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FinTech Loans, Self-Employment, and Financial Performance

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FinTech Loans, Self-Employment, and Financial Performance

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Abstract

Leveraging data from a leading FinTech peer-to-peer lending platform in the United States, allowing us to capture both individuals' successful and unsuccessful loan applications, we test the effect of FinTech loans on subsequent employment choice and future financial performance of *serial borrowers*, those repeatedly soliciting loans on the platform. An analysis of 198,984 loan requests made by 92,382 individuals shows that a failed loan application increases the probability of switching employment status. Self-employed individuals are 22% more likely to switch to becoming an employee following an unsuccessful loan application. This probability increases to 31% for those in the lowest income decile and decreases to 13% for those in the highest income decile. We document an improvement in monthly income and credit access following a successful loan application. However, this enhancement is asymmetric. Monthly income enhancement is 3.11 times larger for self-employed individuals in the lowest income decile relative to individuals in the highest income decile. Access to credit enhancement is 1.85 times larger for self-employed individuals in the lowest credit access decile relative to individuals in the second highest credit access decile.

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1 Introduction

In this paper we examine the impact of an unsuccessful loan application on self-employment decisions of serial borrowers on FinTech platforms, those repeatedly soliciting FinTech loans. We provide robust evidence that unsuccessful FinTech loan applications drive switches in employment status: i) self-employed individuals switch into employment and ii) employees switch into self-employment. This effect is stronger for income constrained self-employed individuals but weaker for income constrained employees. We then investigate the effect of successfully securing a FinTech loan on subsequent financial performance of self-employed individuals. We document that following a successful FinTech loan self-employed individuals enjoy better monthly incomes and higher future access to credit. We further show that this enhancement is stronger for more constrained self-employed individuals, self-employed individuals in the lowest monthly income and credit access deciles. We contribute to the recent literature on credit access and self-employment (Corradin & Popov, 2015; Herkenhoff, Phillips, & Cohen-Cole, 2021) and FinTech loans and future performance (Chava, Ganduri, Paradkar, & Zhang, 2021; Di Maggio & Yao, 2021) by analyzing the impact of FinTech loans on self-employment decisions and future performance of serial FinTech borrowers, those most relying on FinTech loan outcome (Butler, Cornaggia, & Gurun, 2017).

Our empirical approach leverages the universe of serial borrowers on a leading U.S. FinTech loan platform for the period commencing in January 2016 and ending in September 2020. The FinTech context allows us to exploit data on both successful and unsuccessful loan applications, such information is not available in the traditional context (Li & Martin, 2019). Our dataset consists of 198,984 FinTech loan requests made by 92,382 individuals. For each loan application we have platform verified information and Transunion provided information. This dataset is further merged with county-level indicators associated with the loan applicant's location and general economic condition indicators. Given the sequential nature of our research question, our analysis involves a three-stage empirical strategy.

First, we begin our analysis by examining the impact of current FinTech loan application outcome on subsequent self-employment decision. Prior studies have shown that access to credit stimulate self-employment decisions (Corradin & Popov, 2015; Herkenhoff et al., 2021). However, we lack information on the effects of failure to obtain a loan on self-employment decision. Hence, we complement prior work by analyzing serial borrowers on FinTech lending platforms. We suspect that since serial borrowers are marginal in nature, returning to the platform for FinTech loan to fulfill personal obligations, the effect of FinTech loan outcome would depend on current employment status. The response of self-employed loan applicants and employees would differ. We run our analysis on the population of self-employed loan applicants and show that an unsuccessful loan application would lead to discontinuing self-employment activity. Failure to obtain a FinTech loan increases the probability that a self-employed person switches to being an employee elsewhere by 21.63%. A switch out of self-employment after failing to obtain a FinTech loan is only 13.11% for entrepreneurs in the top income decile, but is 30.97% for entrepreneurs in the bottom income decile. Hence, the data indicate that FinTech loans are important enablers of allowing the self-employed population to remain self-employed. The benefits appear to be largely related to purely satisfy credit constraints insofar as high income levels mitigate the switch to being an employee after a failed loan attempt. Turning to the population of employee loan applicants, our analysis shows that failure to secure a FinTech loan increases the likelihood that the employee turns to self-employment. We may infer from this result that some of these switchers are likely necessity entrepreneurs. But not all employee failed loan applications give rise to switches to self-employment with equal probability; instead, employees that had larger incomes are more likely to switch. In particular, employees with a failed FinTech loan application are 8.49% more likely to become self-employed when they are among the top income decile, and only 4.88% more likely if they are among the bottom income decile.

Second, we analyze the impact of current FinTech loan on subsequent self-employed individuals' financial performance. As highlighted by previous literature investigating traditional credit channels, access to credit plays a crucial role in improving entrepreneurs' future income. However, the benefits of access to credit can extend beyond that. For instance, Howell (2020) notes that access to capital facilitates future capital acquisition. As for FinTech loans, scant literature has investigated the effect of loan acquisition on future performance of individuals. However, we still lack insight into the effect of FinTech loans on future financial performance of self-employed individuals. We argue that FinTech loans hold benefits for self-employed individuals since they are timely, customized, less costly, and put less strain on the applicants' assets. Our findings highlight the economic significance of FinTech loans for entrepreneurs. We show that FinTech loans play a crucial role in enhancing self-employment income returns and future access to credit. Specifically, we document that a 1 SD increase in previous successful loan amount improves income increase enhancement by 2.44% and credit line enhancement by 3.52%. Hence, FinTech loan acquisition plays a significant role in improving the income of self-employed individuals and their access to alternative credit channels.

Third, we proceed by analyzing which self-employed individuals benefit the most from FinTech loans. Our results document that marginal self-employed individuals, those with lower incomes and restricted credit access, benefit disproportionately from securing FinTech loans. Specifically, income enhancement is 3.11 times larger for self-employed borrowers that are initially at the lowest income decile relative to those at the top income decile. Credit enhancement is 1.85 times larger for self-employed borrowers in the lowest credit access decile relative to those in the second highest credit access decile. No significant credit enhancement is noted for self-employed borrowers at the top credit access decile. Overall, the data indicate that FinTech loans are particularly important for the marginal self-employed borrowers.

We test competing hypotheses for our results showing the effect of FinTech loan outcome on self-employment decision and subsequent financial performance of self-employed individuals. The first hypothesis is related to reverse causality, where stable employment history drives successful FinTech loan acquisition. We test this hypothesis by estimating a panel vector auto regression (PVAR) model along with a panel Granger causality test. The results of our PVAR model indicate that FinTech loan outcome causes switches into and out of self-employment. However, stable employment status does not affect FinTech loan outcome. The Granger causality test further validates this unidirectional effect. The second hypothesis is related to better self-employed individuals securing larger loans and hence perform financially better subsequently. We test this competing hypothesis by first matching self-employed individuals on previous FinTech loan outcome and amount, individual-level characteristics, and county-level characteristics. After matching the self-employed loan applicants using coarsened exact matching, we run our analysis to validate the effect of FinTech loan outcome on subsequent financial performance. The results using the matched sample show that FinTech loans enhance monthly income and credit access for self-employed individuals, ruling out the alternative competing hypothesis.

Our main contribution is to study the effect of securing a FinTech loan on subsequent self-employment decision and financial performance of serial borrowers. Having information on both successful and unsuccessful FinTech loan applications, we present new evidence that employee serial borrowers do not use FinTech loans to venture into self-employment. However, FinTech loans allow self-employed serial borrowers to sustain their self-employment activity. The results are suggestive of immediate personal credit being used to meet current obligations and maintain current employment status. We provide additional evidence that FinTech loans aid in enhancing the financial performance of self-employed borrowers and that this effect is more pronounced for the marginal self-employed individuals. We view our results as robust evidence that FinTech loans are crucial for self-employed individuals to sustain their self-employment activity and enhance their financial performance, especially for those with limited income and restricted credit access.

We believe that our paper provides a major contribution to two main streams in the literature. First, we add to the literature on credit access and self-employment activity (Corradin & Popov, 2015; Herkenhoff et al., 2021). This literature has mainly focused on how traditional credit access can stimulate self-employment decisions. Given that FinTech lenders serve different borrowers (Tang, 2019), our paper contributes to this literature by investigating the role of FinTech loans in driving self-employment activity. We specifically focus on serial borrowers who repeatedly return to the FinTech platforms. In doing so, we demonstrate the role that FinTech loans play in conditioning self-employment activity, and show the differential role that it plays depending on the borrowers' initial employment status. Second, we add to the literature on FinTech loans and future financial performance (Chava et al., 2021; Di Maggio & Yao, 2021). We specifically show a positive effect of FinTech loans on future financial performance of self-employed individuals, this is different than that documented for general borrowers in previous studies. A possible explanation for this robust finding is that serial borrowers maintain their credit more effectively given their intent to return to the platform in the future. This might not necessarily be true for one time borrowers. Another possible explanation comes from our focus on self-employed loan applicants. Self-employed individuals could be managing their outstanding debt more effectively. Employees enjoy a steady income stream from employment and can afford poor credit performance; whereas, access to credit is a more valuable asset for self-employed individuals.

The remainder of the paper proceeds as follows. Section 2 provides an overview of the institutional setting. Section 3 describes the data and provides some summary statistics. Section 4 discusses the effect of FinTech loan acquisition on self-employment choice and presents the regression results. Section 5 discusses the effect of FinTech loan amounts on the financial performance of self-employed individuals and presents the regression results. Section 6 concludes the paper.

2 Institutional Setting

Fintech platforms such as marketplace lending offer a new form of access to finance that alleviate some of the barriers in the traditional lending channels, as well as advantages that facilitate the entrepreneurship process (Agrawal et al., 2014). Marketplace lending enables a matching of individual lenders to borrowers in a way that alleviates the traditional banks as financial intermediaries. Lenders can evaluate prospective borrowers and make direct decisions about loan applications. Loan applicants can decide whether to pursue these loans and terms; when they do, it is typically in a fast manner that is at a lower transactions cost than that which would be available from a bank or other source of capital. The speed and costs of access along with the efficient matching potentially opens new important opportunities for financing entrepreneurship.

In the United States, Prosper is the first peer to peer (P2P) lending platform. It was established by the end of 2005 and opened to public in February, 2006. Its ability to attract a large number of investors and borrowers, as is necessary of two-sided markets to function (Rochet & Tirole, 2003), made it one of the leading FinTech lenders in the United States. To date,[1] Prosper has extended more than $19 billion in loans to more than 1,140,000 borrowers. Prosper loans are personal loans which are comparable to personal bank consumer loans. Prosper's applicants and investors go through a verification process. This process entails the validation of the individual's identity, social security number, and bank account information. In addition, more personal information is requested from loan applicants (income level, employment status, length of employment, and occupation) which is further verified. Moreover, a comprehensive credit report is extracted through credit reporting agencies. Initially, credit reports were provided by Experian; however, in 2016, Prosper switched to Transunion for credit reporting services. With all this information, Prosper screens out loan applicants with credit scores below 640 and assigns a credit grade to the remaining applicants.

[1] Data accessed on September 30th, 2021 at https://www.prosper.com/about.

The lending process on Prosper changed over time. It was initially based on an auction-mechanism. In this business model, borrowers made an online listing that stated the requested loan amount (maximum of $25,000), its purpose, the duration of the auction (3-10 days), and the maximum interest rate they were willing to pay (from 5% to 35%). The loan request was accompanied by the applicant's location, credit grade, and other employment and traditional financial information. In this auction-type model, once the listing became active, investors could bid through Prosper's website on loans, stating the amount they were willing to fund and the minimum interest rate they were willing to receive (Iyer et al, 2009). They could be funded through two types of auctions: closed auctions, which ended at the borrower's asking rate once the amount bid reached the amount requested; and open auctions, which remained open for a fixed time length, allowing investors to bid down the loan's interest rate, even when the bid amount and the asking rate were already met. This auctioning process was time consuming and gave a competitive advantage to other FinTech lenders whom employed a posted-price mechanism.

In December 20th, 2010, Prosper's switched to a posted-price mechanism with a preset rate. Prosper's proprietary algorithm would evaluate the loan applicant's risk profile and assign a risk grade and a corresponding interest rate. Given the preset interest rate, loan grade, and the other financial and non-financial information, potential investors would evaluate the investment opportunity and make their investment decision. This investment decision would involve deciding whether or not to invest and how much to invest. Contrary, to the auction-model that required full funding, the preset rate model came with the possibility of partial funding (70% of the loan amount). By opting for the partial funding, if the loan applicant failed to secure 70% of their requested loan amount during the updated listing period of 14 days, the listing would expire with no credit being allocated to the applicant. Today, this posted-price mechanism is still in effect with Prosper offering fixed-interest, fully amortizing 3- and 5-year loans repaid monthly. Switching to the posted-price mechanism has allowed a faster capital allocation and loan origination process. Since 2016, on average, a successful loan application raises its required loan amount within 6 hours and the loan originates within 2-3 days.

Borrowers on FinTech lending platform tend to become loyal to this lending mechanism. Di Maggio and Yao (2021) show that FinTech borrowers are 60% more likely to return to the platform to solicit future loans relative to non-FinTech borrowers. This effect is 15% more pronounced for marginal borrowers. Hence, FinTech platforms provide a unique context to track loan applicants at different points in time. Such a context allows us to track loan applicants' employment and financial history at these different points where credit pulls are conducted by the platform with each loan application. Moreover, information regarding the outcome of the previous FinTech loan application (successful or unsuccessful and loan amount) is also available, which will help in providing more insights into the effect of credit access on self-employment decision and subsequent financial performance.

3 Data and Summary Statistics

To construct our dataset, first we extract the universe of loan listings on Prosper from January 1st, 2016 up to September 30th, 2020.[2] Prosper is the first peer-to-peer lending platform in the United States and one of the largest worldwide . We restrict our analysis to marginal individuals, loan applicants who repeatedly solicit loans through the platform during the period of our analysis, in order to identify changes in employment status, income, and credit access. Our analysis is restricted to individuals whose first loan application on the platform coincided with our period of analysis. In total, our dataset includes 198,984 loan requests made by 92,382 individuals. Verified individual-level characteristics regarding employment status, employment history, and income are provided by Prosper. Transunion provides credit information data attaining to these listings. To control for county-level characteristics we merge our loan listings dataset with contemporaneous county-level data extracted from the Bureau of Labor Statistics website (BLS.gov). We additionally control for general economic condition through capturing the annualized S&P500 return between the two loan applications solicited by the individual and whether the loan application is after COVID-19 outbreak in the United States. The loan listings in our data set cover 49 states representing 2,595 counties.

In order to disentangle the relationship between successful FinTech loan acquisition, self-employment decision, and subsequent financial performance, our analysis involves a three-stage empirical strategy. Although the dependent variables differ, our applicant-level controls and county-level controls are consistent across the models' specifications. At the applicant level, we control for previous monthly income (*Monthly Income*$_{T-1}$) and previous credit line (*Credit Line*$_{T-1}$) since monthly income and access to credit might be driven by previous monthly income and credit access. Since employment status might be sticky, we control for previous employment status (*Self-Employed*$_{T-1}$). Additionally, we control for the number of months that the loan applicant has been employed (*Employment History*$_{T-1}$). At the county level, we control for the unemployment rate in the loan applicant's county (*Unemployment Rate*$_{T-1}$) since unemployment could influence the decision to become self-employed. Similarly, we control for the average income in the county where the loan applicant is located (*Average County Income*$_{T-1}$) since the loan applicant's income might be affected by changes in the average county income. Additionally, we control for the percentage of individuals with associate degrees and above (*Higher Education*$_{T-1}$). Lacking information on when employment status switches took place, we control for the time elapsed between two loan requests (*Time since last loan*). To control for general economic conditions, we measure the annualized S&P 500 return (*Annualized Δ S&P500*) between two loan requests and whether the loan request is during COVID-19 period (*COVID-19*). Finally, we control for seasonality by including quarter dummies in all estimation models. We present the list of variables included in our analysis, their definitions,

[2] Our analysis starts in 2016 due to the need for consistency in the constructs reported by the credit reporting agency. In 2016, Prosper switched its credit reporting agency from Experian to Transunion. The constructs reported by these two credit reporting agencies and stored by Prosper are not identical.

and the data sources in Table 1. Due to the skewness of the variables in the analysis and zero values encountered, all continuous variables are transformed using the inverse hyperbolic sine transformation which has a similar interpretation as the natural log transformation, but is defined at zero values.

[Insert Table 1 About Here]

Besides the above controls, we additionally control for the probability that the individual returns to the platform to circumvent any sample selection bias associated with only analyzing loan applicants returning to the lending platform (Chen, 2013). This is done through Heckman-selection correction which involves estimating a probit model, with returning to the platform as our dependent variable. After doing so, the inverse mills ratio (IMR) is generated. This IMR is then associated with each observation and controlled for in all estimation models. The estimation process used to generate the IMR includes a set of exclusion restrictions which are not included in our main analysis. Absent better restrictions, we used state identifiers and the individual's outstanding loans on the platform as our exclusion restrictions. These exclusion restrictions would condition the individual's return to the platform for another loan but should not be associated with our main dependent variables.

In Table 2 we present the descriptive statistics (number of observations, mean, standard deviation, minimum, median, and maximum values) of the variables considered in our models. In Table 3a, we conduct a difference in means analysis between loan applicants who are self-employed and loan applicants who are employees. We note significant differences between these groups. First, in terms of loan applications, we note that, on average, self-employed loan applicants request smaller loan amounts ($8,904 vs $13,428), successfully raise lower amounts ($8,356 vs $10,717), but are more successful in raising their requested funds (85.21% vs 81.73%). In terms of loan applicants' profiles, self-employed loan applicants enjoy higher levels of monthly income ($8,561 vs $6,896), more seasoned employment history (137 months vs 107 months), but lower credit lines ($85,180 vs $91,084). Additionally, self-employed loan applicants' loan requests are more frequent (every 297 days vs 373 days). In terms of geographic location, on average, self-employed loan applicants are located in counties with lower unemployment rates (4.30% vs 4.54%), higher monthly income ($4,596 vs $4,568), and higher levels of individuals with higher education (62.07% vs 61.63%). We note that the periods that self-employed individuals return to the platform are characterized with higher annualized S&P500 returns (38.40% vs 26.99%) and that they returned to the platform less during COVID-19 outbreak in the United States (4.56% vs 9.66%). All these differences are significant at the 1% level. The difference in medians analysis yields the same conclusions.

[Insert Tables 2, 3a, and 3b About Here]

4 FinTech Loan Acquisition and Self-Employment

Financial inclusion and access to credit has significant economic implications for individuals (Célerier & Matray, 2019; Melzer, 2011). The importance of access to credit is amplified for marginal borrowers (Karlan & Zinman, 2010; Zinman, 2010). Marginal borrowers require credit to meet their obligations. Inability to access credit renders them unable to fulfill these obligations (Barr, 2004). FinTech loans have emerged as a substitute form of financing for these individuals (Butler et al., 2017). This is especially true for serial FinTech borrowers who repeatedly return to the lending platform. Hence, FinTech lenders helped in partially filling the financing gap. However, inability to secure a FinTech loan might have its implications on these applicants, these effect could vary given loan applicants' individual-level characteristics.

In terms of the decision to pursue self-employment, consumer credit has been shown to facilitate transition into self-employment. Scholars show that restricted access to credit decreases the probability that an individual indulges in self-employment and entrepreneurial activities (Bruhn & Love, 2014; Corradin & Popov, 2015; Herkenhoff et al., 2021; Schmalz, Sraer, & Thesmae, 2017). This effect is further amplified with stronger creditor protection laws (Ersahin, Irani, & Waldock, 2021). However, among serial borrowers, the effect of loan acquisition on self-employment decision is not necessarily the same. Serial borrowers are in need of credit to meet their obligations (Butler et al., 2017). This is especially true for FinTech lenders who turn to FinTech loans that are more readily available relative to bank loans (Di Maggio & Yao, 2021; Tang, 2019). Since FinTech loans are used by marginal individuals to meet immediate obligations, we suspect that the effect of failure to acquire a FinTech loan on self-employment decisions would differ given initial employment status. For self-employed individuals, we suspect that the inability to secure a FinTech loan would drive these individuals out of self-employment, since without this capital they are unable to sustain their activities. This effect would be more pronounced for self-employed individuals whom are more dependent on FinTech loan application outcome, those with lower incomes. As for employees, their inability to secure a FinTech loan to meet their obligations would rather lead to disgruntlement with current employment status. This would, in turn, lead to switches to self-employment in a quest to better their financial position, necessity entrepreneurship. Unlike self-employed individuals, we suspect that this effect would be stronger for employees with higher income since they are more financially capable of transitioning into self-employment.

To gain preliminary insight into the effect of FinTech loan application outcome on employment status, Table 4 summarizes employment status transitions for FinTech loan applicants (self-employed and employed). It shows that for the 5,463 self-employed individuals that had successful loans, 4,793 (87.74%) remained in self-employment while 670 (12.26%) switched to becoming an employee. For the 1,413 self-employed individuals that failed to obtain a FinTech loan, 1,016 (71.9%) remained self-employed while 397 (28.10%) switched to becoming an employee. The difference in means in employment status for self-employed individuals following a successful vs unsuccessful loan application is significant at the 1% level. Table 4 further shows that for the 71,220 successful loan applicants that were employees, 70,947 (99.62%) remained employees, while 273 (0.38%) switched to self-employment. And for the 28,506 employees that were unsuccessful in obtaining a FinTech loan, 25,438 (89.24%) remained employees while 3,068 (10.76%) switched to self-employment. Overall, the data in Table 4 are consistent with our presumptions that unsuccessful prior loan applications are more likely to lead to switches out of self-employment for self-employed individuals. At the same time, the data indicate that unsuccessful loan applications are also more likely to lead employees to become self-employed. Below, we examine some possible explanations in a multivariate context.

[Insert Table 4 About Here]

To estimate the probability of changing employment status following an unsuccessful FinTech loan application we run a panel logistic regression model with *Δ Employment Status*$_T$ as the dependent variable. *Δ Employment Status*$_T$ is regressed on the independent variable *Unsuccessful Loan*$_{T-1}$ for sub-samples of self-employed and employed individuals, alongside a set of loan-applicant, county-level, and economic-conditions controls, x. We additionally estimate the model for the top and lower income deciles, for each subsample. Hence, for a given loan applicant i at time t, if x is a vector of information about the loan applicant's profile and the corresponding county-level characteristics and economic conditions, we estimate:

$$Pr\left(\Delta\ Employment\ Status_{i,t}\ \middle|x_{i,t-1}\right) = \alpha + \beta_1 Unsuccessful\ Loan_{\ i,t-1} + \beta_2 x_{i,t-1} + \ e_{it} \tag{1}$$

Table 5 presents the marginal effects of the regression estimates of Equation (1). The data indicate that an unsuccessful loan application increases the probability of a switch from self-employment to employment in Column (1). This effect is statistically significant at the 1% level and its economic significance is indicated by the magnitude of the marginal effect which shows that an unsuccessful loan application is associated with a 21.63% increase in the probability of a switch from self-employment to employment. Further, when we break the analysis into deciles by income levels, the data indicate that the highest income decile is associated with the lowest likelihood of an unsuccessful FinTech loan application giving rise to a switch from self-employment to becoming an employee at 13.11%, while the lowest income decile shows the probability at 30.97%. Overall, therefore, the data indicate that FinTech loans are important enablers of allowing the self-employed population to remain self-employed. The benefits appear to be largely related to purely satisfy credit constraints insofar as high income levels mitigate the switch to being an employee after a failed loan attempt. But there remains a significant switching population even amongst the highest income earners, suggesting that there are also time and cost savings that are lost when a self-employed person does not obtain a FinTech loan.

[Table 5 About Here]

Column (1) of Table 5 shows a few significant control variables. For example, having a higher income and longer employment history mitigates the chance of switching from self-employment to employment, as expected these factors relate to wealth and experience that can sustain self-employment. A longer time from the prior successful loan increases the chance of a switch from self-employment to employment, which again is likely related to budget constraints. The data further indicate that access to more credit lines increases the likelihood of a switch to self-employment, which is somewhat unexpected, but might suggest some mismanagement of credit on the part of self-employed and a need to secure more stable income as an employee.

Column (4) of Table 5 considers the subset of employees and factors that caused a switch to self-employment. The data indicate that an unsuccessful loan application increases the probability of a switch to self-employment. We may infer from this finding that these entrepreneurs are potentially necessity entrepreneurs that needed to move to self-employment due to loan failure, or that they intended to switch to self-employment regardless of loan success in order to pursue a business opportunity. This effect is economically significant as the marginal effect shows that following an unsuccessful loan application the likelihood of switches to self-employment increases by 6.52%. This effect is 4.88% for employees at the lowest income decile, and 8.49% for employees at the highest income decile. As such, employees are more likely to become self-employed after a failed loan application if they have more resources that enable them to do so, which suggests that the mix of switchers to self-employment are partly due to opportunity and partly due to necessity. The control variables show that having a higher monthly income is likely to enable a switch to self-employment, while fewer lines of credit is less likely to give rise to a switch to self-employment. Switches to self-employment are more likely in counties with less unemployment and higher county level incomes.[3]

5 FinTech Loan Acquisition and Financial Performance

In Section 4 we have analyzed the effect of unsuccessful loan applications on self-employment for marginal individuals. We highlighted that unsuccessful FinTech loan applications drive self-employed individuals out of self-employment. This effect is stronger for self-employed individuals in the lowest income decile, emphasizing the need of access to credit to sustain self-employment activity. Conversely, unsuccessful FinTech loan applications drives marginal individuals who were employees into self-employment, reminiscent of the idea that "the grass is greener on the other side". This is especially true for employees in the highest income decile whom can afford to become self-employed. Knowing the significant role that FinTech loans play in sustaining self-employment activity among

[3] One might argue that individuals with stable employment history (self-employed or employee) are more likely to successfully obtain a loan rather than successfully obtaining a loan stabilizing employment status. To validate the causality that we argue, we run a panel vector auto regression model (VAR). The analysis shows that the relationship between employment status and successfully obtaining a loan is unidirectional. This is also validated by the granger causality test. The results are presented in Tables A.1 and A.2 of the Online Appendix.

marginal individuals, in this section we proceed to analyze the effect of the loan acquired on subsequent financial performance of self-employed individuals. Namely, we are interested in knowing their effects on future income and access to credit.

5.1 FinTech Loan Acquisition, Monthly Income, and Credit Lines

There are at least 5 reasons why FinTech loans can help self-employed individuals improve their monthly income and credit lines.[4] First, FinTech loans are either unsecured or typically require less security relative to bank loans. It frees up entrepreneurs' liquidity and puts less strain on assets. Second, FinTech uses algorithms to enable credit assessment in a faster and more efficient and accurate way than that which banks typically use. Third, FinTech involves lower cost underwriting which leads to lower processing fees. Fourth, and relatedly, the FinTech process is online and fast, and this online setup has been particularly important during the COVID-19 pandemic. Fifth, FinTech tracks entrepreneurs' occupations, gender, and demographics, which allows them to create customized products to help entrepreneurs.

To analyze the effect of successful loan amounts on changes in *Monthly Income* $_T$ and *Credit Line* $_T$, we restrict our analysis to self-employed individuals. To estimate this model, we run a panel OLS regression model with Δ *Monthly Income*$_T$ and Δ *Credit Line*$_T$ as our dependent variables. Δ *Monthly Income*$_T$ and Δ *Credit Line*$_T$ are regressed on the independent variable *Successful Loan Amount*$_{T-1}$ while controlling for a set of loan-applicant and county-level controls, *x*. Hence, we estimate:

$$\Delta\, Monthly\ Income_{\ i,t}|x_{i,t-1} = \alpha + \beta_1 Successful\ Loan\ Amount_{i,t-1} + \beta_2 x_{i,t-1} + e_{it} \tag{2}$$

$$\Delta\, Credit\ Line_{\ i,t}|x_{i,t-1} = \alpha + \beta_1 Successful\ Loan\ Amount_{i,t-1} + \beta_2 x_{i,t-1} + e_{it} \tag{3}$$

where:

$$\Delta\, Monthly\ Income_{\ i,t} = Monthly\ Income_{\ i,t} - Monthly\ Income_{\ i,t-1}$$

$$\Delta\, Credit\ Line_{\ i,t} = Credit\ Line_{\ i,t} - Credit\ Line_{\ i,t-1}$$

Table 6 presents estimates of the impact of a successful loan application amount on future financial performance. The data indicate that a prior successful loan has a positive and statistically significant effect on subsequent monthly income and credit lines, and these effects are significant at the 1% level in all of the specifications.

[4] https://www.forbes.com/advisor/in/loans/3-things-to-know-before-considering-p2p-lending/

The economic significance is such that a 1-standard deviation increase in prior successful loan amount improves income enhancement (Δ *Monthly Income$_T$*) by 2.44% and credit line enhancement (Δ *Credit Line$_T$*) by 3.52%.[5] To corroborate our findings, we run the Arellano-Bond dynamic panel estimation model which is known to not be prone to selection bias (Arellano & Bond, 1991). The results presented in Column (3) and Column (4) of Table 6 validate our findings.[6]

[Insert Table 6 About Here]

5.2 Asymmetric Effects of FinTech Loan Acquisition

As expected, we highlight the significant role that FinTech loans play in improving the financial performance of self-employed individuals. Following a successful FinTech loan application, these borrowers experience higher monthly incomes and better access to credit. However, these benefits that self-employed individuals enjoy might not be equal. Individuals with lower levels of income and more restrictive credit access, whom are more dependent on the FinTech loan, could benefit more or less from this loan. On the one hand, given the pivotal role that this loan plays, those individuals could efficiently use this loan to enhance their income. This would also help in easing their credit access restrictions and facilitate access to future lines of credit from different sources. On the other hand, self-employed individuals with low levels of income might lack the opportunities to best invest these loans in order to improve their income. Moreover, their limited credit access might mean that these self-employed individuals do not have sufficient exposure and experience in managing credit, which would mean that they would benefit less from the FinTech loan in that regards. With these considerations in mind, we suspect that FinTech loan acquisition might have an asymmetric effect on future performance.

To test whether the effect of successful loan acquisition on monthly income and active credit line is indeed asymmetric, we repeat our prior analysis using a quantile regression model at different deciles. Unlike OLS regression models, where the association between variables is determined at the mean, the decile models allow estimating different slope coefficients at different percentiles (τ). This provides with a more complete picture beyond the mean

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[5] Since all continuous variables (dependent and independent) are transformed using the inverse hyperbolic sine transformation, this calculation involves multiplying the standard deviation of the transformed variable (1 SD of transformed Successful Loan Amount = 3.8724) by the coefficient.
Change in Δ Monthly Income = 0.0063 * 3.8724
Change in Δ Credit Line = 0.0091 * 3.8724

[6] To isolate the effect of individual differences in loan acquisition on subsequent financial performance we perform coarsened exact matching (Iacus, King, & Porro, 2012) where individuals are matched based on their previous loan application outcome and along all main constructs. We run the analysis performed in Table 6 on the coarsened exact matched sample and note that the results are not qualitatively different from those presented in the main analysis. The result of this analysis is reported in Table A.3 of the Internet Appendix.

(Kneib, 2013; Waldmann, 2018). To that end, we estimate the effect of successful loan acquisition on performance and access to credit at all the corresponding deciles (0.10 – 0.90):

$$Q_\tau(Monthly\ Income\ _{i,t}|x_{i,t-1}) = \alpha + \beta_1 Successful\ Loan\ Amount_{i,t-1} + \beta_2 x_{i,t-1} + e_{it} \quad (4)$$

$$Q_\tau(Credit\ Line\ _{i,t}|x_{i,t-1}) = \alpha + \beta_1 Successful\ Loan\ Amount_{i,t-1} + \beta_2 x_{i,t-1} + e_{it} \quad (5)$$

The quantile regressions in Tables 7 and 8 are perhaps indicate that the estimates are highly sensitive to the income levels and the active credit lines of the self-employed individuals in the sample. A higher level of initial income and credit line means that a successful loan application is much less meaningful for securing a higher subsequent income and more credit. For both the income decile estimates in Table 7, and the credit lines decile estimates in Table 8, the effect of a successful FinTech loans is higher for those in the lowest decile. Specifically, income enhancement is 3.11 times greater for the lowest income decile compared to the highest income decile, while credit enhancement is 1.85 times larger for the lowest income decile relative to the second-highest income decile. The highest credit line decile shows an insignificant impact. Overall, therefore, the data provide very strong support for our arguments.

[Insert Tables 7 and 8 About Here]

Some of the control variables in Table 7 and 8 are significant in ways that would be expected. For example, income is positively associated with a longer employment history. Income is lower in counties with higher unemployment, but higher in richer counties. See Table 7. Credit lines are higher with longer employment history and in counties with higher education levels. While credit lines are lower in counties with higher unemployment. See Table 8.

6 Conclusion

We examine how FinTech loan outcome impacts future self-employment decision and financial performance of self-employed individuals. We find that for serial borrowers on the FinTech lending platform, inability to secure a FinTech loan drives switches in employment status. We additionally highlight that this effect is stronger for income constrained self-employed individuals but weaker for income constrained employees. As for future financial performance, we not that successful loan acquisition improves the subsequent financial performance of self-employed borrowers who enjoy higher future monthly income and more access to future lines of credit. This financial performance enhancement is more pronounced for marginal borrowers, those in the lowest income and credit access deciles.

Borrowers turn to FinTech lenders to readily finance personal obligations given the expedited loan origination process. Our evidence suggests that, following an unsuccessful FinTech loan, self-employed applicants switch out of self-employment due to their inability to sustain their activity. This is consistent with our finding that income constrained self-employed individuals are more likely to switch into employment following a failed FinTech loan application. As for employees switching to self-employment following an unsuccessful FinTech loan application, we may infer from the findings that some of the entrepreneurs that switch to self-employment are necessity entrepreneurs, since an employee at the lowest income decile is still 5% more likely to switch in the event of failure to obtain FinTech loan. But there are also opportunity entrepreneurs that switch, as an employee at the top income decile is 8.5% more likely to switch in the event of failure to obtain a FinTech loan. While the structure of our dataset do not enable a precise examination of the differences between necessity and opportunity entrepreneurs, future research with alternative data might investigate these different types of entrepreneurs in relation to FinTech in more detail. Our finding that FinTech loans have greater effects on the financial performance of marginal self-employed individuals highlights the important role that this lending channels plays in filling the financing gap.

Overall, our results show that Fintech lending platforms provide important opportunities for entrepreneurship as it aids self-employed individuals to keep engaging in their pursuits and improves their financial performance over time. We may infer from the evidence here that prior restrictions on FinTech lending in the United States (Cumming et al., 2021) harmed access to capital and entrepreneurship in the United States. More generally, regulations that limit FinTech lending should be carefully examined so that they do not have unintended consequences of inhibiting capital access for those with lower incomes.

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Tables

Table 1
Variable Description and Source

Variable	Description	Source
Δ Employment Status	A dummy variable = 1 if loan applicant's current employment status differs from previous employment status.	PROSPER.com
Unsuccessful Loan	A dummy variable = 1 if the loan application was unsuccessful.	PROSPER.com
Successful Loan Amount	Loan amount successfully acquired by loan applicant.	PROSPER.com
Credit Line	Loan applicant's credit line at time of loan request as reported by Transunion.	PROSPER.com
Monthly Income	Loan applicant's verified monthly income.	PROSPER.com
Employment History	Loan applicant's cumulative employment history (in months)	PROSPER.com
Self-Employed	A dummy variable = 1 if the loan applicant is self-employed.	PROSPER.com
Unemployment Rate	The unemployment rate in the loan applicant's county.	BLS.gov
Average County Income	The average monthly income in the loan applicant's county.	BLS.gov
Higher Education	The % of individuals with a degree beyond high school in the loan applicant's county.	BLS.gov
Time since last loan	The time elapsed since the loan applicant's latest loan request on the platform in years.	PROSPER.com
Annualized Δ S&P500	Annualized S&P500 return over the period t-1 and t.	SPGLOBAL.com
COVID-19	A dummy variable =1 if the current loan was requested during COVID-19, where the first recorded case in the United States was January 21st, 2020.	CDC.gov

Table 2
Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min	Median	Max
Successful Loan Amount	198,984	$ 10,540.25	8,710.67	0	10,000	40,000
Unsuccessful Loan	198,984	18.01%	0.38	0	1	1
Credit Line	198,984	$ 90,643.90	71,037.78	500	71,864	1,553,990
Monthly Income	198,984	$ 7,019.92	4,360.33	227	5,833	33,333
Employment History (in months)	198,984	108.93	106.88	0	72	500
Self-Employed	198,984	7.47%	0.26	0	0	1
Unemployment Rate	198,984	4.52%	1.96	1.60	4.00	24
Average County Income	198,984	$ 4,570.52	1,278.50	2,076.83	4,380	14,170
Higher Education	198,984	61.66%	9.24	24.40	61.70	93
Time since last loan (in years)	106,602	1.00	0.78	0	0.98	3.78
Annualized Δ S&P500	106,602	9.81%	1.14	-89.10%	9.81%	930.45%
COVID-19	198,984	9.28%	0.29	0	0	1

Table 3a
Difference in means

Variable	Employee	Self-Employed	Two tailed t-test
Loan Amount Requested	$13,428.44	$ 9,903.81	***
Successful Loan Request	81.73%	85.21%	***
Successful Loan Amount	$10,716.59	$ 8,355.68	***
Credit Line	$91,084.93	$85,180.14	***
Monthly Income	$ 6,895.53	$ 8,560.94	***
Employment History	106.66	137.05	***
Time since last loan	1.02	0.81	***
Annualized Δ S&P500	26.99%	38.40%	***
COVID-19	9.66%	4.56%	***
Unemployment Rate	4.54%	4.30%	***
Average County Income	$ 4,568.21	$ 4,596.42	***
Higher Education	61.63%	62.07%	***
Number of Observations	184,122	14,862	

Table 3b
Difference in medians

Variable	Employee	Self-Employed	Two tailed t-test
Loan Amount Requested	$11,000.00	$ 10,000.00	***
Successful Loan Amount	$10,000.00	$ 9,400.00	***
Credit Line	$72,280.50	$66,495.00	***
Monthly Income	$ 5,833.33	$ 6,916.67	***
Employment History	70	103	***
Time since last loan	0.98	0.84	***
Annualized Δ S&P500	9.80%	9.95%	*
Unemployment Rate	4.00%	4.00%	***
Average County Income	$ 4,379.75	$ 4,413.42	***
Higher Education	61.70%	62.07%	**
Number of Observations	184,122	14,862	

Table 4
Employment status transition given previous loan application outcome

Employment Status $_{T-1}$	Employment Status $_{T}$	Prior Loan Successful	Prior Loan Unsuccessful	Two tailed t-test
Self Employed	Self Employed	4,793 (87.74%)	1,016 (71.90%)	***
Self Employed	Employee	670 (12.26%)	397 (28.10%)	***
		5,463	1,413	
Employee	Employee	70,947 (99.62%)	25,438 (89.24%)	***
Employee	Self Employed	273 (0.38%)	3,068 (10.76%)	***
		71,220	28,506	

Table 5. Δ Employment Status: Logistic Regression

This table exhibits the results of a logistic regression model with Δ *Employment Status* as the dependent variable. The marginal effects of previous loan outcome, *Unsuccessful Loan,* are presented for the sub-samples and the corresponding upper and lower income deciles. Standard errors are clustered at the county-level and are shown in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	Dependent Variable: Δ Employment Status $_T$					
	Employment Status $_{T-1}$ = Self-employed			Employment Status $_{T-1}$ = Employee		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sub-sample	Income Bottom 10%	Income Top 10%	Full Sub-sample	Income Bottom 10%	Income Top 10%
	dy/dx	*dy/dx*	*dy/dx*	*dy/dx*	*dy/dx*	*dy/dx*
	(*s.e.*)	(*s.e.*)	(*s.e.*)	(*s.e.*)	(*s.e.*)	(*s.e.*)
Unsuccessful Loan $_{T-1}$	0.2163***	0.3097***	0.1311**	0.0652***	0.0488***	0.0849***
	(0.0214)	(0.0704)	(0.0650)	(0.0038)	(0.0092)	(0.0121)
Individual Level:						
Credit Line $_{T-1}$	0.0331***	0.0378	0.0190	-0.0023***	-0.0013	-0.0028***
	(0.0054)	(0.0235)	(0.0140)	(0.0003)	(0.0011)	(0.0007)
Monthly Income $_{T-1}$	-0.0672***	-0.2796***	-0.1000*	0.0039***	0.0047	0.0046**
	(0.0077)	(0.0756)	(0.0533)	(0.0004)	(0.0042)	(0.0018)
Employment History $_{T-1}$	-0.0336***	-0.0320***	-0.0214***	0.0001	0.0002	0.0013***
	(0.0029)	(0.0120)	(0.0075)	(0.0001)	(0.0006)	(0.0004)
County-Level:						
Unemployment Rate $_{T-1}$	-0.3016	-0.7730	0.8639	-0.0792***	-0.1862**	-0.0886*
	(0.3554)	(1.7830)	(0.8478)	(0.0169)	(0.0846)	(0.0496)
Average County Income $_{T-1}$	-0.0098	-0.0297	0.0553	0.0012	0.0106**	-0.0016
	(0.0195)	(0.0978)	(0.0382)	(0.0008)	(0.0044)	(0.0021)
Higher Education $_{T-1}$	0.0685	-0.3432	0.2329	0.0015	-0.0018	-0.0148*
	(0.0662)	(0.3025)	(0.1547)	(0.0029)	(0.0145)	(0.0078)
Other Controls:						
Time since last loan	0.0472***	0.1037**	0.0699**	-0.0052***	-0.0111***	-0.0053**
	(0.0111)	(0.0483)	(0.0290)	(0.0007)	(0.0036)	(0.0021)
Annualized Δ S&P500 $_T$	0.0248***	0.0358	0.0244**	0.0002	0.0016*	-0.0004
	(0.0072)	(0.0317)	(0.0113)	(0.0002)	(0.0009)	(0.0004)
COVID-19 $_T$	0.1317***	0.0466	0.0544	-0.0033***	-0.0018	-0.0097***
	(0.0179)	(0.0691)	(0.0368)	(0.0008)	(0.0045)	(0.0020)
Inverse Mills Ratio	0.0210***	0.0537*	0.0184	0.0006	0.0063***	-0.0022
	(0.0061)	(0.0292)	(0.0142)	(0.0005)	(0.0019)	(0.0015)
Quarter Dummies $_{T-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	6,876	570	687	99,726	9,972	9,972
R-squared	0.1026	0.0942	0.0929	0.2232	0.1595	0.2730

Table 6. Performance & Credit Access Enhancement: Panel OLS and Dynamic Panel Data Model.

This table presents the coefficient estimates on *Successful Loan Amount* in Column (1) – Column (4). In Column (1) we run a panel OLS estimation model with change in *Monthly Income* as the dependent variable. In Column (2) we run a panel OLS estimation model with change in *Credit Line* as the dependent variable. In Columns (3) and (4), as a robustness check, we repeat the analysis conducted in Columns (1) and (2) using the Arellano-Bond dynamic panel data estimation model. Specification checks are also presented. The R-squared values are used to gauge the panel OLS model fit. The autocorrelation and Sargan tests are used to check the model specification of the dynamic panel data model. Standard errors are shown in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	(1)		(2)		(3)		(4)	
Dependent Variable:	Δ Monthly Income $_T$		Δ Credit Line $_T$		Monthly Income $_T$		Credit Line $_T$	
	β/se		*β/se*		*β/se*		*β/se*	
Successful Loan Amount $_{T-1}$	0.0063***	(0.0010)	0.0091***	(0.0016)	0.0202***	(0.0066)	0.0083**	(0.0033)
Individual-Level:								
Monthly Income $_{T-1}$					1.6725***	(0.4987)		
Credit Line $_{T-1}$							0.7060***	(0.1002)
Employment History $_T$	-0.0159***	(0.0022)	-0.0213***	(0.0036)	0.0121	(0.0255)	0.0208	(0.0242)
Self-Employed $_{T-1}$	-0.0725***	(0.0073)	0.0216*	(0.0118)	-0.1773***	(0.0454)	0.0307	(0.0289)
County-Level:								
Unemployment Rate $_T$	0.4135**	(0.1806)	-0.4313	(0.2951)	0.9359	(0.7142)	-0.6662	(0.7342)
Average County Income $_T$	0.0142	(0.0115)	0.0103	(0.0189)	-0.6993*	(0.4205)	0.1627	(0.4164)
Higher Education $_T$	0.0109	(0.0388)	-0.1031	(0.0638)	2.0345*	(1.2280)	-0.1323	(1.2590)
Other Controls:								
Time since last loan	0.1377***	(0.0078)	0.2439***	(0.0127)	0.1715***	(0.0407)	0.2307***	(0.0297)
Annualized Δ S&P500 $_T$	-0.0018	(0.0031)	0.0010	(0.0051)	-0.0070	(0.0118)	0.0148*	(0.0085)
COVID-19 $_T$	-0.0527***	(0.0130)	-0.0414*	(0.0211)	-0.0053	(0.0458)	-0.0272	(0.0414)
Inverse Mills Ratio	0.0067	(0.0045)	-0.0294***	(0.0072)	-0.0220	(0.0220)	-0.0027	(0.0123)
Quarter Dummies $_{T-1}$	Yes		Yes		Yes		Yes	
Specification Checks:								
R-squared within / AR(1)	0.1000		0.2516		-1.49*		-3.22***	
R-squared between / AR(2)	0.1250		0.1869		0.15		0.91	
R-squared overall / Sargan Test	0.1197		0.1883		2.02		3.58	
Number of Observations	9,150		9,150		1,281		1,281	
Number of Individuals	8,205		8,205		1,156		1,156	

Table 7. Performance Enhancement: Quantile Regression Model

This table presents the coefficient estimates on *Successful Loan Amount* across different deciles of the dependent variable *Monthly Income*. Standard errors are shown in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	Dependent Variable: Monthly Income $_T$								
	0.10	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**
	β/se	*β/se*	*β/se*	*β/se*	*β/se*	*β/se*	*β/se*	*β/se*	*β/se*
Successful Loan Amount $_{T-1}$	0.0246***	0.0232***	0.0201***	0.0195***	0.0195***	0.0220***	0.0177***	0.0150***	0.0079*
	(0.0033)	(0.0031)	(0.0032)	(0.0029)	(0.0032)	(0.0035)	(0.0036)	(0.0041)	(0.0044)
Individual Level:									
Employment History $_T$	0.0739***	0.0853***	0.0889***	0.0901***	0.0898***	0.1027***	0.1161***	0.1154***	0.0915***
	(0.0074)	(0.0091)	(0.0068)	(0.0079)	(0.0068)	(0.0080)	(0.0086)	(0.0101)	(0.0093)
Self-Employed $_{T-1}$	-0.0043	0.0009	0.0075	-0.0014	-0.0112	-0.0405	-0.0397	-0.0280	-0.0123
	(0.0208)	(0.0253)	(0.0239)	(0.0270)	(0.0255)	(0.0294)	(0.0300)	(0.0357)	(0.0375)
County-Level:									
Unemployment Rate $_T$	-0.9582	-1.8204***	-1.8198***	-1.5704**	-1.5439**	-0.6976	-1.2986**	-1.8816***	-1.2137
	(0.6004)	(0.5353)	(0.6281)	(0.6843)	(0.6945)	(0.7396)	(0.5570)	(0.6694)	(1.0083)
Average County Income $_T$	0.2605***	0.2131***	0.1984***	0.1896***	0.1754***	0.1562***	0.1124***	0.1067**	0.0930
	(0.0397)	(0.0345)	(0.0374)	(0.0374)	(0.0364)	(0.0500)	(0.0420)	(0.0519)	(0.0566)
Higher Education $_T$	0.1762	0.1230	0.1889	0.1919	0.2003	0.2336	0.2876**	0.1503	0.1782
	(0.1221)	(0.1327)	(0.1250)	(0.1424)	(0.1564)	(0.1617)	(0.1346)	(0.1340)	(0.1824)
Other Controls:									
Time since last loan	0.0309	0.0005	0.0141	0.0066	-0.0035	-0.0089	0.0011	-0.0463	-0.0059
	(0.0235)	(0.0243)	(0.0231)	(0.0250)	(0.0243)	(0.0295)	(0.0337)	(0.0347)	(0.0338)
Annualized Δ S&P500 $_T$	0.0143*	0.0077	0.0022	0.0111	0.0115	0.0085	0.0048	-0.0103	0.0109
	(0.0075)	(0.0095)	(0.0113)	(0.0129)	(0.0096)	(0.0129)	(0.0117)	(0.0102)	(0.0197)
COVID-19 $_T$	-0.0097	0.0414	0.0552	0.0770	0.1077**	0.0230	0.0682	0.0747	0.0287
	(0.0433)	(0.0449)	(0.0521)	(0.0550)	(0.0424)	(0.0504)	(0.0457)	(0.0484)	(0.0571)
Inverse Mills Ratio	0.0077	0.0205	0.0017	-0.0022	0.0156	0.0233	0.0404**	0.0393**	0.0638***
	(0.0170)	(0.0153)	(0.0130)	(0.0146)	(0.0148)	(0.0197)	(0.0182)	(0.0165)	(0.0176)
Quarter Dummies $_{T-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9,150	9,150	9,150	9,150	9,150	9,150	9,150	9,150	9,150
Number of Individuals	8,205	8,205	8,205	8,205	8,205	8,205	8,205	8,205	8,205

Table 8. Credit Access Enhancement: Quantile Regression Model

This table presents the coefficient estimates on *Successful Loan Amount* across different deciles of the dependent variable *Credit Line*. Standard errors are shown in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	Dependent Variable: Credit Line $_T$								
	0.10	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**
	β/se	*β/se*	*β/se*	*β/se*	*β/se*	*β/se*	*β/se*	*β/se*	*β/se*
Successful Loan Amount $_{T-1}$	0.0314***	0.0320***	0.0276***	0.0254***	0.0220***	0.0203***	0.0199***	0.0170***	0.0053
	(0.0070)	(0.0053)	(0.0056)	(0.0046)	(0.0046)	(0.0049)	(0.0048)	(0.0044)	(0.0043)
Individual Level:									
Employment History $_T$	0.0932***	0.0892***	0.0961***	0.0985***	0.1061***	0.1079***	0.1090***	0.1180***	0.0952***
	(0.0124)	(0.0125)	(0.0112)	(0.0091)	(0.0108)	(0.0114)	(0.0117)	(0.0109)	(0.0138)
Self-Employed $_{T-1}$	-0.0896*	-0.1210***	-0.1176***	-0.0845**	-0.0769**	-0.0843**	-0.1134***	-0.1292***	-0.0850**
	(0.0482)	(0.0378)	(0.0412)	(0.0347)	(0.0347)	(0.0356)	(0.0387)	(0.0309)	(0.0334)
County-Level:									
Unemployment Rate $_T$	-2.4735**	-2.5521**	-1.3398	-1.5195*	-1.7616**	-1.7650*	-0.4175	-0.3834	-1.1300*
	(1.1926)	(1.1925)	(1.1821)	(0.7766)	(0.7959)	(1.0681)	(0.6819)	(0.7599)	(0.6043)
Average County Income $_T$	-0.0485	-0.0730	-0.0358	0.0044	0.0207	0.0745	0.0426	0.0563	0.0589
	(0.0902)	(0.0663)	(0.0532)	(0.0484)	(0.0558)	(0.0558)	(0.0495)	(0.0611)	(0.0612)
Higher Education $_T$	0.6025***	0.4350**	0.3952**	0.2612	0.1439	0.1754	0.2256	0.1566	-0.0017
	(0.2247)	(0.1916)	(0.1697)	(0.1719)	(0.1948)	(0.1920)	(0.1840)	(0.1884)	(0.2186)
Other Controls:									
Time since last loan	0.2723***	0.1902***	0.1533***	0.1144***	0.1072***	0.0992***	0.0776**	0.0575*	0.0453
	(0.0664)	(0.0407)	(0.0383)	(0.0301)	(0.0358)	(0.0377)	(0.0315)	(0.0349)	(0.0361)
Annualized Δ S&P500 $_T$	-0.0172	0.0027	-0.0142	-0.0012	-0.0091	-0.0124	-0.0074	0.0087	-0.0019
	(0.0343)	(0.0198)	(0.0171)	(0.0156)	(0.0143)	(0.0111)	(0.0228)	(0.0180)	(0.0137)
COVID-19 $_T$	0.0425	0.1242	0.0429	0.1064**	0.0954*	0.1057	0.0492	0.0539	0.0738
	(0.1010)	(0.0803)	(0.0843)	(0.0519)	(0.0554)	(0.0729)	(0.0487)	(0.0497)	(0.0473)
Inverse Mills Ratio	0.1055***	0.0791***	0.0728***	0.0453**	0.0454**	0.0416**	0.0477***	0.0509***	0.0371*
	(0.0275)	(0.0262)	(0.0202)	(0.0181)	(0.0199)	(0.0190)	(0.0153)	(0.0169)	(0.0211)
Quarter Dummies $_{T-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9,150	9,150	9,150	9,150	9,150	9,150	9,150	9,150	9,150
Number of Individuals	8,205	8,205	8,205	8,205	8,205	8,205	8,205	8,205	8,205

Internet Appendix

FinTech Loans, Self-Employment, and Financial Performance

Douglas Cumming and Ahmed Sewaid

Table A.1 Employment Status and Successful Loan Amount: Panel Vector Auto Regression (PVAR) Model

This table presents the coefficient estimates on *Self-Employed* and *Successful Loan Amount* using a panel vector autoregression model to validate the causality between these two variables. The model controls for individual-level and county-level exogenous variables. Standard errors are shown in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	(1)		(2)	
Dependent Variable:	Self-Employed $_{T}$		Successful Loan Amount $_{T}$	
	β/*se*		β/*se*	
Self-Employed $_{T-1}$	0.4651***	(0.0731)	-0.7813	(1.1522)
Successful Loan Amount $_{T-1}$	0.0046***	(0.0014)	0.3594***	(0.0358)
Individual-Level:				
Credit Line $_{T-1}$	0.0132	(0.0161)	1.6176***	(0.3935)
Monthly Income $_{T-1}$	0.1646***	(0.0568)	7.4171***	(1.4637)
Employment History $_{T-1}$	0.0021	(0.0068)	0.7028***	(0.1937)
County-Level:				
Unemployment Rate $_{T-1}$	-1.4311	(1.1752)	28.3476	(34.9727)
Average County Income $_{T-1}$	-0.2248	(0.2092)	37.7466***	(6.2424)
Higher Education $_{T-1}$	0.0521	(0.6899)	16.1171	(19.0184)
Other Controls:				
Time since last loan	-0.0052*	(0.0028)	0.1086	(0.0718)
Inverse Mills Ratio	-0.0042	(0.0050)	-0.2288	(0.1486)
Number of Observations	14,221		14,221	
Number of Individuals	12,563		12,563	

Table A.2 Causality between Employment Status and Successful Loan Amount: Panel Granger Causality Test

This table exhibits the significance of the two dependent variables in the previously estimated panel vector auto regression model presented in Table 8. The Granger causality test is used to determine the direction of the causality between the two dependent variables.

Eq (1)	Excluded	Chi^2	Prob	Eq (2)	Excluded	Chi^2	Prob
Self-Employed $_T$				**Successful Loan Amount $_T$**			
	Successful Loan Amount $_{T-1}$	11.099	0.001		Self-Employed $_{T-1}$	0.460	0.498
	All	11.099	0.001		All	0.460	0.498

Table A.3 Performance & Credit Access Enhancement: Panel OLS (Coarsened Exact Matching Sample)
This table presents the coefficient estimates on *Successful Loan Amount* in Column (1) and Column (2) for the coarsened exact matching sample. Observations are matched against all constructs restricting the sample to 2,578 observations. In Column (1) we run a panel OLS estimation model with change in *Monthly Income* as the dependent variable. In Column (2) we run a panel OLS estimation model with change in *Credit Line* as the dependent variable. Standard errors are shown in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	(1)		(2)	
Dependent Variable:	Δ Monthly Income $_T$		Δ Credit Line $_T$	
	β/se		*β/se*	
Successful Loan Amount $_{T-1}$	0.0048***	(0.0016)	0.0121***	(0.0021)
Individual-Level:				
Employment History $_T$	-0.0169***	(0.0047)	-0.0223***	(0.0065)
Self-Employed $_{T-1}$	-0.1265***	(0.0133)	-0.0215	(0.0182)
County-Level:				
Unemployment Rate $_T$	0.0157	(0.0157)	0.0002	(0.0217)
Average County Income $_T$	0.0108	(0.0246)	0.0233	(0.0345)
Higher Education $_T$	-0.1374*	(0.0823)	-0.1374	(0.1147)
Other Controls:				
Time since last loan	0.0403***	(0.0037)	0.0498***	(0.0050)
Inverse Mills Ratio	0.0223**	(0.0097)	-0.0253*	(0.0131)
Constant	-0.0522	(0.2078)	-0.1272	(0.2913)
Specification Checks:				
R-squared within	0.1870		0.1656	
R-squared between	0.1649		0.1609	
R-squared overall	0.1642		0.1629	
Number of Observations	2,578		2,578	

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