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"Fintech" is a rapidly expanding segment of the financial market that is receiving much attention from investors and increasing regulatory scrutiny. While the attention is rising, very little is known about the performance of these lending sources on the outcomes of small businesses that make use of them. The Federal Reserve's 2015 Small Business Credit Survey has data on the experiences of business owners with this new funding source and can provide some useful insights into this expanding sector, if compositional differences among the businesses that get bank loans, those that get fintech loans, and those that are denied credit are accounted for. We apply an inverse-probability-weighted regression adjustment and inverse-probability weighting from the treatment effects literature to adjust for compositional difference. We find: (1) online borrowers have characteristics that make them very much like the businesses who were denied credit, (2) the results for online lenders are hard to distinguish from either receiving no financing or receiving a bank loan, and (3) bank borrowers are more satisfied than online borrowers who are more satisfied than businesses who were denied credit. These results should inform the policy discussion on fintech and point to the need for clearer results on the effectiveness of online lenders to small businesses.

JEL Codes: G21, G23, G28, C31.

Keywords: Small business lending, online alternative lenders, fintech, firm growth.

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1 Introduction

'Fintech' is used to describe the rapidly growing set of technology firms providing alternatives to traditional banking services, most often exclusively in an online environment. 'Fintech' firms compete in financial services markets ranging from consumer payment, asset management, and lending and they attracted $19.1 billion in investments in 2015 and another $17.8 billion through the third quarter of 2016, according to KPMG (2016a; 2016b). Despite the substantial investments and growing activity levels, the sector has been lightly regulated and research on the effects of 'fintech' as a financing alternative is only recently begun to occur (US Treasury 2016; Jagtiani and Lemieux 2016; Wiersch and Lipman 2015; Mach et al 2014; Morse 2015).

According to the Federal Reserve's 2015 Small Business Credit Survey Report on Employer Firms (referred to as the "2015 Report" in the reminder of this paper) about 20% of small businesses that sought financing applied with a fintech or online lender[1], versus 52% from small banks and 42% from large banks. Among firms with less than $100,000 of revenue, 30% of firms applied with an online lender. Clearly, it would be helpful for businesses and regulators to know how these new lending alternatives have been working for the small businesses that use them.

We will compare impacts of online lending with traditional finance, where research has long focused on the role of banks in the financing and growth of small businesses. Community banks have long been an important source of credit for small businesses (Berger and Udell 2002; Wiersch and Shane 2013). 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 for small businesses (Deyoung et al 2011; Deyoung et al 2008; Berger et al 2005). As far as we know there is no equivalent literature on online alternative lenders, which began to play an increasingly important role in small business lending over the last few years.

While the value of research on fintech lending to small business is high, the available data on the experiences of borrowers is very limited. Partnerships among Federal Reserve Banks sought to address this shortcoming by including questions on online lenders in small business surveys that have been conducted in some form since 2010 to document the financial needs and outcomes of small businesses and the extent to which access to credit might be hindering the ability of a small business to expand. Unfortunately, this survey is not a stratified random sample of small business and covers primarily the small businesses in the surveying Federal Reserve Districts. The 2015 report indicates that online loans do help the self-reported growth

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

prospects of respondents but successful borrowers are more satisfied with traditional sources of financing.

While these are interesting results that might prove useful to potential borrowers and regulators alike, apart from sample weights to make the sample more representative of the population distribution of firms they include no controls and the exposure and borrowing alternatives of the respondents is likely to vary substantially based on their size, age, revenues, and other characteristics of the management and of the firm. While the geographic limitations of the survey cannot be addressed, this paper will use the semi-parametric modeling of treatment effects literature to more robustly access the impacts and customer satisfaction differences associated with online lenders for representative borrowers. In addition, we will explore the impacts and satisfaction figures for minority-owned businesses.

2 Small Business Credit Survey Design and Coverage

The Small Business Credit Survey (SBCS) is a survey of establishments[2] with less than 500 employees designed and implemented by participating Federal Reserve Banks that 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 impacts firm operation and growth and to help service providers in shaping programs that benefit small business owners.[3]

In 2015, the Federal Reserve Banks of Atlanta, Boston, Cleveland, New York, Philadelphia, Richmond, and St. Louis partnered with over 100 organizations—including chambers of commerce, industry associations, development authorities, and other civic and non-profit partners—to field the SBCS online between September 28 and November 27. The sampling frame consists of 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 email from partner organizations on behalf of the respective Federal Reserve Bank requesting their participation and providing a URL link to the survey.[4] 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 emails to businesses on their distribution list until the

[2] In the remainder of the paper, we use the terms "firm" and "business" interchangeably to refer to surveyed establishments.

[3] See https://www.newyorkfed.org/smallbusiness/small-business-credit-survey-employer-firms-2015 and https://www.clevelandfed.org/community-development/small-business/about-the-joint-small-business-credit-survey.aspx for more information.

[4] Some partners are national organizations and may pull in responses from businesses in states outside of participating Federal Reserve districts (e.g., California, Texas, etc.). Additionally, some Federal Reserve Banks only work with partners in one or a few states in their district, and therefore responses are only received from businesses in those select states.

survey officially closes. In total, responses were collected from 5,420 firms across 26 states. We use data only on employer firms, reducing the sample to 3,459 respondents. Of these, around 1,198 to 1,211 firms (depending on the response rate of the outcome being measured) fall into one of our three treatment groups and are thus eligible for our analysis.

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. If these demographic variables affect the lender a small business chooses to borrow from or expectations about future firm growth, estimates from these data would likely suffer from endogenous sampling—which as Manski and Lerman (1977) show generally results in inconsistent parameter estimation. In order to correct for gross sampling deviations from population data, the SBCS employs a ratio adjustment weighting method along the demographic dimensions of 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.

While the decision to weight data in the case of estimating population descriptive statistics is relatively straightforward, more caution is advised when performing estimation of causal effects, as in the current analysis, in which case weighting the data could actually lead to a less efficient estimator (Solon et al. 2013). Our semiparametric techniques are designed to flexibly account for further, correlated differences in firm demographic and other factors altering the variables of interest. In addition, our analysis will also explore the robustness of all results by repeating the analysis weights excluded.

Basic characteristics of the SBCS sample suggest that in general younger firms with fewer employees and less revenue are more likely to take a loan from an online lender (Table 1). In terms of industry, firms in healthcare, administrative services, and retail are the most common customers for fintech products. A larger proportion of firms operating at a loss also tend to turn to online lenders compared to firms receiving loans from traditional lenders, as do minority-, women-, and veteran-owned businesses. These basic patterns hold in both the unweighted and weighted samples.

[5] Most econometric studies instead weight by an observation's inverse probability of selection. The SBCS poses certain limitations in this regard because the entire sample frame is not known. See Table A1 for comparisons of the weighted and unweighted sample to population characteristics. Table A2 provides a description of the sample weight.

3 Evaluating the Impact of Financial Alternatives for Small Businesses

The outcomes for revenue growth, employment growth, and satisfaction with financing are the focus of this analysis. They are shown in Table 2 with no controls applied other than the weighting to match population statistics. Based on the unweighted sample, firms that are denied financing are the least likely to report future growth, whether in terms of revenue or employment—though the differences are not large. In contrast, firms receiving fintech financing are the most likely to report positive expectations about future growth. After applying weights to the data, patterns shift to where it appears, perhaps surprisingly, that firms denied financing have the most positive expectations about future firm growth, especially in terms of revenue. Still, overall differences in expectations across treatment groups are not large and in either the unweighted or weighted case we cannot conclude that the raw differences in survey results constitute a real impact of receiving certain types of financing or not on expected growth.

Differences in satisfaction levels across treatment groups are much more pronounced, with only 6.6% of firms denied financing being satisfied with their lender(s) compared to 45% among firms approved by fintech lenders and 79.2% among firms approved by traditional bank lenders. This pattern largely remains unchanged in the weighted dataset.

Comparison of uncontrolled outcomes can be misleading. 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 a online lender and likewise if it had been approved by a traditional lender. Additionally, treatment status could be related to factors that also affect expectations about firm growth. For example, younger firms might have a lower chance of receiving financing and they might also be more likely to anticipate future growth compared to older more established firms. In this case, we would be picking up the confounding effect of age on firm growth expectations across treatment groups and unable to measure the true effect of financing alternatives. In Section 3.1, we describe two estimation techniques designed to mimic one or both of these processes in order to obtain more reliable results.

We seek to estimate the average treatment effect of financing alternatives on a random firm for the performance of lending on three outcomes as reported by the small business owners. Ideally, we would like to observe firms with fintech financing, traditional bank financing, and receiving no financing. 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/firm asymptotically irrelevant. These weaknesses imply that confounding variation (like the age and profitability of the business/owner) could impact the likelihood of observing a given financing treatment and, potentially, the outcomes of interest given a financing treatment.

We apply the literature of semi-parametrically 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 firms with their characteristics set equal to an appropriate benchmark level, $X = x$, who received online financing only ($E[Y_i(O)|X = x, w_i = O]$), firms who received bank financing ($E[Y_i(B)|X = x, w_i = B]$), and those firms who sought financing but were denied ($E[Y_i(D)|X = x, w_i = D]$).Using these terms we could evaluate an average treatment effect for online financing as $ATE(O) = E[Y_i(O)|X = x, w_i = O] - E[Y_i(D)|X = x, w_i = D]$ along with a parallel estimate for traditional bank financing, $ATE(B) = E[Y_i(B)|X = x, w_i = B] - E[Y_i(D)|X = x, w_i = D]$. Finally we can also construct a relative treatment effect of online financing relative to bank financing, $RTE(O, B) = E[Y_i(O)|X = x, w_i = O] - E[Y_i(B)|X = x, w_i = B]$.

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 $\hat{p}(w, x_i)$ an estimate that observation *i* experiences treatment *w*. Which in our case is implemented by a simple multinomial logit model:

$$\hat{\mu}(W) = N^{-1} \sum_{i=1}^{N} \frac{I(w_i = W) Y_i}{\hat{p}(w, x_i)}, \text{ where I() is an indicator function.}$$

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 difference in outcomes based on set of characteristics x 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: 1. Unconfoundedness or conditional independence which requires that treatment assignment be independent of the treatment effect when conditioned on appropriate control variables. 2. Overlap of the treatments at X=x, which requires that probability of observing a treatment value must be greater than zero for all X.

In the case of small business lending, firm-specific controls for variables that are likely to alter the approval of loans will be key controls, because observed treatment will depend on these variables. The small business survey has a wealth of variables (including, revenue, profitability, age of firm, and the demographic characteristics of the business owner) that should inform predictions of financing approval. In addition, it is important to have some variation that is plausibly exogenous to the acceptance/approval of financing alternatives. In this case we can appeal to state differences in the availability of community banking options and online funding options. The bottom panel of Table 2 shows that the share of community banks in a given state's market substantially alters the probability of bank financing. In states where community banks have less than a quarter share of the state's branches, 57.8% of small businesses in our sample receive bank financing versus 83.5% in states where over half of branches are community banks. While this evidence points to important state differences, which are also supported by potential regulatory differences, our approach is specifically designed to make sure that other significant controls (revenue, profitability, tenure, sector, etc.) are accounted for in the statistical analysis. Any identified differences in business responses should be independent of the controlled-for characteristics of the small businesses respondents in different states. Throughout our analysis we will also pay careful attention to the empirical overlap of treatments on a range of variables to show that our estimates are appropriate.

4 Adoption of banking alternatives

4.1 Which firms receive which financing?

Firm characteristics are likely to affect whether and what type of financing is received as well as the outcome of interest (e.g., expectations about future firm growth), so we cannot simply compare the sample mean outcome to measure the impact of financing alternatives. Implementing either IPW or IPWRA estimation techniques to control for confounding effects of characteristics entails fitting a logit model to predict the probability of a firm's financing status. We specify a firm's financing status as a function of employee size, age, industry, revenue, profitability, and the demographic variables minority owned, woman owned, and/or veteran owned. Employee size and age are continuous variables while all other covariates are categorical. Each estimation requires a separate logit, because of small sample differences and to account for the model differences, but the results (fully shown in Table A3) are very similar across models.

Table 3 focuses on the key points of differences between firms' financing status. Not surprisingly, the age of the firm, its revenue and profitability, and the demographic characteristics of the owner all help to predict treatment selection. The values shown in Table 3 are the marginal effect of a variable on the financing status: denied financing, online financing, and bank financing. Bank financing is the more likely arrangement for older, more profitable firms with larger revenue streams relative to the other financing cases. With the excluded category being firms who were operating at a loss (not uncommon among these businesses), profitability is associated with a 20 percentage point increase in the likelihood of bank financing and significantly lower likelihood of either being denied financing (-8 percentage points) or receiving online financing (-11.6 percentage points). Revenue, profitability and age of the firm are, of course, all correlated but we are aiming for flexible controls such that combinations of these characteristics are not the source of the differences in reported outcomes. In addition, minority ownership tends to decrease a firm's chance of receiving bank financing relative to being denied financing. While the patterns may not be surprising for the small firms of interest in the analysis, these patterns are also very likely to impact the firms' outlooks.

4.2 Overlap comparisons

The substantial difference seen in probabilities shown in Table 3 motivate the importance of the controls, but it is also important to confirm that each observation has a positive likelihood of obtaining each of the three treatments according to the treatment model. If this is not the case, it will be difficult to reliably predict the counterfactual scenarios (IPWRA) or calculate the weighted mean outcomes (IPW) that are needed to obtain the desired treatment effects.

The overlap plots in Figure 1 show the distribution of predicted probabilities of receiving each financing treatment for firms according to their propensity score (the expected likelihood for a firm of given characteristics to receive a specified outcome). For example, the plot on the top right displays the estimated density of the predicted probabilities for receiving online financing for each firm who actually received no financing, bank financing, and online financing. The figures that are shown are clearly related and can look approximately like mirror images because the three states account for all of the observations. A full set of combinations is shown in Figure A1, where the rows of Figure A1 repeat the overlap analysis for three outcomes: being denied financing, receiving online financing, and receiving bank financing.

Importantly, while profitability, revenues, etc. 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. Perhaps the most complicated case is for receiving online financing. Given the smaller number of firms that we observe to receive online financing, probabilities of receiving online financing have lower values even for those who ultimately received it. Most firms have a propensity score less than 0.2 and none have a score greater than 0.5. But even in this case, there is significant overlap to match banking and no finance up to a propensity of 0.44 for receiving online financing, which covers 98 percent of the realized cases of online financing. This limited range of non-overlap should not be a problem for calculating the average effect of financing alternatives. The other cases are all equally or better covered.

The other fact that the overlap plots show is that measured propensities for firms we observe to receive online financing are very similar to firms that are denied while those receiving bank financing are noticeably different. For example, comparing the chances of receiving bank financing across denied and online groups, the mean propensity score is nearly identical (0.60 versus 0.61). In this sense, it appears on average that many online borrowers having no better chance to be approved by a bank than firms denied would make online financing an option that appears more feasible for firms who would otherwise be rejected for bank financing. Of course, we are interested in the average effects of financing for firms regardless of which option that they actually received.

5 Effects of banking alternatives on firm outcomes

5.1 Effects on revenue and employment growth

While firms in our sample are interested in pursuing financing presumably to expand their operations either with capital or with operating support, ordering and scale of bank and online financing is not clear. Most notably the terms of the financing are not observed and those terms could hinder the growth of firms. Or it could be the case that certain financing is typically provided for capital expenditures which could be due to lower labor requirements (and thus not result in employment growth). With this in mind, we seek to identify the effect of fintech financing on the business outlook for revenue and employment growth. We also measure differences in satisfaction with the lending experience.

Future revenue growth is measured by the owner's short-term expectations (next 12 months) for revenue. Table 4, column 1 reports results for 1,211 of the firms in the SBCS sample that pursued financing and answered the revenue question, when we applied the most flexible model (IPWRA) for adjusting for differences and accounted for unemployment rate differences across states. The estimated potential-outcome means in column one indicate a 76.9% likelihood of reporting future revenue growth for the online financing treatment group versus 78.3% for the bank financing group and 71.2% for those denied financing. Overall most of the sample seems to expect revenue growth after treatment controls are introduced, although the reported likelihood of revenue growth is noticeably lower for those not receiving financing of either type when compared to Table 2 weighted figures. This is likely a result of applying the estimate to older more established firms who typically expect less revenue growth. The other two likelihoods are a little higher when compared to the weighted figures in Table 2.

The average treatment effects are the potential-outcome means of treatment (online or bank) minus the potential-outcome mean for no financing. We now proceed to test for treatment effects, which look for whether the relevant coefficients are significantly different from each other. In the case of this model only the bank and denied groups are significantly different from each other (at the 90% confidence level). Looking over the three alternative models for revenue growth, the results are very similar, with regression adjustment being necessary for any statistically significant differences to be observed between the estimated potential-outcome means. Overall, we conclude that the differences here are small, but that could be due to inherent limitations of the question posed to businesses. In particular, the question makes no effort to quantify the amount of expected growth.

Small businesses which are expecting significant growth might be anticipated to also plan on expanding their workforce. Table 4, column 5 shows results regarding future employment growth. The estimated potential-outcome means are again similar to the raw figures, with the adjustment having the largest impact on the estimate of those denied financing, lowering that estimate by 8 percentages points and moving it from having the highest expected employment growth to the lowest. Put on comparable terms, the potential-outcome means for online and bank financing are very close. As with expectations about revenue growth, statistical differences only exist between the bank and denied groups (55.1% versus 46.8% likelihood of reporting future employment growth). However, differences between denied and online groups are quite close to standard thresholds of significance, with a p-value of 0.123, so it could be simply a matter of needing a larger sample to evaluate.

Overall, the estimated impact of fintech financing on a firm’s self-reported business outlook in Table 4 are somewhat ambiguous. In one respect, they indicate the outcomes of firms with fintech loans are not that different compared to firms with traditional bank loans. However, at the same time, firms in the online treatment group do not perform statistically different from firms that were denied financing.

5.2 Effects on satisfaction with lending experience

There is one final business assessment relevant to the impact of fintech financing, which is the businesses’ satisfaction with their financing. The figures shown in Table 2 revealed that there were significant differences in satisfaction levels, but that could also be substantially affected by the characteristics of the treated samples. The SBCS asks firms whether they are satisfied, dissatisfied, or neutral with regard to the lender or lenders 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. If denied credit, they are prompted to only consider the application process. For firms in each respective treatment group, we measure the percent of firms satisfied with at least one lender they applied with.

Comparing again to the raw results shown for the weighted sample in Table 2, it is clear that the controls are necessary for appropriate comparisons, as the satisfaction figures are higher for both those denied financing and those who received loans from online lenders. Adjusted satisfaction levels are somewhat lower for bank financing. Results in Table 4, column 9 show our preferred model (IPWRA with state unemployment controls). Despite the adjustments for characteristic differences moving the estimated satisfaction levels closer to the alternatives, the differences remain large. Firms with bank financing are approximately 26.8 percentage points more likely to be satisfied with their lender(s) than firms with online financing (75% versus 48.2%). Both groups have much higher satisfaction levels than firms denied financing among which only 8.5% of firms are satisfied with their borrowing experience. All coefficients that are associated with the average treatment effects are statistically different from zero and from each other at the 99% confidence level, including the incremental difference between online and bank financing. In this survey there seems to be a very strong hierarchy of ex post preferences for financing alternatives, with bank financing preferred to online financing which was preferred to being denied financing.

5.3 Robustness checks

Results based on the IPW model specification are also reported in Table 4, which indicate very similar estimates as the IPWRA results discussed in Section 5.1 and 5.2—except perhaps that less definitive patterns emerge regarding revenue outcomes. Also, the coefficients for online financing (columns 6 and 8) are slightly higher than those obtained by the IPWRA models (columns 5 and 7), but the significance of results does not change.

Additionally we also report results of IPWRA and IPW specifications with and without an unemployment control, which holds constant state-level economic conditions that might affect firm outcomes. Results and implications do not change.

Finally, we report unweighted model results for IPWRA and IPW specifications with the unemployment control as an additional robustness check. Table 5 shows that without sample weights, the apparent outcomes of firms in the online financing group improve relative to the other treatment groups. Still, differences between online and bank treatments are not significant when measuring revenue outcomes (columns 1 and 2). In terms of employment outcomes (columns 3 and 4), differences between online and bank treatments are significant at the 95% confidence level. However, this is not too dissimilar from the weighted results in which the same coefficients were nearly significant at the 90% confidence level. Results for satisfaction outcomes remain largely unchanged (columns 5 and 6).

5.4 Exploring effects on minority firms

Given that the treatment model in Section 4.1 identified minority-owned status as a significant predictor of selection into treatment, we thought it important to explore the effects of financing alternatives on minority firms. In contrast to the overall potential-outcome means discussed in Section 5.1 and 5.2, outcomes measured among minority firms reveal more meaningful differences across treatment groups.

The margin plots in Figure 2 show the expected potential-outcome means for the self-reported business outlook and satisfaction levels of minority-owned firms. This allows us to compare, for example, the outcome of minority-owned firms across treatment groups or how minority-owned firms differ from non-minority firms within treatment groups. Specifically, we can see that minority firms with fintech loans report much higher expectations about future revenue growth than minority firms denied financing (94.6% versus 73.0%). The boost in business outlook is similar in terms of employment growth (87.6% versus 65.3%). Both differences are significant at the 99% confidence level and represent much larger treatment effects than were found in the general SBCS sample (reported in Table 4). Additionally, minority firms do not appear to be sacrificing much in terms of the lending experience when taking loans from online lenders versus bank lenders—primarily due to already existing low satisfaction levels with traditional banks. The satisfaction levels of minority firms with fintech loans (44.6%) are lower than satisfaction levels of minority firms with bank loans (56%) but the difference is not statistically significant. In contrast, non-minority firms with fintech loans experience much larger gaps in satisfaction compared to non-minority firms with bank loans (48.7% versus 78.2%).

It is possible that these results could be due to the expansion of credit by fintech lenders among populations that traditional financial institutions have had difficulty serving. As was identified in the treatment model in Section 4.1, being a minority firm reduces the chances of receiving bank financing. Of course, minority firms that receive bank financing also experience a strong boost in business outlook across revenue and employment growth. The fact that some fintech lenders have developed specific loan programs tailored to minority firms—via marketing, websites in Spanish, or other means—could also be influencing the results for minority business owners (e.g., see Lendinero, Balboa Capital, and National Funding).

6 Conclusion and Policy Implications

While there are still many open questions about the value and effects of online business lending, particularly in the long run, the Federal Reserve's 2015 Small Business Credit Survey can provide some useful insights into this expanding sector of the financial market. Importantly, the businesses who take various financing options or are denied credit are not equivalent entities. In order to accurately compare the outcomes of these businesses, adjustments have to be made to account for compositional differences. We found that our three key results were quite similar using inverse-probability-weighted regression adjustment and inverse probability weighting.

1. Online borrowers have characteristics that make them very much like the businesses who were denied credit. This is consistent with fintech firms arranging credit for businesses who do not qualify for traditional bank financing. This suggests making the policy evaluation of the value of fintech loans relative to receiving no financing at all, unless alternatives that would make more bank financing available are being reviewed.
2. The evidence on effects of bank financing is evident in this survey though they remain weak, but the results for online lenders are hard to distinguish from either receiving no financing or receiving a bank loan. The point estimates of effects of online are positive (supporting expectations for growth), but the standard errors of the estimates are too large to be confident in the results. At this point, more information is clearly need to evaluate the impact of online lending to small businesses.
3. While the effects are hard to identify, the ordering of customer satisfaction is clear: bank borrowers are more satisfied than online borrowers who are more satisfied than businesses who were denied credit. As businesses become more aware of the availability and performance of online lenders, they remain unlikely to be fully competitive with banks without increasing their customer satisfaction levels, at least for businesses that could qualify for bank financing. Part of the challenge for a small business owner considering different financing options may be whether he or she understands the financing terms of a given fintech loan, which may not be the case. Such knowledge could conceivably impact both satisfaction with the borrowing experience as well as the perceived outlook of a firm after receiving a loan. Fintech lenders, in contrast to regulated financial institutions, are currently not required by law to disclose specific product terms like the annual percentage rate (APR); prior research suggests that typical small business borrowers in a focus group setting have had difficulty interpreting financing terms of fintech products, sometimes vastly

underestimating the effective interest rate being charged (Lipman and Wiersch 2015).

Table 1: Basic sample characteristics

	Unweighted sample			Weighted sample		
	Denied financing %	Online financing %	Bank financing %	Denied financing %	Online financing %	Bank financing %
Age						
0-2 years	15.0	18.8	7.2	28.0	29.9	18.2
3-5 years	18.0	21.4	9.1	22.0	21.1	13.7
6-10 years	20.9	19.6	12.8	23.2	23.6	17.4
11+ years	46.1	40.2	70.9	26.9	25.3	50.7
Employee size						
1-9 emp	66.5	62.5	35.3	82.2	77.5	58.3
10-49 emp	31.1	33.0	45.7	16.7	20.2	31.2
50+ emp	2.4	4.5	19.0	1.1	2.3	10.5
Industry						
Agriculture	1.5	0.9	2.5	1.1	0.3	2.7
Manufacturing	13.6	14.3	20.8	2.7	3.0	5.2
Transportation	1.9	1.8	3.0	1.7	1.0	2.6
Retail	16.5	15.2	12.3	15.6	13.4	13.5
Wholesale	3.9	5.4	5.7	3.4	5.3	4.9
Finance	2.4	3.6	2.1	6.1	6.4	3.9
Healthcare	3.9	14.3	4.3	5.4	20.2	9.2
Education	2.9	1.8	1.1	6.8	1.4	2.1
Real estate	3.4	0.9	4.3	2.4	0.9	4.1
Hospitality	13.1	9.8	8.0	15.4	12.6	11.8
Prof svc	15.0	9.8	13.6	14.5	9.1	13.1
Admin svc	10.2	14.3	9.2	15.1	19.4	13.7
Construction	11.7	8.0	13.1	9.7	6.9	13.3
Revenue						
<$100K	17.6	10.0	5.5	28.5	15.9	10.7
$100K-1M$	56.8	62.7	32.3	58.8	66.8	44.6
$1M-10M$	24.1	24.5	44.8	12.0	15.3	35.0
$10M+	1.5	2.7	17.3	0.8	2.0	9.7
Profit						
At a loss	38.5	39.1	15.8	38.2	44.5	19.2
Break even	20.5	21.8	17.3	21.3	18.9	17.5
Profitable	41.0	39.1	66.9	40.5	36.6	63.3
Minority-owned business	23.8	20.5	7.4	28.7	27.8	9.9
Female-owned business	34.5	36.6	25.5	41.5	44.3	31.7
Veteran-owned business	14.6	15.2	10.2	13.4	17.4	9.2
N	206	112	968	206	112	968

Note: Of the 968 firms in the Bank financing treatment group, 26 were also approved for financing by an online lender.

Table 2: Treatment group comparison

	Unweighted sample			Weighted sample			
	Denied financing %	Online financing %	Bank financing %	Denied financing %	Online financing %	Bank financing %	N
Outcomes of interest							
Expects future revenue growth	73.0	75.9	72.3	80.3	75.5	76.6	
Expects future employment growth	49.3	56.8	50.1	56.1	55.2	52.2	
Satisfied with 1+ lender	6.6	45.0	79.2	4.3	45.6	77.3	
N	206	112	968	206	112	968	
Community bank share in state							
0% to 25%	27.0	15.2	57.8	34.3	19.5	46.2	282
25% to 50%	13.5	7.3	79.3	17.6	10.8	71.5	786
Over 50%	11.0	5.5	83.5	16.6	7.5	75.9	218

Note: 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”. States are grouped according to the share of community bank branches relative to all bank branches operating within a sate as of 2Q 2010. Data on community banks is from FDIC. Of the 968 firms in the Bank financing treatment group, 26 were also approved for financing by an online lender.

Table 3: Average marginal effects of treatment selection

	Denied financing %	Online financing %	Bank financing %
Profit			
Unprofitable (baseline)	0.258***	0.206***	0.535***
	(0.031)	(0.030)	(0.034)
Break even	-0.028	-0.086**	+0.114**
	(0.048)	(0.039)	(0.051)
Profitable	-0.084**	-0.116***	+0.200***
	(0.039)	(0.034)	(0.042)
Revenue size			
<\$100K (baseline)	0.282***	0.094***	0.624***
	(0.049)	(0.034)	(0.056)
100K-1M	-0.049	+0.061	-0.012
	(0.054)	(0.039)	(0.061)
1M-10M	-0.151**	+0.015	+0.136**
	(0.058)	(0.046)	(0.067)
10M+	-0.227***	-0.018	+0.245***
	(0.069)	(0.062)	(0.083)
Minority status			
Non-minority firm (baseline)	0.184***	0.117***	0.700***
	(0.016)	(0.013)	(0.018)
Minority firm	+0.162***	+0.0748*	-0.237***
	(0.049)	(0.042)	(0.050)

Note: Coefficients represent average marginal effects of treatment selection relative to the baseline probability of the omitted variable in each category: unprofitable, <\$100K, and non-minority firms. For full results of multinomial logit estimates, see Table A3.

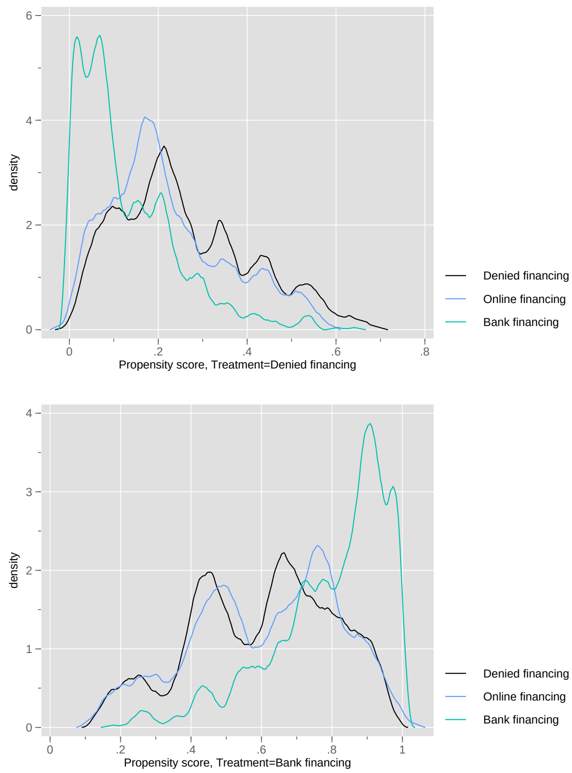

Figure 1: Overlap plots. Predicted probabilities of financing alternatives shown for each treatment group. For full results of multinomial logit estimates, see Table A3.

Table 4: Likelihood of reporting future firm growth or satisfaction with lender, by treatment groups

	Likelihood of reporting future revenue growth				Likelihood of reporting future employment growth				Likelihood of reporting satisfaction with lender			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment groups												
Denied financing	0.712***	0.730***	0.713***	0.729***	0.468***	0.471***	0.469***	0.471***	0.085**	0.087***	0.083***	0.085***
	(0.034)	(0.051)	(0.035)	(0.051)	(0.036)	(0.044)	(0.036)	(0.046)	(0.033)	(0.032)	(0.031)	(0.031)
Online financing	0.769***	0.758***	0.766***	0.755***	0.552***	0.586***	0.554***	0.584***	0.482***	0.494***	0.480***	0.495***
	(0.037)	(0.056)	(0.039)	(0.057)	(0.044)	(0.060)	(0.043)	(0.060)	(0.048)	(0.067)	(0.048)	(0.068)
Bank financing	0.783***	0.782***	0.783***	0.782***	0.553***	0.551***	0.553***	0.551***	0.750***	0.749***	0.750***	0.749***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.022)	(0.022)	(0.022)	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)
Difference of means												
Denied=Online	0.255	0.710	0.314	0.732	0.123	0.113	0.123	0.128	0.000***	0.000***	0.000***	0.000***
Online=Bank	0.690	0.678	0.691	0.656	0.990	0.583	0.979	0.600	0.000***	0.000***	0.000***	0.000***
Bank=Denied	0.054*	0.322	0.064*	0.325	0.037**	0.096*	0.043**	0.111	0.000***	0.000***	0.000***	0.000***
Unemployment control	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Model specification	IPWRA	IPW	IPWRA	IPW	IPWRA	IPW	IPWRA	IPW	IPWRA	IPW	IPWRA	IPW
Sample size	1211	1211	1211	1211	1209	1209	1209	1209	1198	1198	1198	1198

Note: Coefficients reported are potential-outcome means. Standard errors in parentheses. p-values are reported for difference-of-means tests. *** significant at $p<0.01$; ** significant at $p<0.05$; * significant at $p<0.1$. Of the 968 firms in the Bank financing treatment group, 26 were also approved for financing by an online lender.

Table 5: Unweighted Results: Likelihood of reporting future firm growth or satisfaction with lender, by treatment groups

	Likelihood of reporting future revenue growth		Likelihood of reporting future employment growth		Likelihood of reporting satisfaction with lender	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment groups						
Denied financing	0.615***	0.667***	0.363***	0.396***	0.126***	0.125***
	(0.040)	(0.043)	(0.032)	(0.037)	(0.046)	(0.037)
Online financing	0.801***	0.777***	0.606***	0.651***	0.517***	0.547***
	(0.038)	(0.053)	(0.042)	(0.061)	(0.047)	(0.072)
Bank financing	0.737***	0.737***	0.515***	0.515***	0.775***	0.775***
	(0.014)	(0.014)	(0.017)	(0.017)	(0.014)	(0.015)
Difference of means						
Denied=Online	0.001***	0.104*	0.000***	0.000***	0.000***	0.000***
Online=Bank	0.111	0.462	0.041**	0.030**	0.000***	0.002***
Bank=Denied	0.004***	0.117	0.000***	0.003***	0.000***	0.000***
Unemployment control	Yes	Yes	Yes	Yes	Yes	Yes
Model specification	IPWRA	IPW	IPWRA	IPW	IPWRA	IPW
Sample size	1211	1211	1209	1209	1198	1198

Note: Coefficients reported are potential-outcome means. Standard errors in parentheses. p-values are reported for difference-of-means tests. *** significant at p<0.01; ** significant at p<0.05; * significant at p<0.1. Of the 968 firms in the Bank financing treatment group, 26 were also approved for financing by an online lender.

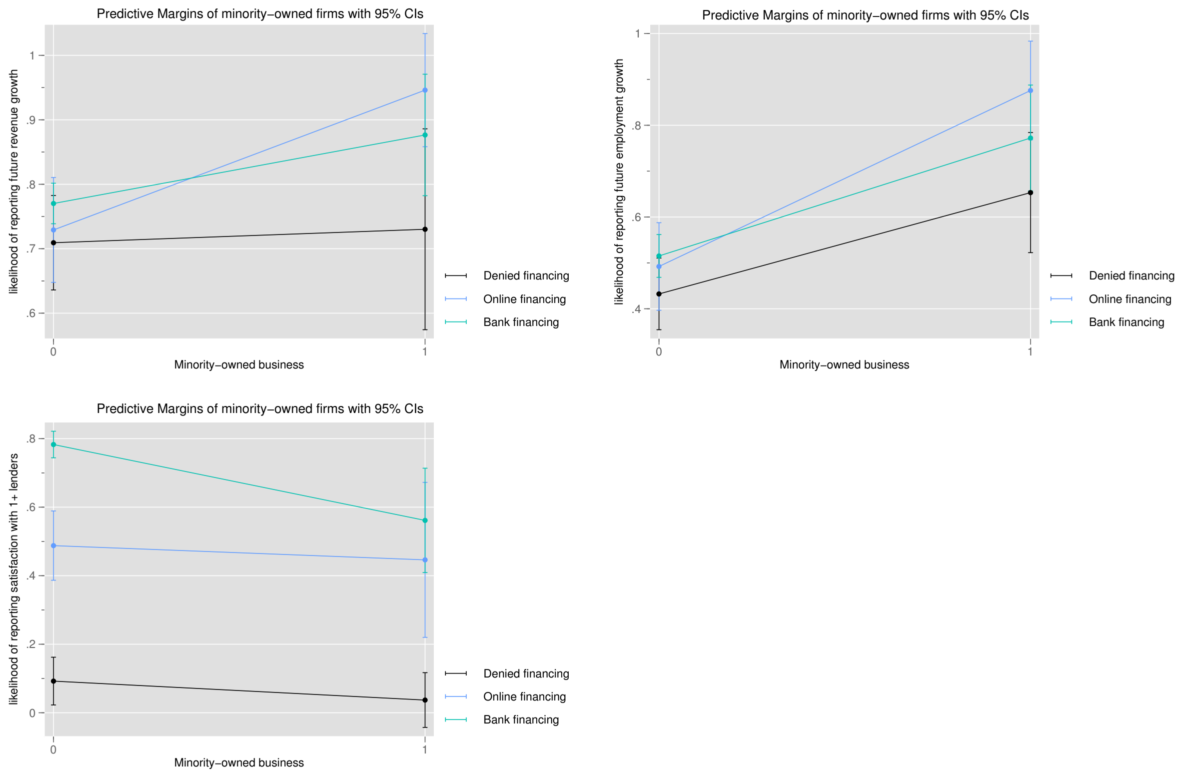

Figure 2: Margin plots. Values shown are the potential-outcome means of minority-owned firms in terms of reported future revenue, future employment, and satisfaction. Based on IPWRA weighted model specifications with unemployment control. Of the 968 firms in the Bank financing treatment group, 26 were also approved for financing by an online lender.

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Table A1: Tabulations of unweighted, weighted, and population variables

	Unweighted sample	Weighted sample	Population
Age			
0-2 years	9.42	20.84	20.85
3-5 years	10.21	13.94	13.96
6-10 years	14.95	20.14	20.05
11+ years	65.42	45.08	45.14
Employee size			
1-9 emp	53.14	73.51	73.53
10-49 emp	36.14	21.41	21.36
50+ emp	10.73	5.09	5.11
Industry			
Agriculture	19.92	17.88	17.81
Manufacturing	16.80	3.75	3.76
Retail	14.51	14.38	14.33
Leisure/hospitality	8.12	10.66	10.67
Finance/Insurance	3.30	6.20	6.31
Healthcare/Education	7.05	12.56	12.61
Real estate/Prof svc	20.38	19.28	19.26
Admin svc/Business Support	9.92	15.28	15.26

Table A2: Sample weight descriptive stats

Percentiles		Four Smallest Values		
1%	225	225		
5%	237	225		
10%	389	225		
25%	796	225	Obs	3,459
50%	1495		Mean	1663.778
		Four Largest Values	Std. Dev.	1180.699
75%	2386	6793		
90%	3469	6793	Variance	1394050
95%	3911	6793	Skewness	1.304091
99%	5775	6793	Kurtosis	4.940495

Table A3: Multinomial logit regressions for probability of receiving financing

	Revenue models				Employment models				Satisfaction models			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Online financing												
Employees	0.002	0.002	0.002	0.002	0.003	0.003	0.003	0.003	0.002	0.002	0.002	0.002
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Age	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Manufacturing	1.098	1.098	1.095	1.095	1.125	1.125	1.121	1.121	1.152	1.152	1.144	1.144
	(1.229)	(1.229)	(1.228)	(1.228)	(1.235)	(1.235)	(1.233)	(1.233)	(1.224)	(1.224)	(1.222)	(1.222)
Transportation	0.642	0.642	0.660	0.660	0.663	0.663	0.690	0.690	1.622	1.622	1.626	1.626
	(1.452)	(1.452)	(1.448)	(1.448)	(1.453)	(1.453)	(1.447)	(1.447)	(1.525)	(1.525)	(1.522)	(1.522)
Retail	0.808	0.808	0.806	0.806	0.732	0.732	0.728	0.728	0.901	0.901	0.891	0.891
	(1.228)	(1.228)	(1.227)	(1.227)	(1.237)	(1.237)	(1.235)	(1.235)	(1.226)	(1.226)	(1.224)	(1.224)
Wholesale	1.481	1.481	1.487	1.487	1.508	1.508	1.517	1.517	1.556	1.556	1.570	1.570
	(1.312)	(1.312)	(1.312)	(1.312)	(1.314)	(1.314)	(1.313)	(1.313)	(1.321)	(1.321)	(1.319)	(1.319)
Finance	1.149	1.149	1.158	1.158	1.182	1.182	1.193	1.193	1.383	1.383	1.412	1.412
	(1.322)	(1.322)	(1.322)	(1.322)	(1.327)	(1.327)	(1.327)	(1.327)	(1.345)	(1.345)	(1.347)	(1.347)
Healthcare	2.633**	2.633**	2.628**	2.628**	2.672**	2.672**	2.666**	2.666**	2.612**	2.612**	2.601**	2.601**
	(1.290)	(1.290)	(1.289)	(1.289)	(1.299)	(1.299)	(1.297)	(1.297)	(1.278)	(1.278)	(1.277)	(1.277)
Education or training	0.628	0.628	0.660	0.660	0.300	0.300	0.327	0.327	0.545	0.545	0.555	0.555
	(1.501)	(1.501)	(1.499)	(1.499)	(1.475)	(1.475)	(1.472)	(1.472)	(1.481)	(1.481)	(1.485)	(1.485)
Real estate	0.146	0.146	0.158	0.158	0.329	0.329	0.342	0.342	0.270	0.270	0.295	0.295
	(1.587)	(1.587)	(1.584)	(1.584)	(1.601)	(1.601)	(1.598)	(1.598)	(1.598)	(1.598)	(1.594)	(1.594)
Hospitality	0.833	0.833	0.825	0.825	0.934	0.934	0.924	0.924	1.060	1.060	1.036	1.036
	(1.240)	(1.240)	(1.239)	(1.239)	(1.249)	(1.249)	(1.247)	(1.247)	(1.243)	(1.243)	(1.241)	(1.241)
Professional svc	0.684	0.684	0.692	0.692	0.710	0.710	0.720	0.720	0.696	0.696	0.716	0.716
	(1.234)	(1.234)	(1.232)	(1.232)	(1.244)	(1.244)	(1.241)	(1.241)	(1.236)	(1.236)	(1.233)	(1.233)
Administrative svc	1.395	1.395	1.398	1.398	1.427	1.427	1.431	1.431	1.495	1.495	1.499	1.499
	(1.216)	(1.216)	(1.216)	(1.216)	(1.223)	(1.223)	(1.221)	(1.221)	(1.214)	(1.214)	(1.213)	(1.213)

(Continued)

Table A3: Multinomial logit regressions for probability of receiving financing *(Continued)*

	Revenue models				Employment models				Satisfaction models			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Construction	0.792	0.792	0.779	0.779	0.864	0.864	0.845	0.845	0.991	0.991	0.953	0.953
	(1.247)	(1.247)	(1.244)	(1.244)	(1.255)	(1.255)	(1.252)	(1.252)	(1.241)	(1.241)	(1.239)	(1.239)
100K−1M	0.720	0.720	0.721	0.721	0.733	0.733	0.737	0.737	0.433	0.433	0.442	0.442
	(0.487)	(0.487)	(0.488)	(0.488)	(0.489)	(0.489)	(0.489)	(0.489)	(0.500)	(0.500)	(0.502)	(0.502)
1M−10M	0.929	0.929	0.943	0.943	0.934	0.934	0.952	0.952	0.670	0.670	0.707	0.707
	(0.602)	(0.602)	(0.597)	(0.597)	(0.607)	(0.607)	(0.600)	(0.600)	(0.616)	(0.616)	(0.609)	(0.609)
$10M+	1.444	1.444	1.461	1.461	1.450	1.450	1.469	1.469	1.122	1.122	1.160	1.160
	(1.238)	(1.238)	(1.230)	(1.230)	(1.247)	(1.247)	(1.240)	(1.240)	(1.250)	(1.250)	(1.242)	(1.242)
Break even	-0.431	-0.431	-0.432	-0.432	-0.388	-0.388	-0.390	-0.390	-0.447	-0.447	-0.447	-0.447
	(0.386)	(0.386)	(0.386)	(0.386)	(0.389)	(0.389)	(0.388)	(0.388)	(0.403)	(0.403)	(0.402)	(0.402)
Profitable	-0.429	-0.429	-0.431	-0.431	-0.445	-0.445	-0.449	-0.449	-0.524	-0.524	-0.530	-0.530
	(0.337)	(0.337)	(0.337)	(0.337)	(0.338)	(0.338)	(0.338)	(0.338)	(0.349)	(0.349)	(0.349)	(0.349)
Minority-owned	-0.141	-0.141	-0.140	-0.140	-0.107	-0.107	-0.105	-0.105	-0.154	-0.154	-0.151	-0.151
	(0.354)	(0.354)	(0.355)	(0.355)	(0.357)	(0.357)	(0.357)	(0.357)	(0.362)	(0.362)	(0.363)	(0.363)
Female-owned	0.094	0.094	0.098	0.098	0.117	0.117	0.123	0.123	0.084	0.084	0.095	0.095
	(0.318)	(0.318)	(0.318)	(0.318)	(0.321)	(0.321)	(0.321)	(0.321)	(0.324)	(0.324)	(0.325)	(0.325)
Veteran-owned	0.595	0.595	0.595	0.595	0.600	0.600	0.604	0.604	0.769*	0.769*	0.775*	0.775*
	(0.409)	(0.409)	(0.410)	(0.410)	(0.413)	(0.413)	(0.413)	(0.413)	(0.431)	(0.431)	(0.431)	(0.431)
Unemployment control	0.013	0.013			0.017	0.017			0.034	0.034		
	(0.040)	(0.040)			(0.040)	(0.040)			(0.043)	(0.043)		
Constant	-1.915	-1.915	-2.110*	-2.110*	-1.928	-1.928	-2.189*	-2.189*	-1.345	-1.345	-1.851	-1.851
	(1.373)	(1.373)	(1.237)	(1.237)	(1.378)	(1.378)	(1.234)	(1.234)	(1.390)	(1.390)	(1.232)	(1.232)
Bank financing												
Employees	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Age	0.012*	0.012*	0.012*	0.012*	0.013*	0.013*	0.013*	0.013*	0.013	0.013	0.013	0.013
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Manufacturing	-0.102	-0.102	-0.102	-0.102	0.183	0.183	0.180	0.180	-0.049	-0.049	-0.055	-0.055
	(0.764)	(0.764)	(0.764)	(0.764)	(0.749)	(0.749)	(0.745)	(0.745)	(0.754)	(0.754)	(0.751)	(0.751)

(Continued)

Table A3: Multinomial logit regressions for probability of receiving financing *(Continued)*

	Revenue models				Employment models				Satisfaction models			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Transportation	-0.293	-0.293	-0.289	-0.289	-0.042	-0.042	-0.024	-0.024	0.673	0.673	0.674	0.674
	(0.915)	(0.915)	(0.916)	(0.916)	(0.907)	(0.907)	(0.904)	(0.904)	(1.064)	(1.064)	(1.059)	(1.059)
Retail	-0.571	-0.571	-0.571	-0.571	-0.305	-0.305	-0.309	-0.309	-0.462	-0.462	-0.474	-0.474
	(0.762)	(0.762)	(0.761)	(0.761)	(0.747)	(0.747)	(0.744)	(0.744)	(0.754)	(0.754)	(0.750)	(0.750)
Wholesale trade	-0.597	-0.597	-0.593	-0.593	-0.291	-0.291	-0.286	-0.286	-0.488	-0.488	-0.481	-0.481
	(0.845)	(0.845)	(0.844)	(0.844)	(0.828)	(0.828)	(0.825)	(0.825)	(0.841)	(0.841)	(0.838)	(0.838)
Finance	-1.206	-1.206	-1.205	-1.205	-0.905	-0.905	-0.895	-0.895	-0.963	-0.963	-0.940	-0.940
	(0.889)	(0.889)	(0.887)	(0.887)	(0.876)	(0.876)	(0.872)	(0.872)	(0.927)	(0.927)	(0.924)	(0.924)
Healthcare	0.503	0.503	0.501	0.501	0.847	0.847	0.842	0.842	0.520	0.520	0.511	0.511
	(0.871)	(0.871)	(0.871)	(0.871)	(0.858)	(0.858)	(0.855)	(0.855)	(0.851)	(0.851)	(0.849)	(0.849)
Education	-0.455	-0.455	-0.449	-0.449	-0.688	-0.688	-0.679	-0.679	-0.865	-0.865	-0.866	-0.866
	(0.973)	(0.973)	(0.971)	(0.971)	(0.979)	(0.979)	(0.977)	(0.977)	(1.031)	(1.031)	(1.032)	(1.032)
Real estate	-0.211	-0.211	-0.210	-0.210	0.265	0.265	0.273	0.273	-0.058	-0.058	-0.041	-0.041
	(0.878)	(0.878)	(0.877)	(0.877)	(0.885)	(0.885)	(0.881)	(0.881)	(0.881)	(0.881)	(0.876)	(0.876)
Hospitality	-0.762	-0.762	-0.765	-0.765	-0.446	-0.446	-0.452	-0.452	-0.539	-0.539	-0.556	-0.556
	(0.783)	(0.783)	(0.782)	(0.782)	(0.772)	(0.772)	(0.768)	(0.768)	(0.782)	(0.782)	(0.778)	(0.778)
Professional svc	-0.513	-0.513	-0.512	-0.512	-0.195	-0.195	-0.188	-0.188	-0.422	-0.422	-0.408	-0.408
	(0.760)	(0.760)	(0.760)	(0.760)	(0.746)	(0.746)	(0.743)	(0.743)	(0.752)	(0.752)	(0.749)	(0.749)
Administrative svc	-0.673	-0.673	-0.673	-0.673	-0.371	-0.371	-0.370	-0.370	-0.558	-0.558	-0.559	-0.559
	(0.765)	(0.765)	(0.764)	(0.764)	(0.751)	(0.751)	(0.747)	(0.747)	(0.757)	(0.757)	(0.754)	(0.754)
Construction	-0.246	-0.246	-0.249	-0.249	0.102	0.102	0.085	0.085	-0.077	-0.077	-0.110	-0.110
	(0.765)	(0.765)	(0.764)	(0.764)	(0.753)	(0.753)	(0.748)	(0.748)	(0.758)	(0.758)	(0.755)	(0.755)
100$K-1$M	0.170	0.170	0.170	0.170	0.203	0.203	0.206	0.206	-0.053	-0.053	-0.044	-0.044
	(0.320)	(0.320)	(0.320)	(0.320)	(0.322)	(0.322)	(0.322)	(0.322)	(0.349)	(0.349)	(0.350)	(0.350)
1$M-10$M	1.062***	1.062***	1.063***	1.063***	1.057***	1.057***	1.071***	1.071***	0.853**	0.853**	0.881**	0.881**
	(0.380)	(0.380)	(0.382)	(0.382)	(0.382)	(0.382)	(0.384)	(0.384)	(0.410)	(0.410)	(0.413)	(0.413)
$10M+	2.156**	2.156**	2.156**	2.156**	2.136**	2.136**	2.149**	2.149**	1.863**	1.863**	1.891**	1.891**
	(0.911)	(0.911)	(0.911)	(0.911)	(0.915)	(0.915)	(0.918)	(0.918)	(0.924)	(0.924)	(0.932)	(0.932)

(Continued)

Table A3: Multinomial logit regressions for probability of receiving financing *(Continued)*

	Revenue models				Employment models				Satisfaction models			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Break even	0.390	0.390	0.390	0.390	0.415	0.415	0.414	0.414	0.370	0.370	0.370	0.370
	(0.304)	(0.304)	(0.304)	(0.304)	(0.308)	(0.308)	(0.308)	(0.308)	(0.323)	(0.323)	(0.321)	(0.321)
Profitable	0.860***	0.860***	0.860***	0.860***	0.827***	0.827***	0.825***	0.825***	0.750***	0.750***	0.748***	0.748***
	(0.255)	(0.255)	(0.255)	(0.255)	(0.258)	(0.258)	(0.258)	(0.258)	(0.273)	(0.273)	(0.274)	(0.274)
Minority-owned	-1.249***	-1.249***	-1.248***	-1.248***	-1.213***	-1.213***	-1.212***	-1.212***	-1.256***	-1.256***	-1.256***	-1.256***
	(0.279)	(0.279)	(0.279)	(0.279)	(0.282)	(0.282)	(0.282)	(0.282)	(0.287)	(0.287)	(0.288)	(0.288)
Female-owned	-0.023	-0.023	-0.022	-0.022	-0.062	-0.062	-0.060	-0.060	-0.046	-0.046	-0.040	-0.040
	(0.219)	(0.219)	(0.219)	(0.219)	(0.219)	(0.219)	(0.219)	(0.219)	(0.226)	(0.226)	(0.226)	(0.226)
Veteran-owned	0.073	0.073	0.074	0.074	-0.003	-0.003	-0.001	-0.001	0.245	0.245	0.249	0.249
	(0.352)	(0.352)	(0.352)	(0.352)	(0.351)	(0.351)	(0.352)	(0.352)	(0.373)	(0.373)	(0.374)	(0.374)
Unemployment control	0.003	0.003			0.013	0.013			0.026	0.026		
	(0.030)	(0.030)			(0.030)	(0.030)			(0.033)	(0.033)		
Constant	0.669	0.669	0.631	0.631	0.517	0.517	0.318	0.318	1.239	1.239	0.853	0.853
	(0.865)	(0.865)	(0.764)	(0.764)	(0.854)	(0.854)	(0.747)	(0.747)	(0.887)	(0.887)	(0.760)	(0.760)
Model specification	IPWRA	IPW	IPWRA	IPW	IPWRA	IPW	IPWRA	IPW	IPWRA	IPW	IPWRA	IPW
Sample size	1211	1211	1211	1211	1209	1209	1209	1209	1198	1198	1198	1198

Note: Coefficient estimates are relative to the base outcome of not receiving any financing. Categorical variables are omitted for industry (Agriculture), revenue (<$100K), profitability (at a loss). Standard errors in parentheses. *** significant at p<0.01; ** significant at p<0.05; * significant at p<0.1.

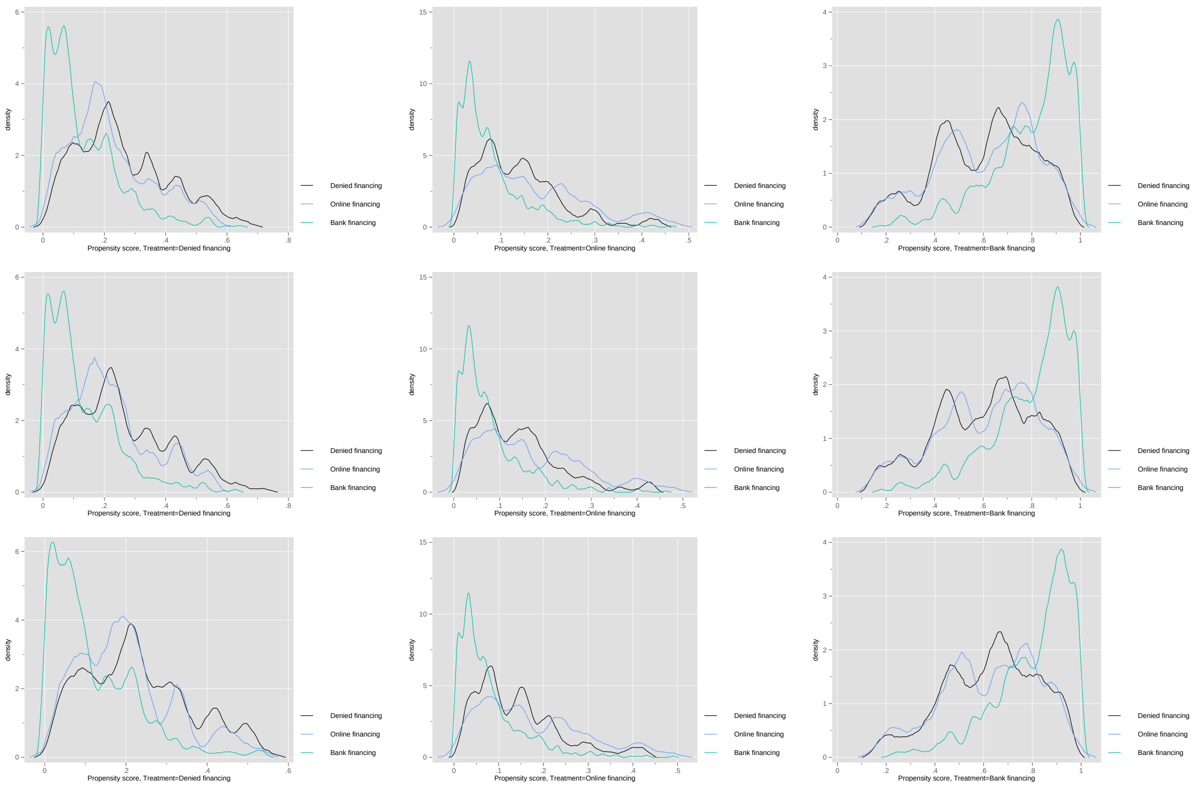

Figure A1: Overlap plots. Predicted probabilities of financing alternatives shown for each treatment group in regards to revenue (top panel), employment (middle panel), and satisfaction (bottom panel) outcomes. Based on IPWRA model specifications with unemployment control. For full results of multinomial logit estimates, see Table A3.