The Rise of Fintech Lending to Small Businesses: Businesses' Perspectives on Borrowing*

Brett Barkley and Mark Schweitzer
Federal Reserve Bank of Cleveland

Online lending through fintech firms is a rapidly expanding segment of the financial market that is receiving much attention from investors and increasing scrutiny from regulators. To assess how fintech firms' entry is altering the choices and outcomes of small businesses that borrow from them, we analyze data from the Federal Reserve's Small Business Credit Survey, a unique data source on the experiences of business owners with new and traditional sources of credit. We find that fintech lenders have substantially expanded the small business finance market by reaching borrowers less likely to be served by traditional lenders and that businesses using online lenders are younger, smaller, and less profitable than the average small or medium-sized enterprise in the United States. After controlling for compositional differences between online and bank borrowers, we find that businesses using fintech lenders generally apply for smaller loan amounts but value the option of fintech loans. Businesses that receive fintech loans expect more revenue and employment growth than those receiving a bank loan; however, they are less satisfied than businesses that borrow from banks but more satisfied than businesses that were denied credit.

JEL Codes: G21, G23, G28, C31.

*Brett Barkley is a data scientist in the Supervision and Regulation Department of the Federal Reserve Bank of Cleveland (brett.barkley@clev.frb.org). Mark E. Schweitzer is a senior vice president in the Research Department of the Federal Reserve Bank of Cleveland (mark.schweitzer@clev.frb.org). The views stated herein are those of the authors and are not necessarily those of the Federal Reserve Bank of Cleveland or the Board of Governors of the Federal Reserve System.

1. Introduction

Fintech firms are a rapidly growing set of technology companies providing alternatives to traditional banking services, most often exclusively in an online environment. Fintech firms compete in financial services markets including consumer payments, asset management, and consumer and business lending. Overall, fintech lenders averaged nearly \$12 billion in quarterly originations through the first half of 2018 (Darden, Dixit, and Mason 2018), and their lending to small businesses increased from approximately \$121 million in quarterly originations during 2013 to \$2 billion in quarterly originations during 2018. The 2020 pandemic and recession affected fintech lenders' existing business models, but several of them had substantial roles in providing Paycheck Protection Program (PPP) loans, with 19 fintech lenders originating more than 250,000 PPP loans amounting to approximately \$6 billion (U.S. Small Business Administration 2020); other PPP loans were made by financial institutions like Cross River Bank, WebBank, and Celtic Bank on behalf of fintech lenders, accounting for an additional \$12.5 billion (Federal Reserve 2020). The entrance of new types of lenders raises potential coordination challenges (Goldstein, Jagtiani, and Klein 2019) and important regulatory issues as new lenders increasingly compete with more heavily regulated banking institutions (Philippon 2018). Despite substantial investments and growing activity levels, fintech lenders have been lightly regulated to date (U.S. Department of the Treasury 2016 and Basel Committee on Banking Supervision 2018).

Only a few studies have explored fintech as a financing alternative for small businesses (Slattery 2014; Jagtiani and Lemieux 2019; and Balyuk, Berger, and Hackney 2020). Of these, our work is closest to Balyuk, Berger, and Hackney (2020). They use state-level changes in bank structures to show that two online-only, small business lenders have increased in the markets where the presence of local banks declined. Similar to our findings, they find that these two fintech lenders offer somewhat riskier loans. But all of these studies, including Balyuk, Berger, and Hackney (2020), have been constrained in their examination of fintech lending by having access only to data that have been released by particular fintech lenders, and those data do not include the set of all possible borrowers.[1] Our analysis complements these studies by using borrower-side data obtained from a survey of small businesses, which allows us to examine a broader set of borrowers and a fuller range of credit outcomes. This is important because, for example, if small businesses denied by banks are similar to businesses approved by fintech lenders, comparing the two provides a more complete picture as to whether fintech is merely substituting for bank credit in places where the latter has declined or truly expanding the credit market.

An older literature has focused on the roles different types of banking entities play in the financing and growth of small businesses. Community banks have long been recognized as an important source of small business credit (Berger and Udell 2002; Wiersch and Shane 2013; Robb and Robinson 2014). Despite a growing market share for large banks in small business lending dating back to the 1990s, several studies have shown that community banks still have an advantage in providing appropriate credit products to this market (Berger et al. 2005; Deyoung, Glennon, and Nigro 2008; Deyoung et al. 2011). As evidence of community banks' staying power in the small business lending market, note that 45 percent of the $525 billion in PPP loans were made by banks with less than $10 billion in assets (U.S. Small Business Administration 2020). We examine how different types of traditional lenders (large banks, community banks, and credit unions) differ from online lenders in providing financing to small businesses and how these new lending alternatives have been working for the small businesses that use them.

To collect data on the financing needs and experiences of small businesses, Federal Reserve Banks have conducted an annual survey of firms (the Small Business Credit Survey, or SBCS), which reached national coverage starting in 2016. Since that time, the SBCS has included questions about online lenders as well as traditional lenders. The survey focuses on measuring the financial needs and outcomes of businesses with fewer than 500 full- or part-time employees.[2] While the survey participants include thousands of small businesses,

[1] Mach, Carter, and Slattery (2014) and Jagtiani and Lemieux (2019) both examine LendingClub's publicly available data. Balyuk, Berger, and Hackney (2020) examine LendingClub and Funding Circle data.

[2] The survey includes nonemployer firms, but for this analysis we focus on businesses with at least one employee.

they are not a stratified random sample. Instead, participants are contacted through partner organizations and then the sample is weighted to reflect national small business characteristics according to census data. At this point, we are aware of no alternative data sources on the experiences of small businesses with both fintech firms and banks.

While banks have historically played an important role in meeting small businesses' financing needs, the SBCS reveals that fintech firms are now a substantial source of credit: in 2018, about 32 percent of small businesses that sought financing applied with a fintech or online lender[3] versus 44 percent with small banks and 49 percent with large banks. We use SBCS data from 2016 to 2018 to analyze the extent to which borrowers using online sources (the term used in the survey) would have been likely to have had their needs met by traditional lenders (a category that includes large and small banks and credit unions). To investigate the value of these loans, we then apply treatment effect estimators which flexibly control for compositional differences of the credit applicants and measure the impact of and ex post borrower satisfaction with online lenders. Overall, we find that fintech lenders have expanded lending to small businesses largely to the benefit of those businesses.

2. Small Business Credit Survey Design and Coverage

The Federal Reserve's Small Business Credit Survey is an annual survey of business establishments with fewer than 500 employees. It collects information about business performance, financing needs and choices, and borrowing experiences. The survey is designed to inform policymakers about how the small business credit environment affects firm operation and growth.[4]

The Federal Reserve partners with more than 400 organizations—including chambers of commerce, industry associations, development authorities, and other civic and nonprofit partners—to field the SBCS via an online questionnaire. The sampling frame consists of

[3]Throughout the paper, we use the terms "fintech lenders" and "online lenders" interchangeably.

[4]See https://www.fedsmallbusiness.org for more information.

businesses on the membership list or registry of partner organizations and is, therefore, a convenience sample. Across each participating Federal Reserve district, businesses receive an e-mail from partner organizations on behalf of the respective Federal Reserve Bank requesting their participation and providing an online link to the survey. Response rates for each partner organization are tracked in real time, and partners with initially low response rates may be encouraged to send out additional e-mails to businesses on their distribution lists until the survey officially closes. In total, responses were collected from 6,614 firms in 2018; 8,169 firms in 2017; and 10,303 firms in 2016 across all 50 states and the District of Columbia.

Unweighted, the SBCS sample is likely to reflect the firms favored by the Federal Reserve's collection process. For example, given that the sampling frame primarily consists of distribution lists of chambers of commerce and industry associations—organizations less likely to be connected to younger, less established firms—it is reasonable to expect that such firms would be underrepresented in the SBCS sample. In order to correct for gross sampling deviations from population data, the Federal Reserve uses a ratio-adjustment weighting method and demographic data on firm age, employee size, and industry to make the sample more representative of the population distribution of firms.[5] Age-of-firm data come from the Census Bureau's Business Dynamics Statistics. Industry and employee size data are from County Business Patterns.

3. Adoption of the Fintech Alternative to Banks

There is no question that fintech lenders are increasingly active in small business finance, but financial regulators need to know whether that activity is expanding access to credit for small businesses. Treasury officials noted in a recent report on nonbank financials, fintech, and innovation (U.S. Department of the Treasury 2018) that the use of alternative models and data sources could expand credit availability particularly for consumers and businesses that might be constrained by traditional credit-scoring models, an observation echoed in a 2019 interagency statement from the five federal financial

[5]Most econometric studies instead weight by an observation's inverse probability of selection. The SBCS poses certain limitations in this regard.

regulators.[6] However, identifying when fintech loans are expanding credit and when they are just substituting for banks and other credit providers has not been previously quantified in this market. In the context of consumer loans, Jagtiani and Lemieux (2018) show that while there are substantive differences between LendingClub's borrowers and those of traditional lenders (suggesting that LendingClub is penetrating potentially undeserved areas), the average FICO score of LendingClub's borrowers "is only very slightly below the average of overall Equifax customers." Jagtiani and Lemieux (2018) interpret this as evidence that much of the expansion might be substantially drawn from firms that previously borrowed or could borrow from traditional banks.

We use information available in the SBCS on the businesses that received financing from an online lender to compare the characteristics of these businesses with those of businesses that received bank loans and those of businesses that were denied financing. In simple comparisons, online borrowers are on average younger firms with fewer employees and less revenue (table 1). A larger proportion of firms operating at a loss also tend to turn to online lenders compared with firms receiving loans from traditional lenders, as do a larger proportion of minority-, women-, and veteran-owned businesses. In terms of industry (though not reported in table 1), firms in health care, administrative services, and retail are the most likely customers for fintech loans. The differences support the argument that online lenders reach groups that are less likely to be served by banks, but these firm characteristics are correlated with each other, so a model is needed to evaluate the relative importance of these factors on the type of financing received, if any.

3.1 Which Businesses Receive Which Financing?

We do not observe the specific factors which banks or online lenders use in their lending decisions, but any of the business characteristics identified in table 1 could be a factor in those decisions. At the same

[6]See "CA Letter 19-11 Interagency Statement on the Use of Alternative Data in Credit Underwriting" at https://www.federalreserve.gov/supervisionreg/caletters/caltr1911.htm.

Table 1. Basic Weighted Sample Characteristics, Survey Years 2016–18

	Denied Financing	Online Lender	Bank/CU Financing
Age			
0–2 Years	24.4	15.6	15.5
3–5 Years	18.8	22.1	12.8
6–10 Years	23.9	27.0	21.3
11–15 Years	13.1	15.9	14.3
16–20 Years	6.0	7.7	10.2
21+ Years	13.8	11.7	25.9
Employer Size			
1–4 Employees	59.1	54.4	37.0
5–9 Employees	20.7	22.6	19.7
10–19 Employees	10.4	13.0	18.2
20–49 Employees	6.9	7.8	14.6
50–499 Employees	2.9	2.2	10.5
Revenue			
< \$100K	25.1	12.2	9.9
\$100K–\$1M	53.6	64.7	42.1
\$1M–\$10M	19.9	21.9	39.2
\$10M+	1.4	1.2	8.7
Profitability			
At a Loss	38.7	35.6	22.4
Break Even	25.2	21.2	16.0
At a Profit	36.1	43.2	61.6
Minority-Owned Business			
Non-minority	74.2	79.2	83.9
Minority	25.8	20.8	16.1
Female-Owned Business			
Male	74.6	79.2	80.9
Female	16.1	17.7	14.6
Did Not Respond	9.3	3.0	4.5
Veteran-Owned Business			
Non-veteran	67.5	72.9	76.1
Veteran	11.5	15.0	10.2
Did Not Respond	21.0	12.1	13.7
Unemployment Rate (Change), 2015–16			
Mean	−0.447	−0.443	−0.403
Unemployment Rate (Change), 2016–17			
Mean	−0.514	−0.510	−0.516
Unemployment Rate (Change), 2017–18			
Mean	−0.471	−0.464	−0.435
N	1,376	1,004	4,904

Notes: Sample characteristics represent the percentage of survey respondents in each treatment group, except for the unemployment rate variables which represent the average change in the state unemployment rate for the state in which a firm is located during the noted time period. Of the firms in the Bank/CU financing treatment group, 164 were also approved for financing by a nonbank online lender after their approval by a bank lender. Of the firms in the Online financing group, 225 were also approved by a bank or credit union after their approval by an online lender.

time, correlations between firm characteristics may result in indirect associations of outcomes with observed characteristics that are not actually the factors used to make lending decisions. We apply a multinomial logit model to identify the factors with the greatest impacts on the funding outcomes of the small businesses that applied for financing. We specify a firm's financing status as a function of its size (in terms of employees), age, industry, revenue, profitability, credit risk status, and the demographic variables minority owned, woman owned, and/or veteran owned with all covariates specified as categorical variables around conventional cutoffs. In addition, we include controls for changes in state unemployment rates to account for local economic conditions.

The multinomial logit model implies that the probability of an outcome, also known as the propensity score, is

$$P\left(w=1|x_i\right)=\frac{e^{X_i\beta_1}}{1-\sum_{o=1}^{O-1}e^{X_i\beta_o}}.$$

The sum of the probabilities of all outcomes w is equal to 1 by construction. In our estimation, financing outcomes are online, bank or credit union, and denied: $w_i = O, B$, or D.

Table 2 shows the average marginal effects of the key variables.[7] Average marginal effects are measured as the difference in propensity scores for a predicted outcome ($w = O$) for a particular variable ($z = 1$) versus ($z = 0$), averaging across all observations of other variables x regardless of the realized outcome of the observations:

$$\begin{aligned}AME\left(w=O,z=1\right)=\sum_{n=0}^{N}&\left(P(w=O|z=1,x_n)\right.\\&\left.-P\left(w=O|z=0,x_n\right)\right)/N.\end{aligned}$$

Because the sample is composed of all businesses applying for credit regardless of outcome, it represents the average effect of a categorical variable for an otherwise typical business applying for

[7]The multinomial logit model's full results are shown in appendix table A.1. The samples vary some based on the outcome questions. We include the largest possible sample for each outcome, so there are four similar but not identical logit models shown in table A.1.

Table 2. Average Marginal Effects of Key Variables on Receiving Financing, Survey Years 2016–18

	Denied Financing	**Online Lender**	**Bank/CU Financing**
Age			
0–2 Years	0.026	−0.054***	0.029
	(0.018)	(0.015)	(0.020)
3–5 Years	0.017	0.051***	−0.067***
	(0.016)	(0.017)	(0.019)
6–10 Years	0.002	0.028*	−0.030*
	(0.014)	(0.014)	(0.016)
11–15 Years	0.001	0.038**	−0.038**
	(0.018)	(0.019)	(0.019)
16–20 Years	−0.041*	−0.001	0.042
	(0.021)	(0.024)	(0.026)
21+ Years	−0.019	−0.049***	0.068***
	(0.015)	(0.013)	(0.016)
Employees	−0.001**	−0.001*	0.002***
	(0.001)	(0.001)	(0.001)
Profitable	−0.044***	−0.019***	0.063***
	(0.007)	(0.007)	(0.008)
Revenue > $1M	−0.052***	−0.036***	0.088***
	(0.011)	(0.011)	(0.013)
Minority-Owned Firm	0.035**	0.001	−0.037*
	(0.017)	(0.015)	(0.019)
Woman-Owned Firm	−0.024*	0.012	0.012
	(0.014)	(0.014)	(0.017)
Veteran-Owned Firm	−0.015	0.056**	−0.041*
	(0.020)	(0.024)	(0.024)
Medium/High Credit Risk	0.057***	0.052***	−0.109***
	(0.008)	(0.008)	(0.009)
Unemployment Rate (Change), 2015–16	−0.053***	−0.036*	0.089***
	(0.020)	(0.019)	(0.022)
Unemployment Rate (Change), 2016–17	0.011	0.027	−0.038
	(0.028)	(0.024)	(0.030)
Unemployment Rate (Change), 2017–18	−0.064**	−0.030	0.093***
	(0.027)	(0.027)	(0.030)
Year			
2016	0.007	−0.058***	0.051***
	(0.010)	(0.009)	(0.011)
2017	0.004	−0.002	−0.002
	(0.011)	(0.011)	(0.013)
2018	−0.011	0.062***	−0.051***
	(0.010)	(0.011)	(0.012)

Notes: Standard errors are in parentheses. ***, **, and * denote significance at $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Employee and unemployment rate variables are continuous; all other variables are discrete. Credit risk is determined by the self-reported business credit score or personal credit score, depending on which is used to obtain financing for their business. If the firm uses both, the higher risk rating is used. Low credit risk is an 80–100 business credit score or a 720+ personal credit score. Medium credit risk is a 50–79 business credit score or a 620–719 personal credit score. High credit risk is a 1–49 business credit score or a <620 personal credit score. For full results of multinomial logit estimates, see table A.1.

credit. The average marginal effects also net to zero across rows because the columns represent the full set of options.

The borrowing outcomes of small businesses do depend on a range of characteristics, but not necessarily monotonically. The effect of a business being in one of the younger age categories (firm age between 3 and 15 years) is to boost the likelihood of receiving credit from an online lender and lower the likelihood of bank financing. In contrast, most age groups of firms are not statistically distinguishable for being denied financing, with statistically significant results only for firms between 16 and 20 years old (−4 percentage points). Those in the oldest age category of small businesses, 21+ years, are most likely to receive bank financing (7 percentage points).

Increased employee counts (included as a continuous variable and its square) make bank financing statistically more likely, with similar reductions in being denied financing or the use of online financing. The negative coefficient on the squared term of employment size (table A.1) implies that these effects diminish as firms grow. That said, for most of the firm sizes in our sample, these effects are not that large: Going from 1 employee to 10 employees increases the likelihood of bank financing by about 2 percentage points and lowers the likelihood of online financing by 1 percentage point.

The profitability of businesses is a critical factor for banks, boosting the likelihood of bank financing by about 6 percentage points. That higher probability of bank lending is mirrored by lower likelihoods of both denials (−4 percentage points) and online-lender financing (−2 percentage points) for profitable firms. The coefficients imply that online-lender financing is more likely for unprofitable firms, all else held constant. Even accounting for profitability, higher-revenue firms are 9 percentage points more likely to receive bank financing, with most of the offsetting probability coming from denials. Finally, being evaluated by a credit bureau as medium or high risk substantially lowers the likelihood of bank financing (by 11 percentage points) and evenly raises the likelihood of both denial and online-lender financing. These key financial variables clearly help to determine which firms receive which financing outcomes.

The demographic characteristics of the heads of businesses are relatively less influential on the outcomes, but there are still some statistically significant differences after accounting for the other variables. Minority status lowers the likelihood of bank financing by roughly 4 percentage points, with the associated higher frequency being in denials. Women-owned businesses have a lower likelihood of being denied financing, while veteran-owned businesses are more likely to receive online financing with an associated lower probability of bank financing.

We included the change in state unemployment rates to account for (generally) improving market conditions on lending outcomes. Banks seem less likely to lend in areas where the unemployment rate is declining (with associated higher levels of denials), but the changes are relatively small in most of this period, a finding that suggests a relatively small role for local economic conditions in the determination of individual lending outcomes.

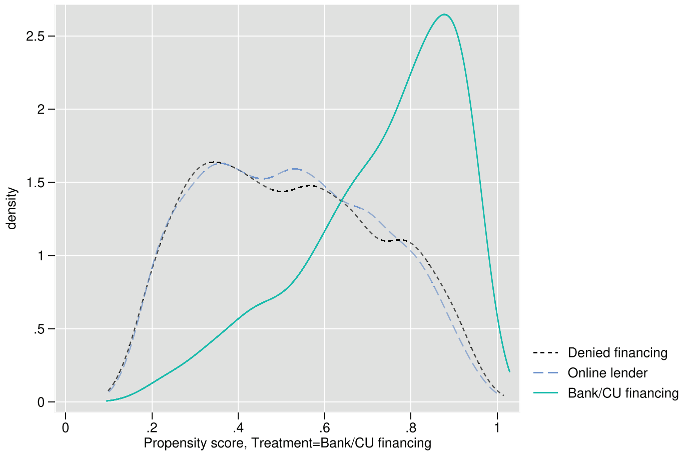
Finally, we included year dummy variables to account for other changes over time. This variable seems to primarily pick up the relative rise in online lending relative to bank lending. All else equal, the outcome of getting online financing is 12 percentage points more likely in 2018 than it was in 2016, with most of that effect being accounted for by offsetting reductions in the likelihood of being a bank borrower.

3.2 Are Online Lenders Expanding the Financing Options of Small Businesses?

The substantial differences seen in the probabilities reported in table 2 motivate the importance of the controls and the value of a model to assess lending decisions by banks and online lenders. We can use the associated propensity scores to evaluate the proportion of online-lender financing that could be substituting for bank financing rather than representing a new source of business financing. The relevant comparison uses the propensity of borrowers to receive bank financing given the full set of characteristics of each small business[8]:

[8] We group the financing received from large and small banks with credit union financing into the category of traditional financing. Credit unions remain a smaller actor in small business financing but are important enough to include: 8 percent of our businesses seeking financing received their first financing from a credit union.

Figure 1. Kernel Density ("overlap") Plots, Survey Years 2016–18



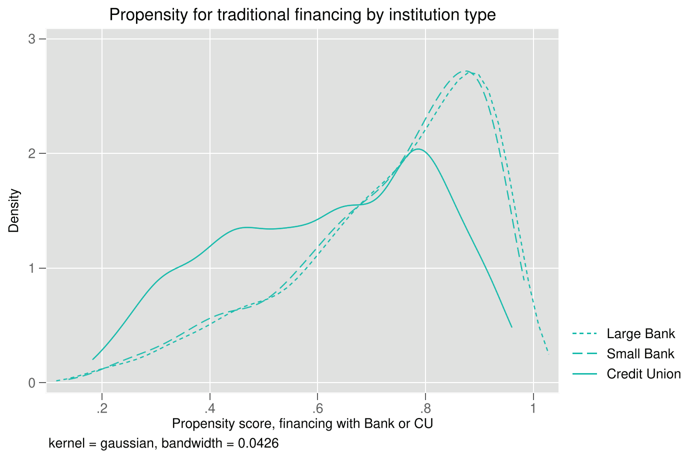
Notes: Predicted probabilities of being approved for bank/credit union financing shown for each treatment group. For full results of multinomial logit estimates, see table A.1.

$P(w = B|x_n)$. These propensities can then be compared for businesses that received online financing, those that received financing from banks, and those rejected for financing (figure 1).[9]

Not surprisingly, the majority of businesses that actually received financing from either large or small banks have propensity scores for traditional financing of above 0.70; the median propensity score for a business that received traditional financing is 0.77. In contrast, online lenders appear substantially more likely to provide credit to firms that the model expects to be denied credit. The median propensity score for businesses that use online-lender financing is 0.51, which is identical to the median propensity score of businesses that were denied credit. This means that half of those either using online financing or being denied financing were evaluated by the model as being in a region of characteristics where bank financing is uncommon.

[9]The estimates are smoothed by a Gaussian kernel density estimator to deemphasize small differences in estimated propensities that particularly appear when the model includes discrete variables.

Figure 2. Kernel Density Plots, Survey Years 2016–18



Notes: Predicted probabilities of being approved for bank/credit union financing shown for firms actually approved by a small bank, large bank, or credit union. For full results of multinomial logit estimates, see table A.1.

To formalize this point, we construct a measure of added lending activity (A) associated with the existence of online lenders. It sums the excess mass of the online lender outcome, whenever the density for online lenders is higher than traditional lenders:

$$A = \sum \left(f_{w=O}\left(z_d\right) - f_{w=B}\left(z_d\right)\right) \cdot I\left(f_{w=O}\left(z_d\right) > f_{w=B}\left(z_d\right)\right),$$

where $z_d(x) = P\left(w = B|x_d\right)$ and the densities, f, are estimated using a kernel density procedure. The summation can then be applied across the full data set. For the period of 2016 to 2018, we would estimate that 44 percent of businesses served by online lenders look unlikely to have been served by banks. This is a conservative estimate of the extra firms financed, because the entry and expansion of online lenders has likely also drawn in more businesses to apply for financing than would have been the case without the new option.

For figure 1 we grouped all of the existing traditional financing options together, but given the long-standing research on the roles of small banks and the relatively recent entry of credit unions into small business finance, it is worthwhile to compare these lenders. Figure 2 shows the densities of propensity scores for traditional financing by the type of institution that provided each business's first financing. This comparison is offered as a way to assess whether the banking options are similar. It is the case that small and large banks are essentially equally likely to provide financing at any given level of the propensity score. Figure 2 does reveal that credit unions more frequently lend to businesses with a lower propensity score for traditional financing. That said, the difference between these categories of lenders is much smaller than the difference between traditional financing and online lending.

4. Using Treatment Effects to Evaluate Financial Alternatives

The expansion of credit to small businesses is an important question, but policymakers and regulators are also interested in whether a credit source is beneficial and appropriate for the borrower. This is a hard assessment to make in the best of circumstances because we observe only one set of outcomes per firm, so the outcomes associated with a counterfactual funding alternative are never observed. Complicating matters is the fact that many small businesses have reasonably high rates of failure, regardless of whether they have borrowed or not. The SBCS does not follow firms, so we cannot measure failures or defaults, but it does include the businesses' assessments for revenue growth, employment growth, and satisfaction with financing after the lending outcome. Table 3 shows business expectations with no controls applied other than weighting to match population statistics. Without compositional controls, firms that received online financing have the most positive expectations about future firm growth for revenue, while firms that were denied financing had the strongest outlook for employment growth. This could be evidence of the value of online financing, but it could also reflect the role of sorting based on the age of the firm: younger (and riskier) firms expect more growth and are more willing to use online financing.

Differences in satisfaction levels across treatment groups are much more pronounced, with only 5.3 percent of firms that were denied financing being satisfied with their lender(s) compared with 37.7 percent among firms approved by fintech lenders, and 69.6 percent among firms approved by traditional bank lenders. These

Table 3. Treatment Group Comparison, Survey Years 2016–18

	Denied Financing	Online Lender	Bank/CU Financing
Outcomes of Interest			
Expects Future Revenue Growth (%)	75.8	76.9	73.2
N	1,376	1,004	4,904
Expects Future Employment Growth (%)	52.9	52.1	50.7
N	1,343	990	4,829
Satisfied with Lender (%)	5.3	37.7	69.6
N	1,243	1,001	4,873

Notes: Respondents are asked in separate questions how they expect revenue and the number of employees to change over the next 12 months with the option to select "Decrease," "No Change," or "Increase." Comparisons of each outcome of interest represent the percentage of respondents who selected "Increase." Of the firms in the Bank/CU financing treatment group, 164 were also approved for financing by a non-bank online lender after their approval by a bank lender. Of the firms in the Online financing group, 225 were also approved by a bank or credit union after their approval by an online lender.

differences are large, but again we should be concerned about the compositional differences.

4.1 Treatment Effects Estimators

Ideally, we would like to observe the counterfactual scenarios of each firm, that is to say, what the expectations of a firm denied financing would have been if it had been approved by an online lender and likewise if it had been approved by a traditional lender. However, by construction, we will never see all three financing treatments for the same owner because they are mutually exclusive. Furthermore, our data are not the product of a large-scale randomized experiment, which could make other important characteristics of the owner or firm asymptotically irrelevant. These weaknesses imply that confounding variation (like the age and profitability of the business) could affect the likelihood of observing a given financing treatment and, potentially, the outcomes of interest given a financing treatment.

To address these issues we apply semiparametrically estimated treatment effects given the likelihood that firms with specific characteristics are provided financing $w_i = O$, B, or D. Specifically, we will estimate potential-outcome means for all firms regardless of outcome, for receiving online financing $(E[Y_i | w_i = O])$, for receiving bank financing $(E[Y_i | w_i = B])$, and for seeking financing but being denied $(E[Y_i | w_i = D])$. Using these terms, we can evaluate an average treatment effect for online financing as $ATE(O) = E[Y_i | w_i = O] - E[Y_i | w_i = D]$ along with a parallel estimate for traditional bank financing, $ATE(B) = E[Y_i | w_i = B] - E[Y_i | w_i = D]$. Finally, we can also construct a relative treatment effect of online financing relative to bank financing: $RTE(O, B) = E[Y_i | w_i = O] - E[Y_i | w_i = B]$.

In our analysis we estimate these values using inverse probability weighting (IPW) and inverse-probability-weighted regression adjustment (IPWRA) as described in Imbens (2004) and Wooldridge (2015). IPW is simply the sample average of the outcome weighting by $\hat{p}(w, x_i)$ the estimated probability that observation i experiences treatment W:

$$\hat{\mu}(W) = N^{-1} \sum_{i=1}^{N} \frac{I(w_i = W) Y_i)}{\hat{p}(w, x_i)},$$

where I() is an indicator function.

Weighting by the inverse of the propensity for an outcome, w, given x_i, balances the observations across the full range of characteristics regardless of outcome. In our case, $\hat{p}(w, x_i)$ is implemented by the simple multinomial logit model discussed previously. An advantage of IPW is that assumptions about the nature of the outcomes with respect to covariates are limited, given an effective model of the probability of treatment.

IPWRA combines this weighting with regression-based adjustment for differences in outcomes based on the set of characteristics x_i solving the following minimization:

$$\hat{\mu}(W) = \min_{\alpha_1, \beta_1} \sum_{i=1}^{N} \frac{I(w_i = W)(Y_i - \alpha_1 - \beta_1 x_{i1}))^2}{\hat{p}(w, x_i)}.$$

While there is no particular justification for different control variables in the two steps, x_i and x_{i1} need not be identical. The IPWRA is a "doubly robust technique" in that it is asymptotically unbiased if either the model of treatment probabilities or the model of conditional means is correct (Wooldridge 2015).

Importantly, regardless of the estimation technique, reliable estimates of these values rely on two assumptions: (i) *unconfoundedness*, or conditional independence, which requires that treatment assignment be independent of the treatment effect when conditioned on appropriate control variables, and (ii) *overlap of the treatments*, which requires that the probability of observing a treatment value must be greater than 0 for all relevant x.

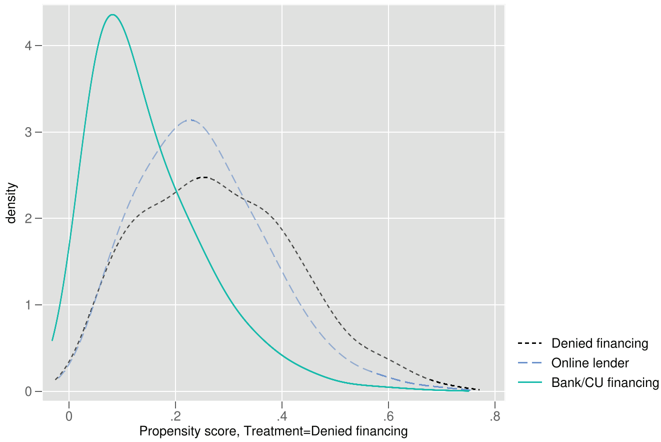
In the case of small business lending, firm-specific variables that are likely to alter the approval of loans are key controls that are likely to satisfy assumption (i). We intentionally included all reasonable variables available in the SBCS including revenue, profitability, age of firm, and the demographic characteristics of the business owner. These variables should inform predictions of financing approval and were shown in table 2 to be important factors.

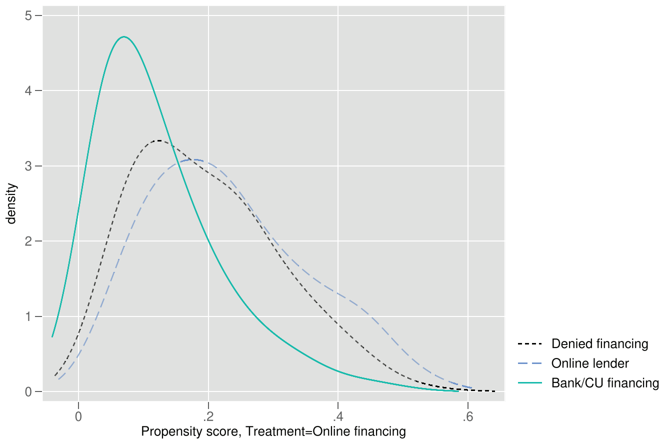
4.2 Overlap of Treatments

For the measurement of the businesses' response to the two lending treatments, it is important to confirm that there are relevant observations to compare according to the treatment model. The fundamental issue is that if online borrowers were always riskier than any observed bank borrower, then it would require strong assumptions to estimate what their outcomes would have been had they received a bank loan. A lack of overlap makes it particularly difficult to reliably predict the counterfactual scenarios that are needed to obtain accurate treatment effects.

The plot in figure 1, while informative about the expansion of credit, is called an overlap plot in the treatment effects literature. It shows the distribution of predicted probabilities of receiving each financing treatment and of denial for firms according to their propensity to receive bank and credit union financing. From an overlap perspective, we want to see that there are observations experiencing each outcome for any given propensity of bank and credit union

Figure 3. Kernel Density ("overlap") Plots, Survey Years 2016–18





Notes: Predicted probabilities of being denied financing and receiving online financing, respectively, shown for each treatment group. For overlap plot of receiving bank/credit union financing, see figure 1. For full results of multinomial logit estimates, see table A.1.

financing. This is generally the case, with the only possible exceptions coming at the far tails of the densities, when none of the outcomes are likely. This is excellent for being able to estimate treatment effects across the full range of firms in the data. Figure 3 completes the set of overlap plots, by showing the plots based on propensities to receive online financing and to be denied financing. The plot on the bottom displays the estimated density of the predicted probabilities for receiving online financing. The plot on the top shows the propensity of denial for the different treatment outcomes. There is again substantial overlap through much of the distribution, although bank borrowers crowd to the left (low online or denial probability) in figure 3, making conclusions about riskier borrowers less robust. Importantly, while profitability, revenues, and so on have a very strong effect on financing treatment, the observed firms do not have most of their mass at opposite ends of the distribution—but rather each example appears to have substantial overlapping cases for each treatment.

5. Effects of Banking Alternatives on Firm Outcomes

5.1 Loan Size Differences

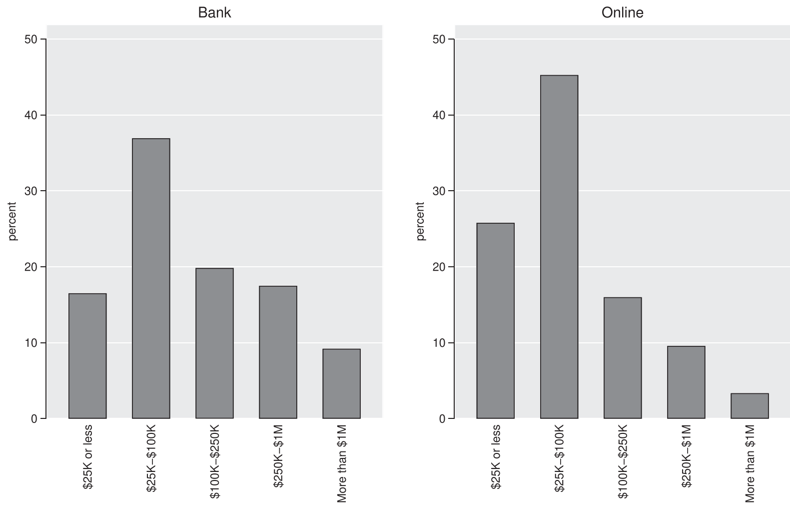
An important difference in alternative lending channels is the size of the loan offered. In order to support a higher survey response rate, the SBCS asks for loan amounts in terms of five bins. The loan application amounts are clearly lower for online loans than for bank loans, but again this could reflect firm differences rather than any difference in the treatment channel.

To counter the tendency for firm characteristics to distort the lender differences, we applied inverse probability weighting to the histograms to produce an estimate of the loan size distribution once the composition is accounted for. Figure 4 shows that after compositional adjustments, applicants at online lenders still make smaller requests, with more than 70 percent of loan applications requesting less than $100,000 versus roughly 56 percent of adjusted loan applications with traditional lenders.

5.2 Revenue and Employment Growth

Businesses typically can use loan proceeds to make capital purchases to support operations, so we should expect approved businesses to anticipate revenue growth and potentially employment growth, although the unobserved terms of the financing may also hinder the

Figure 4. Distribution of Loan Size after Inverse Probability Weighting



growth of firms. Future revenue growth and capital expenditures are measured by the owner's short-term expectations (next 12 months); while not ex post, these measures may show differences in likely outcomes as a result of the financing channel chosen.

In table 4, we report the composition-adjusted potential-outcome mean for being denied financing and then the treatment effects for receiving online or bank financing, followed by the relative treatment effect between online and bank financing. First it is worth noting that regardless of the estimator, the majority of the composition-balanced businesses (75.2 percent) expect revenue and employment growth even if they were denied financing. The results indicate that there is no statistically significant difference in expected revenue growth for either bank or online financing options relative to being denied financing. However, the difference between online and bank financing on revenue and employment growth are statistically significant in all cases.

We might have anticipated online loans being less effective than bank loans either because they are smaller or because their terms might differ unfavorably, but this conclusion is rejected in our analysis. Still, the estimated impact of fintech financing on a firm's

Table 4. Likelihood of Reporting Future Firm Growth or Satisfaction with Lender, by Model Specification and Treatment Group, Survey Years 2016–18

	Potential-Outcome Mean	Average Treatment Effect		
	Denied Financing	Online vs. Denied	Bank/CU vs. Denied	Bank/CU vs. Online
Expects Future Revenue Growth				
IPW	0.752	0.029	−0.013	−0.043**
		(0.028)	(0.023)	(0.021)
IPWRA	0.750	0.032	−0.010	−0.041**
		(0.024)	(0.019)	(0.021)
Expects Future Employment Growth				
IPW	0.527	0.036	−0.018	−0.054**
		(0.032)	(0.026)	(0.024)
IPWRA	0.518	0.043	−0.009	−0.052**
		(0.030)	(0.023)	(0.025)
Satisfied with Lender				
IPW	0.053	0.360***	0.619***	0.259***
		(0.026)	(0.015)	(0.027)
IPWRA	0.055	0.355***	0.616***	0.261***
		(0.025)	(0.015)	(0.026)

Notes: Standard errors are in parentheses. ***, **, and * denote significance at $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Of the firms in the Bank/CU financing treatment group, 164 were also approved for financing by a nonbank online lender after their approval by a bank lender. Of the firms in the Online financing group, 225 were also approved by a bank or credit union after their approval by an online lender.

self-reported business outlook in table 4 is somewhat ambiguous, in that firms in the bank and online treatment groups do not perform statistically differently from firms that were denied financing.

5.3 Satisfaction with the Lending Experience

The SBCS asks firms whether they are satisfied, dissatisfied, or neutral with regard to the lender applied to. Respondents are specifically prompted as they answer the question to consider the application process as well as terms of repayment for lenders that approved their application. The descriptive statistics shown in table 3 reveal that there are significant differences in satisfaction levels with the type of lender businesses used, but this result could also be substantially affected by the characteristics of the treated samples.

After IPW adjustments for composition, just 5.3 percent of applicants for credit are satisfied after a financing denial. Adjusted satisfaction levels are higher for online lenders, with a treatment effect of 36 percentage points, which is statistically different from the denial outcome. Bank financing results in a treatment effect on satisfaction of 61.9 percentage points, which is again statistically significant. Thus the difference after compositional adjustments between satisfaction with online lenders and banks is 25.9 percentage points, with firms more likely to be satisfied with bank lender(s) than with online financing. The same qualitative results are maintained when the IPWRA procedure is applied.

These results suggest room for improvement for online lenders in their customer satisfaction levels. To further investigate where this difference comes from, the SBCS includes an identification of the type of online lender in 2017 and 2018. Table 5 shows the breakdown of satisfaction rates by type of online lender. We neither adjust for composition nor calculate standard errors given the smaller numbers of survey respondents, but merchant cash advance lenders stand out for their relatively low satisfaction figures. That said, average satisfaction rates for all types of online lenders are still below the bank average of 69.6 percent (unadjusted, from table 3).

The 2017 and 2018 surveys also follow up with a question on challenges experienced during the application process. Table 6 shows that the top three challenges reported by businesses applying for

Table 5. Types of Online Lenders Applied to by Applicants in Online Treatment Group, Survey Years 2017–18

	# of Applicants	% of Applicants	% of Applicants Satisfied
Direct Lender	360	57.9	41.9
Retail/Payments Processor	90	14.5	45.6
Peer-to-Peer Lender	58	9.3	39.7
Merchant Cash Advance Lender	87	14.0	26.7
Other	28	4.5	53.6

Notes: Frequency counts and percentages are unweighted. For a survey respondent's two most recent credit applications—if one or both applications were with an online lender—the respondent is asked: *Which type of online lender did you apply to?* The question was not included in the 2016 survey. Percentages in column 2 do not add to 100 because firms were only asked the given question if their application was among their two most recent applications. "Direct Lender" includes OnDeck, Kabbage, Blue Vine, etc.; "Retail/Payments Processor" includes Paypal Working Capital, Square Capital, Amazon Capital Services, etc.; "Peer-to-Peer Lender" includes LendingClub, Funding Circle, etc.; "Merchant Cash Advance Lender" includes RapidAdvance, CAN Capital, BizFi, etc.

Table 6. Challenges Experienced during Application Process, Survey Years 2017–18

	Online Treatment Group		Bank/CU Treatment Group	
	# of Applicants	% of Applicants	# of Applicants	% of Applicants
High Interest Rate	204	32.8	128	4.8
Unfavorable Repayment Terms	118	19.0	53	2.0
Long Wait for Decision	28	4.5	161	6.1
Difficult Application Process	29	4.7	124	4.7
Lack of Transparency	32	5.1	35	1.3
Other Challenges	15	2.4	81	3.1
Experienced No Challenges	114	18.3	745	28.2

Notes: Frequency counts and percentages are unweighted. For a survey respondent's two most recent credit applications, the respondent is asked: *Did your business experience any challenges in applying for the [given product]? Select all that apply.* The question was not included in the 2016 survey. Percentages in columns 2 and 4 do not add to 100 because firms were only asked the given question if their application was among their two most recent applications.

online loans are high interest rates (32.8 percent), unfavorable repayment terms (19 percent), and lack of transparency (5.1 percent). Challenges for bank borrowers are all lower, but their top three challenges are the long wait for decision (6.1 percent), high interest rates (4.9 percent), and the difficult application process (4.7 percent).

6. Conclusion

While there are still many open questions about the value and effects of online business lending, particularly in the long run, our results based on Small Business Credit Survey data provide some useful insights into this expanding sector of the financial market. One important finding is that the businesses that pursue bank or online options or are denied credit are not equivalent entities. Thus, to accurately compare the lending outcomes of these businesses, adjustments have to be made to account for compositional differences. We use a treatment effects approach, which, although it cannot solve underlying sampling defects, can help to evaluate the role of different lending outcomes when the characteristics of firms vary substantially between those outcomes.

The 2018 Treasury report notes the potential for fintech to expand credit "to borrower segments that may not otherwise have access to credit through traditional underwriting approaches." But the Treasury report is able to provide little evidence to support this conjecture. We show that the entry of online lenders has meaningfully altered the range of firms that receive financing, with 44 percent of online borrowers not likely to receive credit from traditional sources. Overall, our evidence suggests that the characteristics of online borrowers are closer to those of businesses rejected for credit than those served by banks, which increases the financing available in the small business financing marketplace.

On the effectiveness of online credit, we find that growth expectations from online lenders are better than those for bank borrowers. This is despite controlling for compositional differences that are strongly predictive of which firms receive credit from banks and from fintech firms, including profitability, revenue growth, and self-reported credit scores of the business or owner. This result is supportive of the position that financial innovation, at least in this case, has been beneficial to borrowers, particularly when combined with the greater financial inclusion shown by fintech lenders.

While the effects on expectations for growth are relatively small, the ordering of customer satisfaction across lender types is clear: bank borrowers are more satisfied than online borrowers, who are more satisfied than businesses that were denied credit. This may point to issues that both the lenders and regulators may want to address as online lending continues to expand.

Table A.1. Multinomial Logit Regressions for Probability of Receiving Financing (i.e., the treatment models used as inputs into outcome models)[a]

	Revenue Model	**Employment Model**	**Satisfaction Model**	**Application Amount Model**
Online Lender				
Employees (Continuous)	−0.000	0.002	−0.001	−0.001
	(0.005)	(0.006)	(0.006)	(0.006)
Employees Squared (Continuous)	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age				
3–5 Years	0.649**	0.611**	0.650**	0.646**
	(0.209)	(0.211)	(0.213)	(0.212)
6–10 Years	0.612**	0.611**	0.660**	0.641**
	(0.212)	(0.214)	(0.216)	(0.216)
11–15 Years	0.664**	0.606*	0.733**	0.726**
	(0.236)	(0.240)	(0.241)	(0.241)
16–20 Years	0.690*	0.699*	0.691*	0.676*
	(0.282)	(0.288)	(0.285)	(0.285)
21+ Years	0.255	0.251	0.278	0.291
	(0.232)	(0.235)	(0.235)	(0.235)
Revenue Size				
$1M+	0.085	0.090	0.056	0.057
	(0.166)	(0.168)	(0.170)	(0.171)
Profitability				
Profitable	0.211	0.186	0.252	0.267*
	(0.131)	(0.133)	(0.134)	(0.135)
Minority-Owned Business				
Minority	−0.190	−0.193	−0.233	−0.231
	(0.161)	(0.163)	(0.164)	(0.164)

(*continued*)

Table A.1. (Continued)

	Revenue Model	**Employment Model**	**Satisfaction Model**	**Application Amount Model**
Female-Owned Business				
Female	0.170	0.174	0.208	0.191
	(0.146)	(0.146)	(0.148)	(0.148)
Did Not Respond	−0.976***	−0.983***	−0.420	−0.435
	(0.254)	(0.262)	(0.277)	(0.277)
Veteran-Owned Business				
Veteran	0.339	0.353	0.317	0.316
	(0.204)	(0.206)	(0.205)	(0.205)
Did Not Respond	−0.340	−0.324	−0.285	−0.281
	(0.182)	(0.186)	(0.186)	(0.187)
Medium/High Credit Risk	0.035	0.041	0.072	0.077
	(0.129)	(0.131)	(0.131)	(0.131)
Revenue Growth in Past 12 Months				
Increased	0.017	0.048	0.037	0.033
	(0.132)	(0.133)	(0.134)	(0.134)
Change in Unemployment Rate (Continuous)				
2015–16	0.050	0.006	0.073	0.072
	(0.169)	(0.170)	(0.172)	(0.172)
2016–17	0.097	0.096	0.035	0.040
	(0.223)	(0.225)	(0.228)	(0.229)
2017–18	0.138	0.041	0.098	0.126
	(0.236)	(0.238)	(0.240)	(0.239)
Survey Year Dummy				
2017	0.390*	0.395*	0.362*	0.367*
	(0.158)	(0.160)	(0.161)	(0.161)
2018	0.770***	0.780***	0.772***	0.772***
	(0.152)	(0.153)	(0.155)	(0.155)
Constant	−0.954***	−1.024***	−1.023***	−1.007***
	(0.279)	(0.283)	(0.284)	(0.284)

(continued)

Table A.1. (Continued)

	Revenue Model	**Employment Model**	**Satisfaction Model**	**Application Amount Model**
Bank/CU				
Employees (Continuous)	0.011**	0.012**	0.011**	0.011**
	(0.004)	(0.004)	(0.004)	(0.004)
Employees Squared (Continuous)	−0.000**	−0.000**	−0.000**	−0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Age				
3–5 Years	−0.196	−0.217	−0.211	−0.232
	(0.169)	(0.171)	(0.173)	(0.173)
6–10 Years	−0.032	−0.037	0.005	−0.012
	(0.170)	(0.173)	(0.175)	(0.175)
11–15 Years	−0.049	−0.109	0.001	−0.001
	(0.184)	(0.186)	(0.190)	(0.191)
16–20 Years	0.368	0.387	0.354	0.350
	(0.221)	(0.227)	(0.225)	(0.225)
21+ Years	0.306	0.277	0.301	0.320
	(0.180)	(0.182)	(0.183)	(0.185)
Revenue Size				
$1M+	0.740***	0.735***	0.719***	0.718***
	(0.125)	(0.126)	(0.129)	(0.130)
Profitability				
Profitable	0.755***	0.759***	0.792***	0.801***
	(0.105)	(0.106)	(0.109)	(0.109)
Minority-Owned Business				
Minority	−0.313*	−0.318*	−0.358*	−0.357*
	(0.138)	(0.140)	(0.141)	(0.141)
Female-Owned Business				
Female	0.153	0.133	0.189	0.177
	(0.125)	(0.126)	(0.127)	(0.127)
Did Not Respond	−0.387*	−0.382	0.099	0.066
	(0.192)	(0.198)	(0.231)	(0.232)

(*continued*)

Table A.1. (Continued)

	Revenue Model	Employment Model	Satisfaction Model	Application Amount Model
Veteran-Owned Business				
Veteran	−0.081	−0.091	−0.138	−0.135
	(0.165)	(0.168)	(0.168)	(0.168)
Did Not Respond	−0.255	−0.261	−0.199	−0.195
	(0.145)	(0.147)	(0.151)	(0.152)
Medium/High Credit Risk	−0.951***	−0.935***	−0.890***	−0.890***
	(0.103)	(0.104)	(0.105)	(0.105)
Revenue Growth in Past 12 Months				
Increased	0.151	0.153	0.163	0.171
	(0.104)	(0.105)	(0.107)	(0.108)
Change in Unemployment Rate (Continuous)				
2015–16	0.475***	0.452**	0.505***	0.498***
	(0.137)	(0.139)	(0.142)	(0.142)
2016–17	−0.147	−0.171	−0.221	−0.215
	(0.194)	(0.195)	(0.200)	(0.201)
2017–18	0.538**	0.516**	0.468*	0.501**
	(0.185)	(0.186)	(0.189)	(0.188)
Survey Year Dummy				
2017	−0.112	−0.118	−0.120	−0.126
	(0.120)	(0.121)	(0.123)	(0.124)
2018	−0.165	−0.153	−0.149	−0.164
	(0.124)	(0.125)	(0.127)	(0.128)
Constant	1.195***	1.173***	1.110***	1.131***
	(0.219)	(0.221)	(0.224)	(0.224)

[a]Variable specification is identical for all treatment models, but coefficient estimates vary given that the sample size varies depending on the outcome question asked in the survey.

Notes: Coefficient estimates are relative to the base outcome of not receiving any financing. Standard errors are in parentheses. ***, **, and * denote significance at $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Credit risk is determined by the self-reported business credit score or personal credit score, depending on which is used to obtain financing for their business. If the firm uses both, the higher risk rating is used. Low credit risk is an 80–100 business credit score or a 720+ personal credit score. Medium credit risk is a 50–79 business credit score or a 620–719 personal credit score. High credit risk is a 1–49 business credit score or a <620 personal credit score.

References

Balyuk, T., A. N. Berger, and J. Hackney. 2020. "What is Fueling FinTech Lending? The Role of Banking Market Structure." Working Paper. http://dx.doi.org/10.2139/ssrn.3633907.

Basel Committee on Banking Supervision. 2018. *Sound Practices: Implications of Fintech Developments for Banks and Bank Supervisors.* Bank for International Settlements. https://www.bis.org/bcbs/publ/d431.htm.

Berger, A., N. Miller, M. Petersen, R. Rajan, and J. Stein. 2005. "Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks." *Journal of Financial Economics* 76 (2): 237–69.

Berger, A. N., and G. F. Udell. 2002. "Small Business Credit Availability and Relationship Lending: The Importance of Bank Organisational Structure." *Economic Journal* 112 (477): F32–F53.

Darden, K., N. Dixit, and T. Mason. 2018. "2018 US Fintech Market Report." S&P Global Market Intelligence. https://www.spglobal.com/marketintelligence/en/documents/2018-us-fintech-market-report.pdf.

DeYoung, R., S. Frame, D. Glennon, and P. Nigro. 2011. "The Information Revolution and Small Business Lending: The Missing Evidence." *Journal of Financial Services Research* 39 (1–2): 19–33.

DeYoung, R., D. Glennon, and P. Nigro. 2008. "Borrower–Lender Distance, Credit Scoring, and Loan Performance: Evidence from Informational-Opaque Small Business Borrowers." *Journal of Financial Intermediation* 17 (1): 113–43.

Federal Reserve. 2019. "2018 Small Business Credity Survey: Report on Employer Firms." Special Report.

———. 2020. "PPPLF Transaction-Specific Disclosures (September 8, 2020)." https://www.federalreserve.gov/monetarypolicy/ppplf.htm.

Goldstein, I., J. Jagtiani, and A. Klein. 2019. "FinTech and the New Financial Landscape." *Banking Perspectives* (Bank Policy Institute). https://www.bankingperspectives.com/fintech-and-the-new-financial-landscape/.

Imbens, G. 2004. "Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review." *Review of Economics and Statistics* 86 (1): 4–29.

Jagtiani, J., and C. Lemieux. 2018. "Do Fintech Lenders Penetrate Areas that Are Underserved by Traditional Banks?" *Journal of Economics and Business* 100 (November-December): 43–54. https://doi.org/10.1016/j.jeconbus.2018.03.001.

———. 2019. "The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the LendingClub Consumer Platform." *Financial Management* 48 (4): 1009–29. https://doi.org/10.1111/fima.12295.

Mach, T. L., C. M. Carter, and C. R. Slattery. 2014. "Peer-to-Peer Lending to Small Businesses." Finance and Economics Discussion Series No. 2014-10, Board of Governors of the Federal Reserve System.

Philippon, T. 2018. "The FinTech Opportunity." Working Paper, Wharton Pension Research Council. https://repository.upenn.edu/prc_papers/1.

Robb, A. M., and D. T. Robinson. 2014. "The Capital Structure Decisions of New Firms." *Review of Financial Studies* 27 (1): 153–79. https://doi.org/10/1093/rfs/hhs072.

U.S. Department of the Treasury. 2016. "Opportunities and Challenges in Online Marketplace Lending." White Paper.

———. 2018. "A Financial System That Creates Economic Opportunities: Nonbank Financials, Fintech, and Innovation."

U.S. Small Business Administration. 2020. "Paycheck Protection Program (PPP) Report: Approvals through 08/08/2020." https://home.treasury.gov/system/files/136/SBA-Paycheck-Protection-Program-Loan-Report-Round2.pdf.

Wiersch, A. M., and S. Shane. 2013. "Why Small Business Lending Isn't What It Used to Be." Economic Commentary No. 2013-10, Federal Reserve Bank of Cleveland.

Wooldridge, J. M. 2015. *Introductory Econometrics: A Modern Approach.* 6th Edition. Boston: Cengage Learning.