 2020. We then split these industries between those with above median returns and those with below median returns. We classify below-median return (i.e., more negative returns) industries as high-exposure industries. Alternatively, we identify high-exposure industries using the Small Business Pulse Survey, which in the initial survey from April 26–May 2, 2020, asked, "Overall, how has the COVID-19 pandemic affected your business?"¹³ To determine exposure, we assign industries above the median in responding that they experienced a "large negative impact."

Finally, we use another dataset with transaction-level information on fintech loan originations from seven of the largest online personal loan lenders. The data were compiled and made available to us through a fintech loan aggregator.¹⁴ While we do not observe loan application and loan offer information on this database, loan origination data allows us to assess whether the origination dry-

¹³ See <u>https://portal.census.gov/pulse/data/</u>.

¹⁴ All loans are originated via online lenders or platforms such as LendingClub, Upstart, and Avant. This dataset encompasses the majority of all personal loans made online—roughly 70% in terms of volume since 2014.

up that we observe in the small business platform also took place in unsecured personal fintech lending.¹⁵

3. The demand, supply, and lending volume around the onset of the COVID-19 crisis

In this section, we study the evolution of the demand, supply, and loan volume for March 2020. A key feature of our data is that we can distinguish the demand for credit from the supply of credit. Specifically, we observe loan applications made by small businesses and sent to specific lenders. Separately, we observe the loan offers made by lenders in response to applications as well as the applications that are rejected. Then, if applicants accept one of the offers, we observe the final deal terms.

3.1 The demand for fintech small business loans

We plot in Panel (a) of Figure 1 the daily number of applicants on business days in March 2019 and March 2020.¹⁶ We see that the number of applicants was higher throughout March 2020 than in March 2019. After March 9, 2020, the number of applicants increased sharply and almost doubled over one week. The number of applicants subsequently decreased, but it was higher every day of the month in 2020 than in 2019. Further, the number of applicants in the second half of March was 76% higher than in the first half.

Panel (a) of Figure 1 shows that demand fell towards the end of March, as aid to small businesses through a stimulus package became more likely. The White House first proposed \$500

¹⁵ We apply only one filter to these data as we aggregate loan volume by origination date. We replace origination volumes on the last day of the month with the average volume from the prior week. Roughly 45% of loans in the dataset are reported as having originated on the last day of the month, which can be attributed to the granularity of reporting by the lenders.

¹⁶ We show results for dollar amounts of the demand for loans and the supply of loans per applicant in Figure IA of the internet appendix.

billion in aid to small businesses on March 17, corresponding to a sharp drop in loan demand.¹⁷ On March 20, the Senate rejected the stimulus program, which was followed by an increase in the demand for loans. Demand then fell after it became certain on March 23 that the stimulus package would become law. Still, the number of applicants remained higher than in 2019, potentially because of the applicants' urgent need for cash amid the expected lead time it would take the government to operationalize its lending program.

As shown in Table A1, in March 2019, the applicant pool consisted of young small businesses with credit scores around the prime/nonprime cutoff. The average FICO score in March 2019 was 652, which, depending on the classification chosen, reflects a subprime or near-prime credit score.¹⁸ Applying small businesses, on average, had annual sales of \$783,253 and were 54 months old. The applicant pool in March 2020 reported significantly better credit metrics. Applicants in March 2020 were more established, operated on a larger scale, and had better FICO scores than applicants a year earlier. The average age of the business of the applicants was 8% higher. The average sales were 33% higher. While the average applicant in 2019 was a near-prime or subprime applicant, the average applicant in 2020 was a prime applicant with a FICO score of 670. Bank balances were 44% higher. Overall, the applicants had better traditional credit metrics in March 2020 than in March 2019. Further, as shown in Table A1, the traditional credit metrics of applicants also improved within March 2020 as the crisis worsened.

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

¹⁸ 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.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/).

[Insert Figure 1]

3.2 The supply of small business fintech loans

When assessing the supply of credit, we focus on loan offers made in response to applications rather than on originated loans. Loan offers are a good metric of loan supply because they indicate lenders' readiness to extend credit, independent of applicants' accepting these offers. Often, applicants reject loan offers after reviewing their specific terms. Even if they accept one offer and proceed with borrowing, they will reject all other competing offers. Panel (b) of Figure 1 shows the evolution of the number of loan offers for March 2019 and March 2020. The panel conveys a clear message. The number of loan offers was high until mid-March 2020 and collapsed. The number of daily offers peaked at about five hundred on March 15, and then plummeted to less than one hundred in the last days of the month. One applicant could receive multiple offers. Not surprisingly, as the number of offers collapsed, the number of offers per applicant fell as well (see Figure IA of the internet appendix).

3.3 Evolution of the loan volume

Finally, we plot the number of loans that takes place on the platform both before March 2020 and during March 2020. Panel (c) of Figure 1 shows the five previous-business-day moving average for the number of loans from January to March 2019 and 2020. Loan volumes were higher by about 30% at the beginning of 2020 relative to 2019, reflecting the rapid growth of the fintech industry. Loan origination was stable in the first quarter of 2019. The line showing the number of loans in 2020 always exceeds the number of loans in 2019 until the middle of March. The number of deals in March 2020 increased before falling precipitously almost to zero. The number of loans

fell sharply before the PPP was proposed and almost all of the fall took place before the stimulus package was approved by Congress.

4. Data-driven lending, model risk, and the fall in supply

In this section, we investigate why the supply of loans falls. Our proposed explanation is that data-driven lending could not properly adjust to the change in economic circumstances and had to shut down because of model risk. For our purpose, the relevant model risk "is having an incorrect model for a particular situation" (Goldman Sachs and SBC Warburg Dillon Read 1998).

We can think of the data-driven lending business model of the fintech lender as a machine that receives application information as input and produces underwriting decisions based on a model that uses quantitative data. The models used in March 2020 were trained with data that did not include a pandemic in modern times, and, therefore, the developments that took place during March 2020 were developments that the models were not designed to address. At some point, the extent to which the models were predictive of loan performance became highly questionable. For instance, a model using pre-pandemic credit metrics was unlikely to be informative about the risk of a loan to an applicant whose state might impose a lockdown that would force the borrower to close its business for a period of time. In March 2020, the performance of a new loan likely depended much on whether borrowers would be able to operate their businesses in the presence of lockdowns and social distancing and whether their customers and suppliers could maintain their normal interactions.¹⁹ As a result, the underwriting models trained on data available before March 2020 were much less informative about the performance of loans than over their training period.

¹⁹ See Fahlenbrach, Rageth, and Stulz (2021) for an analysis of the firm value implications of a sudden stop in revenue.

However, training models on more recent data would not have helped in improving the models since the impact of the pandemic on loan performance could not yet be observed.

The impact on fintech data-driven lenders of the COVID-19 shock was akin to an uncertainty shock. Following Knight (1921) and Kay and King (2020), we define an uncertainty shock as a shock that introduces randomness that cannot be measured, as opposed to a risk shock that introduces measurable randomness. Another way to put this is that, with risk, probabilities can be assigned to possible outcomes of a random variable, but not with uncertainty. The existing literature finds that uncertainty and uncertainty aversion can be useful concepts to make sense of events that happen during crises (Caballero and Krishnamurthy 2008). The COVID-19 shock was an uncertainty shock for fintech lenders to the extent that they no longer knew the extent to which they could rely on their quantitative models. While they could reliably estimate default probabilities before the shock, their models stopped being helpful to estimate these probabilities after the shock. Importantly, they could not even quantify the extent to which their models had become inaccurate as doing so would require observing loan performance over time. Further, for the same reason, it was not an issue of updating data used to train models. They could attempt to adjust their models, but there was no way for them to test the reliability of such adjustments.

With a business model that relies on hard data as inputs to models that guide their lending decisions, small business fintech lenders were not in a position to adjust lending decisions to reflect the evolution of the COVID-19 shock. Their models had an actuarial basis: they inferred from the credit metrics of an applicant how a loan to borrowers with similar metrics performed in the past. Their models did not have data fields that they could populate with information about the spread of COVID-19 and its implications for the future performance of loans. As a result, they kept making loans as they did before the COVID-19 shock with minimal adjustments to reflect the new

risks. We would therefore expect to find that loan decisions were little affected by the exposure of applicants to the shock. We find support for this COVID-risk insensitivity in Section 4.1.

Absent financial constraints, a fintech lender that makes loans following a model's recommendations will do so if the model is believed to be reliable. Faced with a shock that makes the model potentially unreliable, the lender will decrease lending when it starts to believe that the model may have become less reliable and then stop lending altogether when it concludes that it can no longer follow the model. At that point, we would expect the lender to cease making loans until it figures out how to adjust the model or until it can use its model again because the economic environment has become normal again. We find support in Section 4.2 for this prediction. In Section 4.3, we address possible other explanations for our findings.

4.1 The COVID-risk insensitivity of data-driven lending

In this section, we show first that the drop in supply cannot be traced to tighter screening of applicants exposed to the COVID-19 shock. Next, we show that the loan terms were not adjusted to reflect the dramatic changes in credit conditions and markets discussed earlier and the COVID-19 exposure of applicants. Finally, we show that loan supply fell similarly for prime and nonprime borrowers.

4.1.1 Loan supply and applicants exposure to the impact of COVID-19

In this section, we investigate the response of the supply of fintech loans to the exposure of applicants to the COVID-19 shock. We consider industry and geographic determinants of exposure. Our regressions use a dependent variable that takes a value of 100 if the applicant receives an offer and zero otherwise.

In Column (1) of Table 1, Panel A, we estimate a benchmark model that shows the decrease in the loan supply without controlling for exposure. We first estimate the benchmark model for March 2020. The explanatory variables are indicator variables for the last three weeks of March 2020. We see that supply fell in the second week of March 2020 and decreased steadily throughout the month. In the last week, the probability that an applicant received an offer was thirty-three percentage points lower than at the beginning of March. At the beginning of March, the unconditional probability of receiving an offer was 48.1%, dropping to 15.1% by the end of the month. In Column (2), we estimate the same model but over the first quarter of 2020. The results show a larger drop in supply. In Columns (3) and (4), we add applicant controls to the regressions estimated in Columns (1) and (2). Applicant controls include the owner's FICO score, log of firm age (in months), log of annual sales, average bank balance, the number of days with a negative balance, and the average monthly number and amount of credits and debits. We also include industry fixed effects for the industry of the applicant. We report only the coefficients on FICO (multiplied by 100), ln(Age), and ln(Sales). We see that using applicant controls and industry fixed effects actually worsens the estimates of the drop in supply. This may not be surprising since the credit metrics of the applicants improved as discussed in Section 3.

[Insert Table 1]

We now turn to more direct measures of COVID-19 exposure in Panel B of Table 1. Specifically, we use an indicator variable for March starting when the WHO declares a pandemic emergency on March 12 (I(Post 3/12)) and an indicator variable for high-exposure industries (I(Below Median Industry Returns)). We identify high exposure industries as discussed in Section 2.3. by using a high-exposure indicator variable for industries with below-median (i.e., more negative) stock return over the first twelve days of March 2020. We then interact these two indicator variables. The sample is again from January to March 2020. We find no evidence that an applicant's probability of receiving an offer was lower if the applicant was in a highly exposed industry after March 12. Internet Appendix Table A3 uses an alternative definition of high-exposure industries that is based on responses to the initial Small Business Pulse Survey that asked small businesses how the COVID-19 pandemic affected them as discussed in Section 2.3. In contrast to the return-based definition, this definition is an ex-post definition. The results are similar.

Finally, in Panel C of Table 1, we use geographic measures of exposure. First, we use an indicator variable for whether a state is in lockdown. Second, we use the percentage of the population staying at home as the granularity of this measure is at the county level. For applicants where the county is unavailable, we take the average of the state on the date of the application. The data were obtained from SafeGraph, which uses cell phone data to track mobility. For the US, the percentage staying home reported by SafeGraph increased from 23.8% on March 1 to 39.9% on March 31.²⁰ We report the estimates in Panel C of Table 1. In the first two columns, we estimate the regression for March and have no controls but include application-date fixed effects. In Columns (3) and (4), we add applicant controls, county fixed effects, and industry fixed effects. Lastly, in Columns (5) and (6), we re-estimate the regressions of Columns (3) and (4) but include January-March 2019 in the sample. The coefficient on the indicator variable for whether a state is in lockdown (I(State lockdown)) is not statistically different from zero in any of the specifications. The coefficient on the percentage of the population working from home (% Population home) is only marginally significant in Column (4) when saturated with controls using the March 2020 sample. The economic significance of that coefficient is such that this variable explains little of

²⁰ The sample is smaller than in IA Table A1 because some applicant addresses do not geocode to available SafeGraph counties.

the decrease in the probability of receiving a loan offer. Specifically, a one standard deviation increase in the percent of the population at home leads to a lower offer probability of 3.9 percentage points.²¹

The evidence in Table 1 shows that the evolution of the probability of applicants receiving a loan offer in March 2020 is insensitive to proxies for the exposure of applicants to the COVID-19 shock.

4.1.2 COVID-insensitivity of loan offer terms in March 2020

We examine how the terms of the offered loans evolved in response to the COVID-19 shock and how they accounted for the COVID-19 exposure of applicants. We report the results in Table 2. In Panel A we regress offer terms on an indicator for the week of the offer, the control variables used previously, industry fixed effects, and lender fixed effects. We also estimate the regressions without lender fixed effects; the overall conclusions are similar. The odd columns use the sample period of March 2020, and the even columns use the sample period of January to March 2020. Column (1) shows results when the dependent variable is the annual percentage rate (APR) and the sample period is March 2020. The indicator variables are not significant. As expected, APR decreases as FICO score, business age, and sales increase. In Column (2), the sample period is the first three months of 2020. The indicator variable for the last week of March is positive and significant. The APR was higher that week by five percentage points, which is roughly 10% of the standard deviation of APR before March 2020. In Columns (3) and (4), the dependent variable is the maturity of loans. None of the week indicator variables are significant except the one in the last week of March in Column (3), which is negative and significant at the 5% level. Finally, in

²¹ In IA Table A2 we find that adding COVID exposure variables does not have much of an impact on the week indicators in March, suggesting that the effects that we uncover are not the economic drivers.

Columns (5) and (6), the dependent variable is the log of the loan amount. Again, only one week indicator in Column (6) has a significantly negative coefficient.

In Panel B of Table 2, we analyze whether an industry's exposure to COVID-19 affects the terms of the loans businesses are offered. We use the same approach as in Panel B of Table 1. We find no evidence that the APR was different after March 12 for the sample as a whole and no evidence that it increased for the most exposed industries after that date. Maturity increased for the most exposed industries after that date. Maturity increased for the most exposed industries after that date. Naturity increased for the most exposed industries after that date. Maturity increased for the most exposed industries after March 12 when we do not include control variables, but there is no effect when we do. Finally, the loan amount increased after March 12 for the whole sample when we do not include control variables.²²

In Panel C of Table 2, we regress each offer's terms on the location COVID-19 exposure variables used in Panel C of Table 1 and applicant controls. We have application date, industry, lender, and county fixed effects. The sample is from January to March 2020, though the results are the same when only looking at applications in March 2020. The variables of interest are the variables that measure COVID-19 exposure locally. No variable has a significant coefficient.

[Insert Table 2]

Overall, we find strong support for the hypothesis that data-driven lending makes lending unresponsive to changes in economic circumstances when the changes are unusual in that they were not of a type experienced during the training period.

4.1.3 Prime versus nonprime applicants

From Merton (1974), we would expect the supply of loans to drop less for safer applicants in response to an increase in applicants' credit risk. To test this formally, we distinguish between

²² In Internet Appendix Table A4, we report results where we define COVID-19 exposure using the Pulse Survey. We find similar results.

prime and nonprime applicants and interact this prime applicant dummy with week indicators in March. Prime applicants are defined as applicants with a FICO score above 660. The dependent variable is set to 100 if the applicant receives an offer and zero otherwise. If safer applicants experience a less significant decline in supply we would expect the interactions with weeks in March to be positive. We report the results in Table 3. Regressions in Columns (1) and (2) are at the applicant level, so we examine whether the applicant receives at least one offer from any lender. Regressions in Columns (3) and (4) exploit the richness of our data and are at the application-lender level, so we examine whether each lender who received the application chose to make an offer.²³ Therefore, unlike previous regressions where we look at whether an applicant received an offer from *any* lender, we include all offer solicitations in these tests. Each application was sent to 5.5 lenders on average, so these regressions include substantially more observations.

[Insert Table 3]

In Column (1), we estimate the model without controls. As before, the coefficients on the weekly indicator variables indicate a sharp drop in the probability of receiving an offer during March. The indicator variable for prime applicants has a positive coefficient that is highly significant, meaning that the likelihood of a prime applicant receiving at least one offer was higher by 17.1 percentage points than that of a nonprime applicant receiving at least one offer. The interaction of the prime indicator variable and the weekly indicator variables has a positive significant coefficient in the second week (the base includes January through the first week of March) of 3.5 percentage points, an insignificant coefficient in the third week, and a larger negative coefficient of -8.8 percentage points in the last week that the lender is active. In Column (2), we re-estimate the regression, but we now control for applicant characteristics as well as the number

²³ Loan applications submitted to the platform are almost always sent to multiple lenders to solicit loan offers if they pass the initial screening. The data allow us to identify not only when an offer is made but also when lenders decline to make offers.

of active lenders on the platform. Controlling for the number of active lenders on the platform accounts for a potential mechanical relation between the number of lenders and the probability of receiving an offer. We see that the significance of the coefficient on the interaction between the prime indicator variable and the indicator for the second and third week drops substantially. The coefficients on the number of lenders on the platform are positive and statistically significant. The other coefficients are similar, except that the coefficient on the prime indicator variable is much lower.

Turning next to the regressions at the application-lender level, Column (3) repeats the regression of Column (2). We find that there is no interaction with a positive coefficient. We find that the interaction for the last week of March has a significant negative coefficient. We would expect the interactions to be positive if lenders cut back lending more for nonprime borrowers than prime borrowers but, again, no interaction has a positive coefficient. Column (4) repeats the analysis in Column (3) with lender fixed effects, i.e., a within-lender analysis. We find two interactions with a significant negative coefficient, namely the one for the third week of March and the one for the last week of March, but no significant positive coefficients on the interactions. A clear takeaway from this table is that lenders did not simply shift supply to safer applicants as the pandemic unfolded. Supply was cut across the board but, given the higher initial probability of receiving an offer for prime applications, the change in supply as measured by the change in the probability of receiving an offer was actually larger for that group.²⁴

²⁴ As further evidence of this conclusion, we plot the probability of receiving an offer for prime and nonprime applicants from the beginning of January to the end of March in IA Figure A2.

4.2 Lender dropouts

If the dark side of data-driven lending is that lenders do not adjust their underwriting to account for unusual economic circumstances absent during the training period of their models as we just showed, their only choice is to ration and eventually stop lending. We find that many lenders went from having a steady offer rate to an offer rate of zero or close to zero in a short period of time.

Figure 2 presents evidence for sharp drops in fintech lending activity. Panel (a) gives an example of the typical evolution of the supply of a lender. After the offer rate collapsed, the number of applications went to zero because the platform was no longer sending applications to this lender as the lender had dropped out. Panel (b) shows the decrease in the number of active lenders in March. The decrease is steady through the last three weeks of March. The *Wall Street Journal* reported on lenders dropping out from a platform on March 28, stating, "About half a dozen lenders that have found borrowers through Fundera Inc., an online marketplace for small business loans, have paused new extensions of credit."²⁵ Finally, Panel (c) shows the number of offers in 2020 in ascending order. The figure shows that many lenders dropped out in March and that our supply results are not due to one or two of the largest lenders becoming inactive. From this figure, one can also observe the timeline of lender dropouts, with one lender becoming inactive as early as March 14 and many others becoming inactive soon after March 17.

[Insert Figure 2]

Lenders do not appear to have dropped out because their models told them to drop out. It seems, instead, that they dropped out as their models recommended making more loans since applicants

²⁵ "People need loans as coronavirus spreads. Lenders are making them tougher to get" by Anna Maria Andriotis and Peter Rudegeair, *Wall Street Journal*, March 28, 2020.

in March 2020 appeared to be more creditworthy than before. We do not have access to lender models, but we can reverse-engineer their models using their lending decisions in 2019. To perform this analysis, we estimate a logistic regression model for each of the twenty most active lenders that predicts whether a lender will make an offer in 2019, given an applicant's credit metrics. For this analysis, we use lender-applicant level data with all solicitations made for credit from the platform. The regression model uses bins for FICO, revenue, and age in addition to the other controls previously used to allow for nonlinear relationships. We use the logistic model to obtain a prediction of the likelihood of whether a lender will make an offer to an applicant in 2020, Predicted Offer. We then regress the Predicted Offer variable on indicator variables for eight weekly event time indicators (the week of the dropout is week zero, the week before is -1, and so on) and lender fixed effects. The dropout date is defined as the day that the lender stopped making offers entirely. We estimate the regression over the first three months of 2020, so that it includes all applicants to the lenders who drop out and those who do not drop out. Week -8 is the omitted week and includes all applications submitted to a lender from January to seven weeks before the lenders drop out or the end of March. Lenders who did not drop out are included in the regression and assigned an event time indicator of -8. Panel (a) of Figure 3 reports the estimates for the eight weekly event time indicators. We show that the predicted offer likelihood increases close to the time of a lender's exit using lender fixed effects. Hence, the information that the lender would have had is that the model suggested making more offers just when it decided to exit. The signals of our reverse-engineered models would have clashed with what lenders could observe, namely, among other metrics, the dramatic drops in the stock market, the huge increase in the VIX, and the large increase in the credit spread for the riskiest borrowers.

[Insert Figure 3]

When we reverse-engineer the models, we assume that the models use only borrower characteristics and do not include macroeconomic variables. We investigate whether the results reported in Panel (a) of Figure 3 differ if we add macroeconomic variables to our reverse-engineered models. For that exercise, we need to use macroeconomic variables observed at a high frequency since low frequency variables would not change sufficiently to affect outcomes during March 2020. For instance, the unemployment rate could be a useful indicator for the risk of default of small business loans, but the unemployment rate published in March does not reflect the impact of COVID-19. We use the seven-day average high-yield bond credit spread (CCC) as a measure of aggregate credit risk and we use the 30-day S&P 500 return as a measure of stock market performance. Both of these measures change substantially during the month of March. Adding these measures to our reverse-engineered models does not change our inferences as can be seen in Panel (b) of Figure 3.

To assess whether lenders stuck to their models in March 2020 for the terms of their offers, we compare the APR a lender offers to the APR we would predict based on a reverse-engineered APR model for the lender. As for offers, the reverse-engineered model is estimated for each of the top twenty lenders in 2019 using applicant characteristics and macro variables. In Panel (a) of Figure 4, we report the weekly average difference between the predicted APR and the actual APR across lenders. We estimate confidence bands using two standard errors of the estimated standard error of the residuals for each day. We see that during March 2020 the average residual is insignificantly different from zero for all weeks. In stark contrast, we show in Panel (b) of Figure 4, the CCC credit spread increases by almost eight hundred basis points in March. The evidence in Panel (a) of Figure 4 suggests that lenders were setting APR as if the world had changed little since 2019.²⁶

²⁶ In the Internet Appendix Figure A3 we display the residuals from lender APR models that do not include macro variables. The takeaway is the same.

[Insert Figure 4]

We next explore the behavior of lenders as they near the dropout date with respect to the probability of an offer being extended and the APR of loan offers. We do so in event time, where the event week is when the lender stopped making offers entirely. We use the same regression approach as for Figure 3. The regressions are estimated over the sample period January-March 2020. We have eight weekly event time indicators (the week of the dropout is week zero, the week before is -1, and so on). We estimate the regressions with a lender fixed effect and an application fixed effect. With these fixed effects, we estimate in Panel (a) of Figure 5 how an applicant's probability of receiving an offer depended on how close the lender was to dropping out. None of the event time indicators are significantly negative except the one for the event week. This evidence supports the view of a sudden stop in the last week. In Panel (b) of Figure 5, we use the same approach to estimate how a lender's proximity to dropping out impacted the rate quoted on loan offers the lender made. It turns out that lenders who dropped out did not adjust their loan offers' APR before dropping out.

[Insert Figure 5]

The small business fintech lenders on our platform differ greatly with respect to the median FICO score of their borrowers (Johnson, 2021). Lenders with a lower median FICO score are lenders who make riskier loans. A safer lender can cope with model errors better than a riskier lender because applicants of a safer lender have better ability to deal with adverse shocks, so that if their risk is understated by the model, there is a better chance that they will still be able to repay the lender than if they were riskier applicants. We would therefore expect the probability that a riskier lender makes an offer in March to fall faster than the probability that a safer lender makes an offer. To distinguish the risk of lenders, we separate lenders into those whose median FICO

score is a median score corresponding to a prime applicant, meaning a FICO score greater than 660 in 2019.

In Table 4, we show estimates of regressions like those of Table 3, except that now the prime interaction indicator variable measures the risk of the lender, i.e., whether its median FICO score is for a prime borrower, rather than that of the applicant. Column (1) has no fixed effects, Column (2) has industry fixed effects, and Column (3) has both industry and lender fixed effects. All three columns show similar estimates for the interactions between the prime indicator variable and the indicator variables for the second to the last week of March. Each interaction coefficient is significantly positive at the 1% level, indicating that more conservative lenders kept making offers at a higher rate than riskier lenders controlling for borrower characteristics despite having a lower likelihood of making offers before the pandemic.

[Insert Table 4]

Comparing Tables 3 and 4, we see that applicant characteristics explain little, if any, of the drop in the likelihood of an offer, while lender characteristics are much more successful. The riskiest lenders reduced their offers faster.

Why does the riskiness of the lender play an important role in the decrease in supply? Does it have to do with model differences? One approach to evaluate the role of models is to see how the probability to make an offer changes over time for prime versus nonprime lenders. For this analysis, we use the approach of Figure 3. We estimate the probability of making an offer to a given applicant whose file is forwarded to a lender using as a reverse-engineered model as before a logistic model estimated over the first three months of 2019. We report the results in calendar time in Panel (a) of Figure 6 separately for prime and nonprime lenders. We see that prime lenders are predicted to make more offers in March before they exit, but nonprime lenders are predicted

to make significantly more offers. Such a result would be obtained if nonprime lenders received applications from financially stronger applicants using traditional credit metrics. The signals from the models for nonprime lenders were more sharply inconsistent with what the lenders were seeing anywhere else about the impact of COVID-19 than the signals the prime lenders were receiving. The evidence in Panel (b) of Figure 6 shows that, while prime lenders that kept making loans stuck to their models, nonprime lenders cut back their lending while their models told them to increase lending. They do not appear to cut back lending to make safer loans and do not appear to increase rates as one would expect if they were financially constrained. Further, as we estimate Figure 6 separately for high and low exposure industries in Internet Appendix Figure A4, we find more evidence of COVID insensitivity as the COVID-19 exposure of borrowers does not explain the differential evolution in lending of the prime and nonprime lenders.

[Insert Figure 6]

4.3 Potential complementary or alternative explanations

In this section, we present several potential complementary or alternative explanations for the drop in supply and discuss why they do not call into question our explanation of the role of model risk as an explanation for the drop in supply.

4.3.1 Financial constraints

A possible explanation for the drop in supply is that lenders became unable to fund new loans even though they would have wanted to underwrite new loans. Such an outcome could result from lenders or investors having suffered losses on the value of existing loans. In this case, the lenders' losses could have created a debt overhang (Myers 1977) that made it unattractive for lenders to raise funds, as these new funds would have benefitted their creditors.²⁷ Another possible explanation is that the lenders' funders became unwilling to fund the lenders because they were making losses on investments that led them to become more cautious. A third possible explanation is that lenders made losses on loans they held as the borrowers stopped paying interest on these loans, so that the funds they would have used to make new loans were less than expected.

The financial constraint explanation is not wholly separate from the model risk explanation. As lenders kept making loans even though their models were no longer adequate, they were more likely to make losses on these loans and hence became more likely to be financially constrained. Further, funding might have become difficult to obtain because funders were concerned about the sustainability of the business model due to model risk. We do not have data on lender balance sheets, but it seems quite plausible that financial constraints may have played a role in the drop in supply. However, while the financial constraint explanation can explain why lenders stopped lending, it cannot explain why lenders did not adjust their lending decisions for COVID-19 exposure and why lenders did not attempt to reduce their risk. This COVID-insensitivity of lending decisions is explained by the dark side of data-driven lending; this explanation has to play a key role in any attempt to explain the drop in supply.

The only publicly traded fintech small business lender in March 2020 was On Deck Capital, Inc. (On Deck). In contrast to private small business lenders, it had disclosure obligations as a public firm. It issued an 8-K on March 23, 2020. This 8-K specified that they had no problems with their financial situation at the time and that they maintained excess financial capacity. It stated that the firm had experienced an increase in demand for loans but had tightened its underwriting

²⁷ DeYoung et al. (2015) examine lending to small firms by community banks during the global financial crisis and find evidence of an effect of a loan overhang that reduced lending to small firms. Greater riskiness of existing loans makes banks behave as if they were more risk averse in their model.

standards and suspended all new originations to certain industries. In the earnings call for Q1 that took place on April 30, they elaborated on their decisions in March by stating that:

"In mid to late March, we also saw a surge in new loan applications and line of credit draws as borrowers anticipated needed cash with the slowing of economic activity and the lockdowns that were coming. Recognizing that these requests carried a higher degree of risk, we proactively tightened credit policies and slowed originations dramatically."

This discussion is useful in that lending models are supposed to control for risk. Here, the models did not address the risk and the firm had to make decisions outside the models. The steps that On Deck took in March essentially reduced its originations by 80%. However, it experienced an increase in delinquencies on existing loans that eventually put it in financial distress.

4.3.2 Operational constraints

As we saw, demand increased sharply in early March. Such an increase meant that the platform and lenders had to process more applications than was typical. They might have had difficulties coping with the higher volume of activity. As a result, they might have responded to fewer applications promptly. We have data on the speed with which lenders responded to applications and the speed with which they closed loans. Surprisingly, there is no evidence that they either took more time to respond to applications or that it took more time for loans to close. Throughout our study period, the median number of days to respond to an application is one. We also find that the mean number of days is lower in March than in earlier 2020 or March 2019. It follows that operational difficulties cannot explain the drop in supply. Lenders do not appear to have been overwhelmed.

4.3.3 Lenders dropping from the platform but still lending

Another concern is that some lenders may have decided it was no longer worthwhile to lend through the platform but continued to lend outside the platform. Such lenders would not be financially constrained. We are unaware of why this behavior might have occurred, but we investigated this possibility. It is difficult to assess whether lenders stopped lending separately from the platform because most lenders are private firms that do not report their lending activities publicly. We use the web's Wayback Machine to track the evolution of the websites of the thirty most active lenders on the platform. For nine lenders, we find direct evidence on their websites that they stopped lending. In some additional cases, the lender's website disappeared. In the remaining cases, it is impossible to reach a conclusion based on the evolution of the website. By April, many companies direct traffic to PPP loans rather than direct loans. More generally, looking at lenders on the platform and other lenders, we find that many lenders made important business model shifts away from fintech lending per se and transformed themselves into utilities for banks.

4.3.4 Paycheck Protection Program (PPP)

A complicating factor in the analysis is that the CARES Act was eventually signed into law by President Trump, and the PPP loan program was implemented. As the adoption of the CARES Act became highly likely, lenders may have expected the demand for their loans to fall as potential borrowers would anticipate switching to PPP loans. Some could also conclude that lending through the PPP program would be more profitable than continuing to make conventional loans, as demand for such loans would mostly disappear for a while. However, lending through the PPP program would have required reconfiguring their systems and hence might have forced them to stop lending to do so. Before the disbursal of PPP funds, it was not entirely clear 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.²⁸ We expect lenders to drop out in the last week of March if they anticipated being involved in PPP. We find that only four of the lenders on the platform switched to making PPP loans. Since so many lenders dropped out before the last week and the lenders' participation in the PPP program seems low, the PPP program does not seem to be a credible explanation for what we observe.

5. Lending resilience and crises

The model risk explanation for the collapse of fintech small business lending is based on the use of a data-driven lending model. With such a model, a fintech makes loans based on hard data only. It uses a model to infer from the hard data whether a loan is worthwhile and what the terms of the loan should be. The model's reliability is based on training data. If the economic circumstances are sufficiently different from the economic circumstance during the training period, the model is likely to become unreliable. Absent a reliable model, lending has to be cut back and stopped. The COVID-19 crisis was such a dramatic change in the economic environment that we would expect other data-driven lenders to have behaved like the small business fintech lenders. We show that this was the case in Section 5.1 where we consider fintech lenders who lend to individuals (as opposed to small businesses). In Section 5.2, we show that banks that make small

²⁸ 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 <u>https://newsroom.kabbage.com/news/kabbage-partners-with-sba-authorized-bank-to-deliver-paycheck-protection-program-loans-to-small-businesses/</u>.

business loans using collateral and soft data in addition to hard data can adjust to changes in the economic environment better and did so during the COVID-19 crisis. In Section 5.3, we discuss evidence from the global financial crisis (GFC) about the model risk of data-driven lenders compared to banks that also use soft data.

5.1 Other fintech lending during the COVID-19 crisis

5.1.1 Fintech lenders: Unsecured personal loans

We first consider the dynamics of personal fintech loans during the COVID-19 crisis. Fintech lenders that make personal loans rely on hard data and these loans are not collateralized. Figure Internet Appendix A5 reports the number of originated loans from a large loan aggregator of personal fintech loans, which covers most of that market (see further details in Johnson et al. 2022). Loan originations fell sharply for personal fintech loans. The tipping point for the sharp decline in loan volumes began on March 20. Over the course of the next two business days, the volume of loans fell from normal levels to less than half of the typical daily volume. Put another way, the number of loan originations in January and February of 2020 was roughly 3,300 per day and by the end of March it had dropped to 1,500 per day. As with fintech small business lending, the decline is not unique to the subprime population. Looking only at prime borrowers with FICO scores greater than 660, loan volumes fell by 50% in the last week of March.

5.1.2 Fintech lenders: Mortgage lending

In 2020, the mortgage market was dominated by nonbanks. Nonbanks include fintech lenders who have been very successful in mortgage lending (Buchak et al. 2018; Fuster et al. 2019) as well as other lenders. Irrespective of whether a nonbank is a fintech or not, it does not have the soft data

and relationships that a bank would have. In 2020, nonbanks accounted for 69% of the originations for the top fifty lenders. Most of the mortgage market consists of conforming mortgages that are guaranteed against default by agencies and securitized. Jumbo mortgages have a higher principal amount than conforming mortgages, so that they do not have a guarantee from an agency. Fuster et al. (2023) examine the resilience of the mortgage market in 2020. They use a database that mostly nonbank lenders use to post mortgage offers. The number of lenders posting offers in the conforming market hardly changed during March for prime borrowers. For borrowers with FICO of 640, the number of lenders is 120 on the day of the declaration of a national state of emergency on March 13, 2020. This number drops rapidly to about eighty but bounces back almost the whole way by the end of March. In contrast, for jumbo borrowers with FICO of 640, the number of borrowers drops from sixty to almost zero and stays there for the whole of 2020. Similarly, for borrowers with FICO of 680, the number of borrowers drops from one hundred to less than twenty in March and does not exceed twenty again until September. It is clear from this evidence that for mortgages with a risk of default the collapse in the number of lenders is even more dramatic than the collapse in the number of lenders we document for small business lending. Though this evidence shows a lack of resilience of the jumbo market for low FICO score borrowers from nonbanks, this lack of resilience may be due to the lack of appetite of investors. These investors are mostly banks, so banks did not step away because of distress considerations. It is more likely that they did so because they could not assess properly the risk of these mortgages using their existing models. It is noteworthy that Wells Fargo stopped buying jumbo mortgages from third parties but continued offering them to borrowers maintaining high liquid balances.²⁹

²⁹ See "Wells Fargo curtails jumbo loans amid market turmoil," by Ben Eisen, *Wall Street Journal*, April 4, 2020.

5.2 Banks: Small business lending

Next, we compare the small businesses loan origination on our platform to that of banks. Specifically, we focus on small banks, which are typical lenders to small businesses. The H8 release by the Federal Reserve Board provides weekly data for banks' balance sheets and has data for "small" banks, i.e., banks outside the top twenty-five largest banks. In Figure 7, Panel (a), we report the changes in C&I (commercial and industrial) outstanding loans of small domestically-chartered banks and the loan volume recorded on our platform. Until March 11, 2020, the weekly changes in the total loans outstanding on banks' balance sheets fluctuated around zero, so loan originations were of a similar magnitude as loan repayments. On the week of March 11 2020, small banks' loan balances shot up by over \$30 billion, representing a nearly 5% increase in loans outstanding. Note that banks lend to safer borrowers than the average borrower on our platform. The contrast between the supply of bank loans and the supply of fintech loans holds if we restrict the fintech loans to prime loans as shown in Panel (b).

[Insert Figure 7]

Another source for banks' lending behavior during March 2020 is the small business lending survey from the Federal Reserve Bank of Kansas City (FRBKC).³⁰ The FRBKC survey 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 FRBKC survey also reports that about 20% of respondents experienced an increase in credit-line usage, but there seems to be no evidence of an overall increase in credit-line drawdowns for small businesses, so the increase in lending does not seem to come from increased credit-line usage.^{31,32}

³⁰ See Federal Reserve Bank of Kansas City Small Business Lending Survey, June 24, 2020.

³¹ The survey provides mixed evidence on overall loan demand: on net, small banks reported a decrease in loan demand but larger banks reported an increase.

³² Biz2Credit, a lending platform, has a lending index purportedly showing that loan approval rates by banks fell in March. This evidence does not conflict with our evidence. A decrease in approval rates is consistent with an increase in loan volume if

5.3 Data-driven lending and crises before COVID-19

Relationships and soft information in small business lending are useful because of their duration and because they arise from interactions with borrowers over multiple products. Small business borrowers are typically located in close proximity to the banks when relationship lending is involved. However, banks also make small business loans using hard information, mainly using credit scoring. Existing evidence shows that the probability of default of small business loans increases with distance from the bank. The distance of borrowers from the bank is higher with banks that use credit scoring and the use of credit scoring mitigates the adverse effect of distance. However, it is generally the case that soft-information relationship-based loans perform better when distance to the borrower is small than loans that use hard information (DeYoung, Glennon, and Nigro 2008).

With the global financial crisis, small business lending fell. However, it fell significantly more at large banks than small banks. Chen, Hanson, and Stein (2017) investigate the pullback from large banks. Part of their explanation for why large banks withdrew is that these banks realized "that the transition to automated underwriting had not significantly lowered costs or improved underwriting quality." They cite the experience of Bank of America, which used credit scoring to make loans below \$150,000 until 2007. It suffered significant losses and "eventually exited that market segment due in part to poor loans underwritten largely based on credit score data." (Mills and McCarthy 2014).

DeYoung, Gron, Torna, and Winton (2015) show that small business lending increased for banks that were most focused on relationship small business lending. They conclude that "in a true relationship lending context, credit is made available when it is most needed." This benefit of

applications increase more than the decrease in approval rates. Note that it is unclear how the Biz2Credit Small Business Lending Index is constructed, but it appears that it is constructed from querying applicants on the Biz2Credit website.

relationship lending is also emphasized by Bolton et al. (2016) who explicitly emphasize relationship banks' "ability to learn about changes in the borrower's creditworthiness and adapt lending terms to the evolving circumstances in which the firm finds itself." They note that relationship banking is "an important mitigating factor of crises." Not all evidence on relationship lending is equally positive, however. Specifically, Berger et al. (2024) find that relationship borrowers were charged higher rates in 2020 than other borrowers because they were more dependent on their relationship bank.

Models were used extensively to make subprime and non-conforming mortgage loans in the runup to the global financial crisis. These models eventually performed poorly. One reason for why they performed poorly is that applicants could take steps to make themselves more attractive when evaluated by models. In other words, they could game the models (Rajan, Seru, and Vig 2015). Eventually, the market concluded that they could no longer trust the implications of the models for the performance of securitizations of these mortgages, which led the market for private securitizations to freeze and then largely disappear (Gorton 2008).

In summary, the evidence from this section is that the lack of resilience of data-driven lending is not limited to small business lending during the COVID-19 crisis. We found that there was a lack of resilience for personal fintech loans as well as for non-conforming loans to borrowers with lower FICO scores. We also found that a lack of resilience played an important role in the global financial crisis. In contrast, there is evidence of resilience for relationship lending in crises both during the COVID-19 crisis and during the GFC.

6. Conclusion

In this study, we examine the evolution of fintech small business lending during the COVID-19 crisis period of March 2020 using unique data from a lending platform that allows us to examine the demand for and supply of loans separately. We find that demand increased in response to the COVID-19 shock and the average loan applicant became more creditworthy based on historical characteristics. However, paradoxically, at a time when fintech lenders' advantage over banks in responding to demand rapidly would have been most valuable, they were not able to respond.

We provide evidence that the data-driven lending model of fintech lenders was a major factor in the collapse of small business fintech lending. Such models are trained on past data and are expected to be predictive when applied in situations that are similar to the data they were trained on. However, data-driven lending has model risk, in that a model may no longer be appropriate when the economic circumstances become very different from the ones of the period it was trained on. In that case, data-driven lending comes to a standstill when lenders realize that they cannot rely on their models anymore. Consistently, we find that fintech lenders kept lending almost as if there was no pandemic until shortly before they stopped lending or reduced their lending to almost nothing. In other words, the lenders did not adjust their lending for the change in circumstances and for how the pandemic affected individual applicants. We find little impact of differential geographic or industrial exposures to COVID-19 on the likelihood of offers and on the terms of loans. When we reverse engineer the models that fintech lenders used before the pandemic, we find that these models suggested that they should make more offers during the pandemic because the credit quality of applicants increased when using traditional credit risk metrics. This lack of flexibility of lending practices to changes in economic circumstances is what one would expect when models were not designed to deal with new economic circumstances. As a result, while datadriven lending has many potential advantages, it suffers from a lack of resilience when economic circumstances not experienced during the training period come up. Models still give answers, but the answers are no longer appropriate.

We show that during the COVID-19 crisis data-driven lending for personal loans and nonguaranteed mortgages also experienced a lack of resiliency. Further, we find that issues with datadriven lending were also important during the global financial crisis of 2007-2009. In contrast, relationship lending is more resilient to crises. Small banks kept lending to small businesses during the COVID-19 crisis before PPP. In the global financial crisis, there is also evidence that small banks focused on relationship lending kept making loans to small businesses. In contrast, large banks that were more likely to use credit scoring methods cut back or even stopped programs of lending to small businesses.

The dark side of data-driven lending that we demonstrate for small business fintech lending during the COVID-19 crisis has two implications. First, while lenders keep using their models as economic circumstances change so that the models become less predictive, they increasingly may make loans that they would not make if they knew the true probability of default as opposed to the one given by their models. Lenders who recognize faster that the degree to which they are exposed to model risk has changed are less likely to make such loans. Second, once lenders recognize the problem and withdraw from lending, businesses that expected to have access to fintech lending no longer have access, so that borrowing needs are no longer met that could be met if the lenders had models that were predictive under the new circumstances. Because the dark side of data-driven lending manifests itself in unusual economic circumstances, it also manifests itself when small businesses are likely in the most need of emergency funding. The adverse effects of the dark side of data-driven lending were mitigated in March 2020 by the arrival of massive government

stimulus and by the much larger size of the lending of banks to small business. However, we would

expect issues with the dark side of data-driven lending to occur again and they could become more

important as the importance of data-driven lending increases.

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Figure 1. Small Business Loan Demand and Supply

The figure shows how demand and supply 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 total number of offers made through the platform in March 2019 and 2020. Panel (c) plots the number of funded loans smoothed using 5-previous-business-day moving averages. Weekends are excluded.



(c) Number of funded loans



Figure 2. Lender Dropouts Dynamics

These figures provide evidence on the supply shock to credit at the lender level. Panel (a) depicts the fraction of applicants that a particular lender accepts in the first three months of 2020 as well as the number of applications the lender received from the platform. Panel (b) shows the average number of daily active lenders from the prior business week. A lender is considered active if on a given day it extends an offer to at least one applicant. Weekends and observed holidays are excluded from weekly averages. Panel (c) shows the number of offers extended by individual lenders and the date of the application. Lenders included in this figure are the 20 lenders with the highest volume in 2020. Lenders are sorted by loan offer volume in 2020 and displayed in descending order on the y-axis.



(c) Offers by lender and application date



Figure 3. Lenders' Predicted Offers

Plotted are the coefficients and standard errors from a regression of predicted offer on dummies for each week leading up to lender dropout. Predicted offer is a value that is determined from predictions of logistic regressions for each lender in 2019 where the dependent variable is an indicator equal to 1 if an offer is made and the independent variables are the applicant's credit metrics. These credit metrics include bins for FICO score, annual revenue, and firm age as well as all other credit controls used throughout the paper. In Panel (b) the model also includes macro variables—30 -day rolling returns on the S&P 500 index and the 7-day rolling average of the spread on high-yield bonds. Logistic regressions are run at the application-lender level. Lender exit is the date when a lender no longer makes offers on the platform and it occurs during week 0. Week -8 is the omitted week and includes all applications submitted to a lender from January to seven weeks before the lenders drop out or the end of March. The plotted regression includes lender fixed effects. Standard errors are clustered at the lender by date level.

(a) Predicted likelihood of making offers: Model with applicant characteristics



(b) Predicted likelihood of making offers: Model with applicant characteristics and macro variables



Figure 4. Residual Loan Rates and Risk

This figure shows the daily price dynamics of fintech small business loans, high-yield spreads, and the CBOE volatility index (VIX). Plotted in Panel (a) is the average APR residual on offered fintech small business loans. The residual is the difference between the predicted APR and the offered APR where the predicted APR is determined using lender specific "reverse-engineered" models. The estimation procedure regresses the offered APR on 30 -day rolling returns on the S&P 500 index, 7-day rolling average of the spread on high-yield bonds, bins for FICO score, annual revenue, and firm age as well as all other credit controls used throughout the paper on applications from 2019. The coefficients from this estimation are then applied to 2020 loan offers to predict APR. In addition to the average APR residual, confidence bands that reflect two standard deviations around the mean are indicated by the shaded region. Plotted in Panel (b) is the median high-yield spread on corporate bonds rated CCC (blue dashed line) and the level of the VIX (solid red line).

(a) Average APR residual





VIX

---- High-Yield Bond Spread

Figure 5. Lender Dropout Event Study

This figure shows the dynamics of offer likelihood and interest rates in the weeks leading up to lender dropouts. Plotted in Panel (a) are the coefficients and standard errors from a regression of the offer indicator on dummies for each week leading up to lender dropout. Lender exit is the date when a lender no longer makes offers on the platform and it occurs during week 0. Week -8 is the omitted week and includes all applications submitted to a lender from January to seven weeks before the lenders dropout or end of March. Regressions are run at the application-lender level and include both applicant and lender fixed effects. In Panel (b) the regression is the same, but the dependent variable is the offered interest rate (APR). Standard errors are clustered at the lender by date level.

(a) Normalized Offer likelihood of lenders making offers before dropping out



(b) Normalized APR in lenders' offers before dropping out



Figure 6. Nonprime vs. Prime Lenders' Predicted and Actual Offers

Plotted are normalized predictions and offers for nonprime and prime lenders in the first three months of 2020. In Panel (a), predicted offer is a value that is determined from predictions of logistic regressions for each lender in 2019 where the dependent variable is an indicator equal to 1 if an offer is made and the independent variables are the applicant's credit metrics and macro variables. These credit metrics include bins for FICO score, annual revenue, and firm age as well as all other credit controls used throughout the paper. The macro variables are 30-day rolling returns on the S&P 500 index and the 7-day rolling average of the spread on high-yield. Panel (b) shows the average normalized offer rate. Normalization in both panels is based on the lender-level average in the first two months of the year. 95% confidence intervals are displayed.



(a) Predicted offers



Figure 7. Fintech vs. Bank Loan Origination Volumes

This figure shows the evolution of fintech and bank small business lending during the first three months of 2020. The dashed line (left y-axis) shows the 5-previous-business-day rolling sum of funded fintech loans made on the platform. The solid line (right y-axis) shows the weekly change in outstanding C&I (commercial and industrial) loans reported by small US chartered banks—a proxy for new small business originations by banks. In Panel (b), Fintech loan originations are limited to borrowers with prime credit scores as a cleaner comparison to bank loans. Prime borrowers have FICO scores equal to or greater than 660.

(a) Fintech loans and bank loans



(b) Prime fintech loans and bank loans



Table 1. Loan Supply in March 2020 and Exposure to COVID-19

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. Applicant controls are included in Columns (2) and (4) These controls are the FICO score of the owner, the log of firm age, the log of sales, the average bank balance, the number of days with a negative balance, the average monthly number and amount of credits and debits, and industry fixed effects. To save space, only the coefficients on indicators for weeks in March are included, but all week indicators are included in the base week when the sample period extends prior to March. In Columns (1) and (2), the sample is limited to applications received in March 2020. The sample used in Columns (3) and (4) includes January and February 2020. Industry fixed effects are included in all but Columns (1) and (3). In Panel B, I(Below Median Industry Returns) is an indicator equal to 1 if the cumulative returns for the applicant's industry were below the median cumulative return from March 1 to March 12. In Panel C, 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. Standard errors are clustered by application date in Panel A and clustered by application date and county in Panels B and C. Standard errors are reported in parentheses. * p<.1; ** p<.05; *** p<.01.

Dependent variable	I(Offer)*100					
	(1)	(2)	(3)	(4)		
I(March 9-15)	-9.26**	-11.09***	-15.94***	-16.80***		
	(3.41)	(3.58)	(3.07)	(3.33)		
I(March 16-22)	-25.42***	-30.47***	-32.10***	-36.40***		
	(3.40)	(3.02)	(3.05)	(2.68)		
I(March 23-29)	-33.05***	-38.46***	-39.72***	-44.13***		
	(2.17)	(2.32)	(1.61)	(1.76)		
FICO		5.87***		6.97***		
		(1.08)		(0.63)		
ln(Age)		2.94***		2.34***		
		(0.62)		(0.47)		
ln(Sales)		3.46***		4.60***		
		(0.45)		(0.33)		
Sample period	Mar 2020	Mar 2020	Jan-Mar 2020	Jan-Mar 2020		
Applicant controls	No	Yes	No	Yes		
Industry FE	No	Yes	No	Yes		
R^2	0.08	0.16	0.11	0.20		
Observations	7,285	7,285	15,970	15,970		

Panel A: Loan Supply in March 2020

Table 1. Loan Supply in March 2020 and Exposure to COVID-19 (Cont.)

Dependent variable	I(Offer)*100				
	(1)	(2)	(3)	(4)	
I(Below Median Industry Returns)	-2.01		1.28		
	(2.33)		(1.12)		
I(Post 3/12) * I(Below Median Industry Returns)	1.49	2.93	-2.16	0.02	
	(2.53)	(2.73)	(1.61)	(1.80)	
FICO		6.06***		7.10***	
		(1.06)		(0.76)	
ln(Age)		2.71***		2.07***	
		(0.65)		(0.51)	
ln(Sales)		1.49***		2.39***	
		(0.46)		(0.37)	
Sample period	Mar 2020	Mar 2020	Jan-Mar 2020	Jan-Mar 2020	
Application date FE	Yes	Yes	Yes	Yes	
Industry FE	No	Yes	No	Yes	
County FE	No	Yes	No	Yes	
Applicant controls	No	Yes	No	Yes	
R^2	0.10	0.31	0.12	0.34	
Ν	6,802	6,802	15,344	15,344	

Panel B: Offers and industry exposure to COVID-19

Panel C: Offers and geographical exposure to COVID-19

Dependent variable	I(Offer)*100					
	(1)	(2)	(3)	(4)	(5)	(6)
I(State Lockdown)	-3.97		-3.02		-3.43	
	(2.91)		(2.67)		(3.23)	
% Population Home		-1.85		-43.78*		-22.67
		(22.81)		(24.69)		(20.64)
FICO			6.02***	5.99***	7.04***	7.03***
			(1.06)	(1.07)	(0.76)	(0.75)
ln(Age)			2.68***	2.66***	2.05***	2.05***
			(0.64)	(0.64)	(0.51)	(0.51)
ln(Sales)			1.49***	1.48***	2.40***	2.39***
			(0.46)	(0.46)	(0.37)	(0.37)
Sample period	Mar 2020	Mar 2020	Mar 2020	Mar 2020	Jan-Mar 2020	Jan-Mar 2020
Application date FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes
County FE	No	No	Yes	Yes	Yes	Yes
Applicant controls	No	No	Yes	Yes	Yes	Yes
R^2	0.10	0.10	0.31	0.31	0.35	0.35
Observations	6,802	6,802	6,802	6,802	15,344	15,344

Table 2. Offer Terms and Exposure to COVID-19

This table shows the effect of time, geographical, and industry exposure to the pandemic on offered loan terms. The dependent variables are the interest rate of the loan in APR, the maturity in months, and the natural log of loan amount. Panel A examines whether offered loan terms change over the course of March 2020, controlling for firm characteristics and holding constant the lender. Panel B examines the effect of COVID-19 industry exposure on loan terms using the same key independent variables as in Table 1. 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. *I(Below Median Industry Returns)* is an indicator equal to 1 if the cumulative returns for the applicant's industry were below the median cumulative return from March 1 to March 12. In Panel C, the proxies for geographical COVID-19 exposure are an indicator for whether the state has been ordered to be on lockdown (*I(State Lockdown)*) and the fraction of individuals in the county that are home all day on the date the application was submitted(% *Population Home*). Standard errors are clustered by application date and lender and are reported in parentheses. * p<.1; ** p<.05; *** p<.01.

Dependent variable	A	APR		Maturity		ln(Loan Amount)	
	(1)	(2)	(3)	(4)	(5)	(6)	
I(March 9-15)	0.06	-0.45	-0.02	-0.05	0.03	-0.01	
	(1.01)	(1.18)	(0.15)	(0.13)	(0.04)	(0.03)	
I(March 16-22)	2.71	2.18	0.10	0.07	-0.06	-0.09*	
	(1.88)	(1.34)	(0.40)	(0.28)	(0.06)	(0.05)	
I(March 23-29)	5.02*	5.11**	-0.61*	-0.56	0.02	-0.02	
	(2.48)	(2.25)	(0.31)	(0.37)	(0.14)	(0.14)	
FICO	-5.79***	-6.87***	0.60***	0.63***	0.14***	0.14***	
	(1.44)	(1.43)	(0.17)	(0.12)	(0.03)	(0.02)	
ln(Age)	-4.68***	-4.51***	0.52**	0.63***	0.09***	0.08***	
	(1.42)	(1.01)	(0.19)	(0.18)	(0.03)	(0.02)	
ln(Sales)	-1.24**	-1.09	0.06	0.04	0.27***	0.30***	
	(0.57)	(0.70)	(0.08)	(0.06)	(0.07)	(0.05)	
Sample period	Mar 2020	Jan-Mar 2020	Mar 2020	Jan-Mar 2020	Mar 2020	Jan-Mar 2020	
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	
Applicant controls	Yes	Yes	Yes	Yes	Yes	Yes	
R^2	0.83	0.82	0.98	0.96	0.67	0.66	
Observations	2,400	8,192	2,400	8,192	2,400	8,192	

Panel A: Changes in loan offer terms in March 2020

Panel B: 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)	-2.47	1.07	0.52*	0.15	0.16**	-0.02
	(1.89)	(1.98)	(0.30)	(0.26)	(0.07)	(0.06)
I(Below Median Industry Returns)	2.87***	3.24***	-0.40***	-0.37***	0.07*	-0.02
	(0.96)	(1.01)	(0.15)	(0.10)	(0.04)	(0.03)
I(Post 3/12) * I(Below Median Industry Returns)	1.87	-0.13	-0.58*	-0.35	-0.04	-0.06
	(1.60)	(1.66)	(0.30)	(0.25)	(0.05)	(0.06)
FICO		-6.82***		0.62***		0.14***
		(1.48)		(0.12)		(0.02)
ln(Age)		-4.64***		0.66***		0.08***
		(1.01)		(0.18)		(0.03)
ln(Sales)		-0.97		0.03		0.30***
		(0.72)		(0.07)		(0.05)
Sample period	Jan-Mar 2020	Jan-Mar 2020				
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Applicant controls	No	Yes	No	Yes	No	Yes
R^2	0.81	0.82	0.95	0.95	0.37	0.66
Observations	8,192	8,192	8,192	8,192	8,192	8,192

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

Dependent variable	APR (%)		Ma	turity	ln(Loan Amount)	
	(1)	(2)	(3)	(4)	(5)	(6)
I(State Lockdown)	0.40		-0.67		0.11	
	(3.53)		(0.46)		(0.12)	
% Population Home		15.06		-0.16		-0.24
		(21.78)		(2.39)		(0.53)
FICO	-6.83***	-6.83***	0.61***	0.61***	0.14***	0.14***
	(1.49)	(1.49)	(0.13)	(0.13)	(0.02)	(0.02)
ln(Age)	-5.10***	-5.10***	0.66***	0.66***	0.09***	0.09***
	(1.14)	(1.15)	(0.18)	(0.19)	(0.02)	(0.02)
ln(Sales)	-1.38*	-1.38*	0.03	0.03	0.31***	0.31***
	(0.70)	(0.70)	(0.04)	(0.04)	(0.05)	(0.05)
Sample period	Jan-Mar 2020	Jan-Mar 2020				
Application date FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Applicant controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.84	0.84	0.96	0.96	0.72	0.72
Observations	8,192	8,192	8,192	8,192	8,192	8,192

Table 3. Supply Cuts and Applicant Risk

This table examines the differential impact in offer likelihood during March 2020 for prime and nonprime applicants. The dependent variable is an indicator equal to 100 if an offer is extended to the applicant. The prime applicant indicator is equal to one if the applicant has a FICO score that is equal to or greater than 660. The omitted week includes all applications from January to the first week of March. The observation level in Columns (1) and (2) is at the applicant level and in Columns (3) and (4) it is at the application-lender level. Applicant controls used in previous tables are included as indicated with an additional control for the number of lenders still actively making loans at the time of the application. Columns (2)-(4) include industry fixed effects. Column (4) includes lender fixed effects. Standard errors are clustered at the application date level and are reported in parentheses. * p < .1; ** p < .05; *** p < .01.

Dependent variable	I(Offer)*100				
	(1)	(2)	(3)	(4)	
I(March 9-15)	-18.43***	-16.07***	-4.91***	-4.16***	
	(3.49)	(3.10)	(1.13)	(1.18)	
I(March 16-22)	-33.61***	-19.80***	-5.35	-3.81	
	(2.06)	(2.48)	(3.31)	(2.91)	
I(March 23-29)	-36.90***	-7.20	1.50	2.80	
	(1.52)	(5.00)	(5.38)	(4.66)	
I(Prime Applicant)	17.12***	3.47**	3.13***	4.41***	
	(1.02)	(1.50)	(0.67)	(0.68)	
I(March 9-15) * I(Prime Applicant)	3.48**	2.95*	0.06	-0.80	
	(1.43)	(1.71)	(1.05)	(1.16)	
I(March 16-22) * I(Prime Applicant)	-1.01	-0.71	0.00	-1.75*	
	(2.44)	(2.76)	(0.92)	(0.98)	
I(March 23-29) * I(Prime Applicant)	-8.76***	-8.69***	-2.34**	-4.15***	
	(1.71)	(1.66)	(0.97)	(1.28)	
# Active Lenders		2.28***	0.75*	0.81**	
		(0.30)	(0.38)	(0.32)	
FICO		5.94***	7.04***	8.44***	
		(0.92)	(0.51)	(0.56)	
ln(Age)		2.38***	1.85***	2.30***	
		(0.47)	(0.23)	(0.26)	
ln(Sales)		4.53***	0.61***	1.44***	
		(0.33)	(0.22)	(0.26)	
Sample period	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2020	
Industry FE	No	Yes	Yes	Yes	
Lender FE	No	No	No	Yes	
Applicant controls	No	Yes	Yes	Yes	
R^2	0.14	0.20	0.05	0.12	
Observations	15,970	15,970	69,978	69,978	

Table 4. Supply Cuts and Lender Risk

This table examines the differential impact on the likelihood of extending a credit offer during March 2020 for *lenders* with different risk appetites prior to the pandemic. The dependent variable is an indicator equal to 100 if an offer is extended to the applicant. *I(Prime Lender)* is an indicator equal to 1 if the lender's median borrower in 2019 had a FICO score equal to or greater than 660. The omitted week includes all applications from January to the first week of March. The observation level is at the application-lender level. Applicant controls used in previous tables are included as indicated with an additional control for the number of lenders still actively making loans at the time of the application. Column (2) includes industry fixed effects. Column (3) includes lender fixed effects. Standard errors are clustered at the application date level and are reported in parentheses. * p<.1; ** p<.05; *** p<.01.

Dependent variable	I(Offer)*100				
	(1)	(2)	(3)		
I(March 9-15)	-6.32***	-7.54***	-6.51***		
	(1.27)	(1.40)	(1.38)		
I(March 16-22)	-10.45***	-10.19***	-8.45***		
	(0.88)	(3.07)	(2.82)		
I(March 23-29)	-11.28***	-5.14	-3.73		
	(0.60)	(5.32)	(4.65)		
I(Prime Lender)	-2.57***	-8.08***			
	(0.37)	(0.39)			
I(March 9-15) * I(Prime Lender)	5.03***	5.83***	4.45***		
	(0.73)	(0.75)	(0.83)		
I(March 16-22) * I(Prime Lender)	8.84***	9.86***	7.58***		
	(1.62)	(1.55)	(1.26)		
I(March 23-29) * I(Prime Lender)	10.26***	11.33***	9.37***		
	(2.25)	(2.00)	(1.63)		
# Active Lenders		0.74*	0.78**		
		(0.38)	(0.33)		
FICO		9.78***	10.70***		
		(0.40)	(0.44)		
ln(Age)		2.03***	2.30***		
		(0.24)	(0.26)		
ln(Sales)		0.79***	1.50***		
		(0.24)	(0.27)		
Sample period	Jan-Mar 2020	Jan-Mar 2020	Jan-Mar 2020		
Industry FE	No	Yes	Yes		
Lender FE	No	No	Yes		
Applicant controls	No	Yes	Yes		
R^2	0.00	0.06	0.12		
Observations	69,978	69,978	69,978		

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).
Asse Deals Delance	The average daily balance in the business's (or owner's) bank account measured using bank
Avg Bank Balance	statements from the prior three months.
# Dave Nametica Dalanaa	The number of days in the previous three months with negative balances in the business's (or
# Days Negative Balance	owner's) bank account.
# Manthly Cardita	The average number of credits in the bank account of the owner/businesss each month over the
# Monthly Credits	prior three months.
Monthly Credit Amount	The total amount of credits received each month and averaged over the prior three months.
# Mandha Dabita	The average number of credits in the bank account of the owner/businesss each month over the
# Monthly Debus	prior three months.
Monthly Debit Amount	The total amount of debits received each month and averaged over the prior three months.
# Active Lenders	Number of lenders that are still actively making loans on the application date.
I(State I a aladaraa)	An indicator variable equal to one if the applicant's state has been ordered on lockdown at the
I(State Lockdown)	time of application.
	The fraction of individuals in the county that are home all day on the date the application was
% Population Home	submitted. This is calculated using data from SafeGraph which tracks the movement of
	individuals through cell phones.
I(Office)	An indicator variable equal to one if the applicant received a loan offer within 30 days of the
I(Oller)	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).
I(Prime Applicant)	An indicator equal to 1 if the applicant's FICO score is greater than or equal to 660
I(Duines Landar)	An indicator equal to 1 if the median FICO on transacted deals for a given lender during 2019 is
I(Prime Lender)	greater than or equal to 660.
	An indicator equal to one if the cumulative returns for the applicant's industry were below the
I(Below Median Industry Returns)	median cumulative return from March 1 to March 12.
L(D (2/12)	An indicator equal to one if the application is received after March 12, 2020, the day after the
I(POST 3/12)	World Health Organization declared COVID-19 a global pandemic.