Crowdlending, Self-Employment, and Entrepreneurial Performance

Douglas Cumming [1]
Florida Atlantic University

Ahmed Sewaid [2]
MBS College of Business and Entrepreneurship

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[1] College of Business, Florida Atlantic University, Boca Raton, Fl, USA. e-mail: cummingd@fau.edu
[2] MBS College of Business and Entrepreneurship, KAEC, Saudi Arabia. e-mail: asewaid@mbsc.edu.sa

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ABSTRACT

Access to finance is crucial for sustaining entrepreneurial activity. Building on social identity theory, we suggest that the psychological cost of loan rejection by a crowdlending platform is higher than that of a rejection by a traditional financial institution. The data indicate that a failed crowdlending loan attempt is associated with a 13.26% increase in the probability of transitioning out of self-employment. This effect is 1.69 times that of revolving lines of credit, and 2.77 times that of non-revolving lines of credit. We highlight that these effects are amplified for marginal borrowers, credit- and income-constrained entrepreneurs. Additionally, we show that successful crowdlending enhances self-employed individuals' future income and future access to traditional lines of credit. Implications for policy and practice are discussed.

Keywords: Crowdlending, Fintech, Entrepreneurship

1. INTRODUCTION

Access to finance is widely regarded as one of the main impediments of entrepreneurship and innovation (Audretsch, 2007; de Rassenfosse and Fischer, 2016; Howell, 2020; Johan et al., 2014; Keuschnigg and Nielsen, 2002; Tykvova, 2017). Entrepreneurs face pronounced hurdles in accessing external finance due to the pronounced information asymmetries and agency costs associated with entrepreneurial endeavors (Colombo et al., 2021). Entrepreneurial firms normally lack a long track record of successful past performance and have little to offer to financers in the form of collateral. Given that there are no mandated reporting requirements for entrepreneurial firms that are not listed on a stock exchange, there are significant adverse selection costs in financing entrepreneurs (Cumming and Johan, 2017; Stiglitz and Weiss, 1981).

Recently, crowdlending has emerged as a new form of finance that alleviates some of the barriers to entrepreneurial finance. Moreover, it provides advantages that facilitate the entrepreneurship process (Agrawal, Catalini, and Goldfarb, 2014). Crowdlending enables a matching of individual lenders to borrowers in a way that eliminates the need for traditional banks as financial intermediaries (Cumming and Hornuf, 2022). Lenders can evaluate prospective entrepreneurs and make direct decisions about loan applications. Entrepreneurs can decide whether to pursue these loans and terms. Since the decision on a crowdlending loan application is made by the crowd and not by a financial institution, its implications for the loan applicant would differ from that of a conventional loan.

In this paper we examine the impact of a rejected crowdlending loan application on transitions out of self-employment. This effect is compared to that of inability to access traditional lines of credit. We build on social identity theory to highlight the reasons why a rejected crowdlending loan application differs from institutional rejection by conventional financial institutions. Our empirical approach leverages the universe of serial borrowers on a leading U.S. crowdlending platform. Serial borrowers are loan applicants who have repeatedly solicited loans on the crowdlending platform. Our data coverage is for the period commencing in January 2016 and ending in September 2020. The crowdlending context allows us to exploit data on both granted and rejected loan applications, such information is not available in the traditional context (Li and Martin, 2019, Sewaid et al., 2021a). Our initial dataset consists of 198,984 crowdlending 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 multi-stage empirical strategy.

First, we begin our analysis by examining the impact of crowdlending loan outcome on transitions out of self-employment. Prior studies have shown that access to credit stimulates *entry into* self-employment (Herkenhoff et al., 2021). We complement prior work by examining how loan outcomes, having become an entrepreneur, affect the decision to *maintain* self-employment status. Moreover, we extend the literature to a different type of credit, crowdlending, and contrast it to traditional sources of credit. This extension to the literature is interesting since crowdlending loan applications are granted or rejected by the crowd rather than by a longstanding institutional body. This makes the loan application outcome a personal experience since it is perceived as a decision by peers. Our analysis highlights that failure to obtain a crowdlending loan increases the probability of transitioning out of self-employment by 13.26%. This effect is 1.69 times more pronounced than that of the inability to access revolving lines of credit and 2.77 times more pronounced than the of the inability to access non-revolving lines of credit. This suggests that, for applicants, the effect of crowd rejection is more severe than institutional rejection. This effect is not the same across all applicants. Credit- and income-constrained loan applicants are more severely affected by crowdlending loan rejection.

Second, we analyze the impact of crowdlending loans on subsequent entrepreneurial performance. As highlighted by previous literature investigating traditional credit channels, access to credit plays a crucial role in improving entrepreneurs' future income. We argue that this effect is amplified for crowdlending loans since they are timely, customized, less costly, and put less strain on the applicants' assets. Moreover, given that crowdlending loan applicants identify with the community on the crowdlending platform, feeling accepted by the crowd can serve as a motivation that drives them to work harder. We document that a 1 SD increase in previous crowdlending loan amount improves income enhancement by 2.99%. The magnitude of this enhancement is 1.64 times that of non-revolving lines of credit. Hence, crowdlending plays a significant role in improving the income of self-employed individuals.

Third, we argue that access to crowdlending loans can extend beyond improving entrepreneurial performance. Improved entrepreneurial performance allows entrepreneurs to accumulate assets. Moreover, by staying current on crowdlending loans, entrepreneurs can build their reputation and establish legitimacy which is reflected in the credit scores. Traditional lenders can make use of the positive signal of successful crowdlending in the past to infer that the borrower is of high quality and worth extending credit. Hence, crowdlending loans can facilitate future capital acquisition (Howell, 2020). Indeed, our analysis shows that a 1 SD increase in crowdlending loan amount is associated with a 3.29% increase in credit line access enhancement. This effect holds for both revolving and non-revolving lines of credit. This highlights the significant role that crowdlending platforms can play in eliminating barriers to accessing financing.

Our main contribution is to study the effect of crowdlending loans on maintaining self-employment activities and its effect on entrepreneurial performance and access to traditional sources of credit. We believe that our paper provides a major scholarly contribution to two main streams in literature. First, we add to the literature on credit access and self-employment activity (Dehejia and Gupta, 2021; Herkenhoff et al., 2021). This literature has mainly focused on how traditional credit access stimulates entry into self-employment. We highlight that credit access is crucial for maintaining self-employment activities. Our results compare a new asset class, crowdlending loans, to traditional sources of credit, revolving and non-revolving. Given the lending dynamics of crowdlending platforms we highlight how the effect of a rejection on the platform is more severe relative to the inability to access traditional sources of financing.

A second contribution of our study is that it adds to the literature on crowdlending and future financial performance (Chava et al., 2021; Di Maggio and Yao, 2021). We specifically show a positive effect of crowdlending 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 relative to employees. 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.

From the policy implication angle, our findings are related to a number of other papers in the literature. First, there is a large literature on regional availability of capital, and how regions with more sources of capital have more entrepreneurship (Audretsch, 2007). Second, there are papers which show that legal changes that enable regions to have access to crowdlending subsequently have more entrepreneurs in that region (Cumming et al., 2022). Third, there is work which shows having access to sources of capital, including but not limited to crowdlending, can subsequently lead to raising other forms of capital (Kaminski et al., 2016; Signori and Vismara, 2018). Based on a transaction-by-transaction analysis of crowdlending and subsequent entrepreneurial outcomes, our findings highlight the economic significance of crowdlending. These findings can aid policymakers in designing programs and policies to stimulate the supply of capital in a region to improve the quality and quantity of entrepreneurship.

2. INSTITUTIONAL SETTING

In the United States, Prosper is the first crowdlending 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 and Tirole, 2003), made it one of the leading crowdlending platforms in the United States. To date,[3] 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,

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

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.

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 (Lin and Viswanathan, 2015). 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 crowdlenders whom employed a posted-price mechanism.

In December 20th, 2010, Prosper 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. Moreover, crowdlending markets are relatively stable in comparison to bank debt-financing. During the COVID-19 crisis in 2020, for example, crowdlending dropped off to a much less pronounced degree than bank loans in the United States (Cumming et al., 2021). Worth noting, during the period 2016-2020, crowdlending was a leading indicator of bank lending (Cumming et al., 2021).

Borrowers on crowdlending platforms tend to become loyal to this lending mechanism. Di Maggio and Yao (2021) show that crowdlending borrowers are 60% more likely to return to the platform to solicit future loans relative to non-crowdlending borrowers. This effect is 15% more pronounced for marginal borrowers. Hence, crowdlending 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 crowdlending 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 entrepreneurial performance.

3. HYPOTHESES DEVELOPMENT

3.1 Loan Rejections and Self-Employment Transitions

The different factors conditioning individuals' transition into self-employment have long attracted the interest of both researchers and policymakers interested in understanding the drivers of entrepreneurial activity (Lofstrom et al., 2014). This is of particular importance since transitions into self-employment are associated with higher business formation rates enhancing an economy's productivity and growth (Audretsch et al., 2006). However, it is worth noting, transitions into self-employment are not irreversible. A considerable portion of individuals who engage in self-employment do not persist, such that exits from self-employment are common (Wennberg and DeTienne, 2014; Koch et al., 2021). Existing research highlights numerous factors that drive exit from entrepreneurship. This research focuses mainly on individuals' motivations (Block and Sandner, 2009), degree of engagement (Westhead et al. 2005), and career pattern (Koch et al., 2021) with limited to no attention dedicated to the role that access to finance can play in sustaining the entrepreneurial activity, having pursued entrepreneurship.

Access to finance has been found to facilitate entry into entrepreneurship (Deloof et al., 2018; Bertoni et al., 2021). Having pursued entrepreneurship, the financial returns of the entrepreneurial venture can be very volatile (Hsu, 2006). At some instances, this could require entrepreneurs to solicit external financial resources to meet their financial needs (Kirsch, Goldfarb, and Gera, 2009). To solicit a loan, entrepreneurs can tap traditional financial institutions or alternative sources of financing (Block et al., 2021). Crowdlending has emerged as a financing mechanism that stimulates entrepreneurial activity (Cumming, et al., 2022). On crowdlending platforms, borrowers personalize their loan request (Lin, Prabhala, and Viswanathan, 2012) and develop a connection with the platform where they feel part of a larger community of like-minded individuals (Belleflamme, Lambert, and Schwienbacher, 2014). This is a connection that borrowers have with their financiers on the platform and does not exist in the traditional context.

The inability to access financial resources, when needed, financially constrains an entrepreneur. This constraint could ultimately lead the entrepreneur to exit entrepreneurship due to financial reasons (Cassar and Friedman, 2009). However, there are also psychological costs involved when an entrepreneur is denied a loan by either crowdlending platforms or traditional financial institutions. The psychological cost associated with a loan rejection could lead to a loss of self-esteem which is closely linked to the loan applicant's social identity. Individuals derive self-esteem from acceptance and validation (Baumeister, Twenge, and Nuss, 2002). By having a loan application rejected, it leads to feelings of personal rejection and invalidation which leads to discouragement and self-doubt. This sense of discouragement can be further intensified through the loss of motivation which would be a result of viewing one's efforts being in vain (Amabile, 1993) or through the negative emotions associated with this rejection which are overwhelming and debilitating (Keltner and Haidt, 1999). Hence, discouragement as a result of loan rejection would lead self-employed individuals to transition out of self-employment. The magnitude of this effect would differ given the financing channel tapped since the psychological costs of being rejected via a crowdlending platform vs. a traditional financial institution are not identical.

Traditional financial institutions are longstanding institutions which are perceived as trustworthy and legitimate (Lerner and Tufano, 2011). This is because, relative to crowdlending platforms, financial institutions are subject to more rigorous regulatory oversight and have a long-established reputation for providing financial services (Agrawal et al., 2014). When rejected by a traditional financial institution it is more likely that the loan applicant perceives this rejection as a result of the institution's objective assessment of their creditworthiness. Moreover, they would view this as an institutional rejection rather than a personal judgment. On the other hand, on crowdlending platforms, decisions on loan applications are made by peers on the platform. According to social identity theory (Tajfel and Turner, 1979), individuals define their identity based on their memberships in social groups. Given the sense of community on the platform (Belleflame et al., 2014), loan applicants and fund providers feel part of the same social group. Hence, when a loan applicant is rejected by individuals belonging to the same social group, this rejection is perceived as a more personal form of rejection. This is especially true since loan applicants feel more invested in the platform and its community which results in viewing this rejection as a loss of social support. Indeed, prior studies show that individuals experience greater social identity threat when receiving negative feedback from peers (Greenberg, Ashton-James, and Ashkanasy, 2007).

Besides incurring higher psychological costs following a crowdlending loan rejection due to social identity threat, another potential driver of the higher psychological costs associated with the crowdlending loan rejection is social comparison. Social comparison theory suggests that individuals evaluate their own abilities by comparing them to others (Festinger, 1954). On crowdlending platforms, loan applications are public and an individual can compare their profile with the profile of other loan applicants (Lin et al., 2012). Given the sense of community on the platform, when individuals apply for a loan, they would feel more closely identified with other loan applicants on the platform. They might perceive their peers who have been approved for loans on the platform more similar to themselves than they would perceive customers of traditional financial institutions. Thus, a loan rejection on the crowdlending platform would lead to a more negative self-evaluation and a feeling of inferiority. Hence, the psychological costs associated with loan rejection are aggravated in the crowdlending context, leading to a higher sense of discouragement. With these arguments in mind, we hypothesize:

> **Hypothesis 1a (H1a):** *A rejected crowdlending loan application is positively associated with a transition out of entrepreneurship.*

> **Hypothesis 1b (H1b):** *The association between a rejected crowdlending loan application and a transition out of entrepreneurship is stronger than that of traditional financing mechanisms (revolving and non-revolving lines of credit).*

The importance of access to credit is amplified for marginal borrowers (Karlan and Zinman, 2010; Zinman, 2010). Marginal borrowers are those who require credit to meet their obligations and inability to access credit renders them unable to fulfill these obligations (Barr, 2004). A marginal borrower in this sense would be a credit-constrained entrepreneur or an income-constrained entrepreneur. If an entrepreneur is constrained in terms of credit sources or income, then the outcome of a crowdlending loan application is more critical. In terms of psychological cost, the effect of loan rejection is amplified for marginal borrowers. Bandura (1997) highlights that resource scarcity exposes individuals and makes them more vulnerable. This would lead them to a sense of helplessness and despair. Negative information is overweighed and would be perceived as a social confirmation of their inferiority (Ito, Urland, Willadsen-Jensen, and Correll, 2006). Hence, the psychological cost associated with a loan rejection is amplified for marginal borrowers leading to a higher sense of discouragement which would be reflected in their transitions out of self-employment. Thus, we hypothesize:

> **Hypothesis 2a (H2a):** *The positive association between a rejected crowdlending loan application and a transition out of entrepreneurship is more pronounced for credit-constrained entrepreneurs.*

> **Hypothesis 2b (H2b):** *The positive association between a rejected crowdlending loan application and a transition out of entrepreneurship is more pronounced for income-constrained entrepreneurs.*

3.2 Crowdlending Loans and Entrepreneurial Performance

Entrepreneurs pursuing innovative projects seek capital that ideally has low transaction costs and quick access. Transactions costs are low for crowdlending platforms. The direct transaction costs (separate from interest expenses) of raising capital on a crowdlending platform are typically 2.5-5% of the proceeds raised (Agrawal et al., 2014), which compares favorably to the typical 7% for obtaining a large company that lists on a stock exchange (Chen and Ritter, 2000; this 7% is up to 50% for smaller listings as reported in Johan, 2010). Other sources of capital such as angel finance can have very large transaction costs in terms of legal fees that may be as large as 50% of the proceeds raised (Bonini et al., 2018). Crowdlending platforms may or may not charge higher interest rates depending on risk rating of platform, and the comparable terms of the available banks (Cumming and Hornuf, 2022). But borrowers on crowdlending platforms often have a time advantage, they are able to quickly access funds to meet unexpected needs and opportunities. Conversely, immediate borrowing needs might be viewed negatively by a bank manager that might see time pressures as a signal of risks and lead to a denial of credit. Bank managers seek repayment and minimizing the loan loss ratio which makes them slower to pursue a loan in an entrepreneurial start-up due to their career concerns. As such, they focus on financial statements and collateral to assess repayment likelihood. The time involved for the bank to conduct their due diligence is potentially longer than the time it takes to raise a crowdlending loan (Allen et al., 2021; Berg et al., 2022). By contrast, crowdlending platforms offer a matching of personal interests of the individuals lending money and the entrepreneurs seeking the funds in a cost-effective and time efficient manner. Crowdlending platforms have informational advantages and algorithms that enable a better matching of borrowers and lenders Allen et al., 2021; Berg et al., 2022).

Besides the cost-saving (tangible and intangible) associated with crowdlending loans, there are additional considerations associated with the crowdlending mechanism that could potentially lead to superior future entrepreneurial income, relative to traditional forms of financing. Similar to the micro-credit context where borrowers identify with future borrowers (Khandker, 1998), borrowers on crowdlending platforms identify with the community on the platform. This is a feeling that is not experienced by borrowers in the traditional financing context. By identifying with the community on the platform and given the personal nature of feeling accepted by the crowd, belonging to a social group can serve as a motivation for entrepreneurs (Haslam, Jetten, Postmes, and Haslam, 2009). This would drive entrepreneurs to work harder and achieve more as they strive to meet the expectations of their social group. This increased effort and motivation alongside the speed and lower costs associated with crowdlending platforms can contribute towards better future entrepreneurial income. Thus, we suggest:

> **Hypothesis 3a (H3a):** *A successful crowdlending loan is positively associated with future entrepreneurial income.*

> **Hypothesis 3b (H3b):** *The positive association between a successful crowdlending loan and future entrepreneurial income is stronger than that of traditional financing mechanisms (revolving and non-revolving lines of credit).*

Crowdlending has served as a popular alternative source of finance for entrepreneurs who were unable to tap traditional lines of credit (Walthoff-Borm, Schwienbacher, and Vanacker, 2018). An issue that these borrowers initially had in accessing traditional lines of credit is associated with information asymmetries (Cumming and Hornuf, 2022). Through tapping crowdlending, entrepreneurs are able to access credit to meet their current obligations. This could also aid in accessing future lines of credit from traditional lenders. By staying current on the crowdlending loan, the entrepreneur shows that they are not misappropriating the funds, this mitigates concerns associated with adverse selection and moral hazard. The entrepreneur would be able to establish legitimacy which is reflected in their credit scores. Hence, traditional lenders can make use of the positive signal of successful crowdlending in the past to infer that the borrower is of high quality and worth extending credit. Worth noting, crowdlending loans allow for better future income. Entrepreneurs can take advantage of this and expand their asset base. This would enhance the entrepreneur's legitimacy and reputation since an entrepreneur's asset base is used as a traditional screen by banks for providing credit (Allen et al., 2021; Berg et al., 2022). Hence, we hypothesize:

> **Hypothesis 4 (H4):** *Successful crowdlending enhances entrepreneurs' abilities to access traditional lines of credit (revolving and non-revolving lines of credit).*

4. DATA AND METHODOLOGY

4.1 Data

To construct our dataset, first we extract the universe of loan listings on Prosper from January 1st, 2016 up to September 30th, 2020.[4] Prosper is the first crowdlending platform in the United States and one of the largest worldwide. To capture changes in employment status, income, and credit access between two points in time we restrict our analysis to loan applicants who repeatedly solicited loans through the platform during the period of our analysis. Our analysis is restricted to individuals whose first loan application on the platform coincided with our period of analysis. In total, our initial dataset includes 198,984 loan requests made by 92,382 individuals. Given that we investigate the effect of crowdlending loans on subsequent transitions in self-employment and future performance of self-employed individuals, we limit our observations to

[4] 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.

subsequent loan applications by individuals who were initially self-employed. Our final dataset consists of 6,876 subsequent crowdlending loan applications.

For the observations included in our analysis we have verified individual-level characteristics regarding employment status, employment history, and income which 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.

4.2 Measures

4.2.1 Dependent Variables

The analysis employed to disentangle the relationship between crowdlending loan outcomes and subsequent self-employment decisions and entrepreneurial performance involves multiple stages. First, to investigate the effect of crowdlending loan outcome on subsequent employment choices, we instrumentalize the variable Δ *Employment Status* $_t$. This variable takes the value 1 if a self-employed individual transitions out of self-employment and 0 otherwise. Second, to investigate the effect of the crowdlending loan on subsequent entrepreneurial performance of self-employed individuals, we use two proxies for the entrepreneurs' financial performance, Δ *Monthly Income* $_t$ and Δ *Credit Line* $_t$ (*Revolving* and *Non-Revolving*), where:

$$\Delta \textit{ Monthly Income}_t = \textit{Monthly Income}_t - \textit{Monthly Income}_{t-1} \tag{1}$$

$$\Delta \textit{ Credit Line}_t = \textit{Credit Line}_t - \textit{Credit Line}_{t-1} \tag{2}$$

4.2.1 Independent Variables

In our analysis we capture previous loan outcome using two proxies. In order to investigate the effect of crowdlending loan outcomes on subsequent employment decision, we use the dummy variable *Crowdlending Loan Rejected* $_{t-1}$. It takes the value 1 if previous crowdlending loan application was unsuccessful and 0 otherwise. To compare this effect relative to the effect of not accessing traditional credit, we instrumentalize the variables *No Revolving Credit Line Accessed* and *No Non-Revolving Credit Line Accessed*. These variables take the value of 1 if there was no increase in the revolving/non-revolving credit lines between time *t-1* and *t*, and 0 otherwise.

In order to investigate the effects of crowdlending loan on future entrepreneurial performance we note that the size of the loan could play a differential role. Hence, we instrumentalize our variable *Crowdlending Loan Amount* $_{t-1}$. This variable corresponds to the loan amount that originated in the previous crowdlending loan application. If previous loan application was unsuccessful, this variable takes the value 0.[5] To compare this effect relative to the that of traditional credit, we instrumentalize the variables *Revolving Credit Extended* and *Non-Revolving Credit Extended* which captures the extended credit lines (revolving and non-revolving) to the loan applicant over the period *t-1* and *t*.

4.2.3 Control Variables

At the applicant level, we control for borrowing experience on the platform (*Crowdlending Borrowing Experience*), previous monthly income (*Monthly Income* $_{t-1}$), previous credit line (*Credit Line* $_{t-1}$), and the number of months that the loan applicant has been employed (*Employment History*). At the county level, we control for the unemployment rate in the loan applicant's county (*Unemployment Rate*), average income in the county where the loan applicant is located (*Average*

[5] As a robustness check, we investigate the effects of a successful crowdlending loan (a dummy variable) on future entrepreneurial performance. The results are not qualitatively different from the main results reported.

County Income), and the percentage of individuals with associate degrees or above (*Higher Education*). Lacking information on when employment status switches took place, we control for the time elapsed between the 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 the two loan requests and whether the loan request is during COVID-19 period (*COVID-19*). Finally, we control for seasonality by including quarter and year dummies in all estimation models. We present the list of variables included in our analysis, their definitions, 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 (Sewaid et al., 2021b). In Table 2 we present the descriptive statistics (number of observations, mean, standard deviation, minimum, and maximum values) of the variables considered in our models.

[Insert Tables 1 and 2 About Here]

4.3 Descriptive Statistics

4.3 Empirical Strategy

In order to disentangle the relationship between successful crowdlending loan acquisition, self-employment decision, and subsequent entrepreneurial performance, we start by addressing any potential issues related to selection bias. To circumvent any sample selection bias associated with only analyzing loan applicants returning to the crowdlending platform we control for the probability that the individual returns to the platform (Chen, 2013; Sewaid et al., 2021a). 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 loan amounts 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.

Having controlled for the probability that the loan applicant returns to the platform, we proceed to address selection issue associated with who actually gets the loan. To address this we conduct coarsened exact matching (Iacus et al., 2012) where initially self-employed individuals with a failed crowdlending loan application (1,413 loan applications) are matched with initially self-employed individuals whose previous crowdlending loan application was successful. This one-to-one matching is performed along several dimensions (monthly income, credit lines, employment history, and credit scores) that affect the individual's abilities of securing a loan on the crowdlending platform. As a result of this process we were able to match 1,411 individuals who were initially self-employed but had a failed loan application with 1,411 initially self-employed individuals whose previous loan application was successful. Our final sample consists of 2,822 self-employed individuals.

Our analysis involves a multi-stage empirical strategy. Although the dependent variables differ, our applicant-level controls and county-level controls are consistent across the models' specifications. Using our matched sample, we first move to estimate the probability of transitioning out of self-employment following an unsuccessful crowdlending loan application. We run a logistic regression model with *Δ Employment Status* as the dependent variable. *Δ Employment Status* is regressed on the independent variables (*Crowdlending Loan Rejected*, *No Revolving*

Credit Accessed, and *No Non-Revolving Credit Accessed*), alongside a set of loan-applicant, county-level, and economic-conditions controls. Second, to analyze the effect of credit on changes in *Monthly Income* we run a panel OLS regression. Δ *Monthly Income* is regressed on our independent variables (*Crowdlending Loan Amount*, *Revolving Credit Extended*, and *Non-Revolving Credit Extended*) while controlling for a set of loan-applicant and county-level controls. As for the ability of crowdlending to help with access to traditional credit we regress our dependent variables that capture changes in *Credit Line*, *Revolving Credit Line*, and *Non-Revolving Credit Line* on *Crowdlending Loan Amount* while controlling for a set of loan-applicant and county-level controls.

5. RESULTS

5.1 Effect of Crowdlending Loan Acquisition on Employment-Status Transitions

[Insert Table 3 About Here]

Prior to running our main empirical analysis, in Table 3 we run a difference-in-means analysis to present preliminary insight into the effect of crowdlending loan application outcomes on self-employment decisions for both the full-sample and the matched sample. Our analysis of the full sample 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. As for the 1,413 self-employed individuals that failed to obtain a crowdlending loan, 1,016 (71.9%) remained self-employed while 397 (28.10%) switched to becoming an employee. The difference-in-means analysis indicates that failure to obtain a crowdlending loan results into transitions out of self-employment. This preliminary result is significant at the 0.1% level and we observe similar results for our matched sample as reported.

[Insert Table 4 About Here]

To examine some possible explanations in a multivariate context, Table 4 presents the marginal effects of the logistic regression model. In Column (1), we present the control model. We then proceed to analyze the effect of not accessing non-revolving credit lines on transitions out of self-employment. Our results indicate that inability to access non-revolving credit lines increases the probability of switching out of self-employment by 7.39%. In Column (3), we analyze the effect of inability to access revolving credit lines and show that it increases the probability of switching out of self-employment by 7.86%. In Column (4), we add our main independent variable, *Crowdlending Loan Rejected*, to our control model. The data indicates that an unsuccessful crowdlending loan application increases the probability of a transition out of self-employment by 13.26%. This provides support for H1a at the 0.1% significance level. In Column (5) we analyze the persistence of this effect while controlling for not accessing traditional lines of credit (revolving and non-revolving), the results continue to hold. Moreover, the magnitude of this effect is 1.69 times that of revolving lines of credit, and 2.77 times that of non-revolving lines of credit. This provides support for H1b at the 0.1% significance level and highlights that the effect of being rejected by the crowd is more intense than not being able to access credit via traditional financing sources.

In Hypothesis 2 we argue that the effect of crowdlending loan rejection is more intense for marginal borrowers who are most financially vulnerable. In Column (7) we observe that the effect of a rejected crowdlending loan application is more pronounced for individuals who were unable to access revolving credit lines. Specifically, we note that failure to obtain a crowdlending loan increases switches out of self-employment by 6.91%. However, this effect increases to 20.32% for loan applicants who were unable to access revolving lines of credit. This provides support for H2a at the 1% level. In Columns (8) and (9) we break the analysis into top and bottom income quartile. The data indicate that at the highest income quartile, an unsuccessful crowdlending loan application is associated with an 8.69% increase in the likelihood of switching from self-employment to becoming an employee. Whereas, at the lowest income quartile, the effect of a rejected crowdlending loan application is more severe. We specifically note that for a self-employed applicant in the lowest income quartile, a rejected crowdlending loan application is associated with a 25.15% increase in the probability of switching out of self-employment. This effect is 2.89 times that of self-employed applicants in the top income quartile which provides support for H2b. Taken together, our results indicate that the effect of a rejected crowdlending loan application is more severe for marginal self-employed individuals, those who are credit- and income- constrained. 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. However, 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 crowdlending loan. Overall, therefore, the data indicate that crowdlending loans are important enablers of allowing the self-employed population to remain self-employed.

5.2 Effect of Crowdlending Loan Acquisition on Monthly Income and Credit Access

[Insert Table 5 About Here]

Table 5 presents estimates of the impact of a successful loan application amount on future financial performance. Column (1) presents the control model. In Column (2) we introduce the non-revolving lines of credit extended to our model and show that a 1 standard deviation (SD) increase in non-revolving lines of credit extended is associated with a 2.17% improvement in income enhancement (Δ *Monthly Income* $_t$). In Column (3) we analyze the effect of revolving credit lines on income enhancement and note that a 1 SD increase in revolving credit lines is associated with a 2.41% improvement in income enhancement. In Column (4) we introduce our main independent variable, *Crowdlending Loan Amount*, to the control model. The results of the empirical analysis indicate that a 1 SD increase in the crowdlending loan amount acquired is associated with a 2.99% increase in Δ *Monthly Income* $_t$. This result supports H3a at the 0.1% significance level and highlights the role that crowdlending platforms can play in improving the financial performance of entrepreneurs. In H3b we argue that the impact of crowdlending loans on future financial performance is more pronounced relative to traditional sources of financing. We report the corresponding results in Column (5) and find that indeed the impact of crowdlending loans on future financial performance is 1.64 times more pronounced relative to non-revolving lines of credit. However, relative to revolving lines of credit, the amplified effect of crowdlending loans is not economically significant. This provides partial support for H3b.

[Insert Table 6 About Here]

In Table 6, we report the results pertaining to H4. In H4 we propose that crowdlending loans, given its accessibility and benefits, can allow entrepreneurs to tap traditional sources of financing in the future. In Column (2) we report the association between crowdlending loan amounts and changes in credit lines. We note that a 1 SD increase in crowdlending loan amount is associated with a 3.29% increase in credit line access enhancement. This effect holds for both revolving and non-revolving lines of credit. Hence, we note that the significance of crowdlending platforms lies in their ability to establish entrepreneurs' credibility and standing, which can eventually aid them in accessing conventional funding sources.

5.3 Robustness Tests

In order to validate the robustness of our results, we conduct a series of robustness checks. First, one might argue reverse causality. Individuals with unstable employment history as employees or entrepreneurs are more likely to fail in acquiring a crowdlending loan rather than failure to acquire a crowdlending loan causing switches in employment status. To validate the causality that we argue, we run a panel vector auto regression model (VAR). Our analysis shows that obtaining a crowdlending loan stabilizes employment status and that self-employed individuals sustain their activities following a successful crowdlending loan. However, stable employment status is not significantly associated with crowdlending loan outcome. The results of the panel VAR suggest a unidirectional effect, supporting our argued causal effect. The results are reported in Table 7. Additionally, we further validate the suggested causality by running a Granger causality test. The results of the Granger causality test further confirm that the relationship between crowdlending loan outcome and employment status is unidirectional, crowdlending loan outcome affects employment status and not the reverse. The results are presented in Table 8.

[Insert Tables 7 and 8 About Here]

Second, although our two-step analysis and our inclusion of the Inverse Mills Ratio and the matching of observations mitigates selection issues, we further validate the results presented in Tables 5 and 6 using the Arellano-Bond dynamic panel data model. As presented, the results are not qualitatively different from those discussed in the main results. Third, to isolate differences pertaining to county-level differences, we split our observations into counties with higher levels of education vs counties with lower levels of education, counties with higher levels of unemployment vs counties with lower levels of unemployment, and counties with higher average income vs counties with lower average income. We repeat our main analysis, and the results are not qualitatively different from those presented in the main analysis. Fourth, we replaced our independent variable, *Crowdlending Loan Amount*, with a dummy variable which is equal to 1 if the loan applicant has successfully acquired the previous loan requested and 0 otherwise. We operationalize *Revolving Credit Extended* and *Non-Revolving Credit Extended* similarly. We repeat our analysis, and our main findings hold. Finally, to mitigate the effect of possible outliers in the sample we winsorized and trimmed the data, we repeat the analysis and the results are in line with the results reported earlier. These robustness tests garner confidence in the results reported in the main analysis.

6. DISCUSSION AND CONCLUSION

In this paper we examine how crowdlending loan outcome impacts the decision to maintain self-employment and the future entrepreneurial performance of loan applicants. We theorized that the inability to secure a crowdlending loan drives switches in employment status. We argue that the effect of rejection by the crowd is more pronounced relative to institutional rejection. This prediction is based on the attributes of the crowdlending mechanism and builds upon social identity theory. We further hypothesized that this effect would be stronger for credit- and income-constrained self-employed individuals due to their vulnerability. Using large sample evidence from serial borrowers on a crowdlending platform and controlling for selection in the applying for and allocation of loans, we find empirical support for these propositions. We further theorized that crowdlending loans better affect entrepreneurs' future financial performance, since the improved speed, efficient matching of borrowers and lenders, and commitment to the crowd would enable entrepreneurs to better manage their entrepreneurial ventures. The data examined strongly supports our contentions.

Our findings have important implications for researchers. Contributing to the literature on determinants of self-employment, we highlight the role that financial access plays in maintaining self-employment status (Wennberg and DeTienne, 2014). Our analysis shows that borrowers turn to crowdlending to readily finance personal obligations given the expedited loan origination process. Our evidence suggests that, following an unsuccessful crowdlending loan, self-employed applicants switch out of self-employment. This can be driven by a financial or a psychological constraint. The amplified effect of a rejected crowdlending loan relative to the inability to secure a conventional loan indicate that the psychological and motivational constraint of crowd rejection is a crucial driver of switches out of self-employment. This is consistent with our finding that credit- and income- constrained self-employed individuals are more likely to switch out of self-employment following a failed crowdlending loan application. Financially constrained self-employed applicants are more vulnerable; hence, this leads to an aggravated discouragement following rejection. Besides the discussed channels, future research could build on our findings to investigate alternative channels through which loan outcome affects the decision to continue/discontinue entrepreneurial activity.

Our findings offer implications for entrepreneurs and policymakers. For entrepreneurs, our findings highlight the role that crowdlending play in aiding self-employed individuals to sustain their activities. Crowdlending loans can fill the financing gap that self employed individuals' face and can even substitute other traditional financing sources. Moreover, due to the crowdlending lending mechanism, our findings show the subsequent financial benefits of securing a crowdlending loan. Hence, crowdlending loans do not necessarily need to serve as a last resort. For policymakers, our results show that crowdlending platforms provide important opportunities. We may infer from the evidence here that prior restrictions on crowdlending in the United States

(Cumming et al., 2022) harmed access to capital and entrepreneurship in the United States. More generally, regulations that limit crowdlending should be carefully examined so that they do not have unintended consequences of inhibiting capital access.

Despite the unique structure of the platform's data (Prosper) enabling the empirical exercise in this paper, a potential limitation of our analysis is that our data are based on a single platform, one of the largest crowdlending platforms, and a single country, the United States. Different crowdlending platforms may use different matching algorithms and offer different speed advantages, so we are unable to fully ascertain if our findings are unique to this single platform (see also Dushnitsky et al., 2016, 2020; Dushnitsky and Fitza, 2018; Dushnitsky and Matusik, 2019). Hence, future research might leverage data from alternative crowdlending platforms to investigate how differences in platform structures and lending mechanisms could have different real economic effects on self-employment and entrepreneurial performance. Also, future research could examine data from other countries with different institutional settings since the institutional environment may mitigate or exacerbate the impact of entrepreneurial finance on economic outcomes (Li and Zahra, 2012; see more generally Boudreaux et al., 2019; Klein, 2000). However, despite these limitations, the paper provides timely insights for both theory and practice.

In conclusion, the theory and evidence in this paper are highly consistent with the view that crowdlending platforms are indeed crucial for entrepreneurship. In the data examined in this paper, these impacts of crowdlending on entrepreneurship are more pronounced than that for non-revolving and revolving lines of credit. The growth of crowdlending offers entrepreneurs new strategic tools to better ensure success with their ventures. The new evidence presented here offers some insights into these developments, as well as implications for future research and practice. As future FinTech innovations and data emerge from various FinTech platforms around the world, there will be growing opportunities for academics, entrepreneurs, and policy makers to explore the implications of these developments to extend our body of knowledge on the intersection of technology, entrepreneurship, and finance.

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Tables

Table 1. Variable Description and Source

Variable	Description	Source
Self-Employed	A dummy variable = 1 if the loan applicant is self-employed.	PROSPER.com
Δ Employment Status	A dummy variable = 1 if loan applicant's employment status at time t differs from employment status at t-1.	PROSPER.com
Crowdlending Loan Rejected	A dummy variable = 1 if the crowdlending loan application was rejected at t-1.	PROSPER.com
No Revolving Credit Line Accessed	A dummy variable = 1 if no revolving credit line was extended to loan applicant between time t-1 and t as reported by Transunion.	PROSPER.com
No Non-Revolving Credit Line Accessed	A dummy variable = 1 if no non-revolving credit line was extended to loan applicant between time t-1 and t as reported by Transunion.	PROSPER.com
Crowdlending Loan Amount ($)	Crowdlending loan amount successfully acquired by loan applicant at t-1.	PROSPER.com
Revolving Credit Extended ($)	Revolving credit lines extended between time t-1 and t as reported by Transunion.	PROSPER.com
Non-Revolving Credit Extended ($)	Non-revolving credit lines extended between time t-1 and t as reported by Transunion.	PROSPER.com
Crowdlending Borrowing Experience	The number of prior crowdlending loan applications on the platform.	PROSPER.com
Credit Line ($)	Loan applicant's credit line at time of loan request as reported by Transunion.	PROSPER.com
Revolving Credit Line ($)	Loan applicant's revolving credit line at time of loan request as reported by Transunion.	PROSPER.com
Non-Revolving Credit Line ($)	Loan applicant's non-revolving 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
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
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	Max
Crowdlending Loan Rejected $_{t-1}$	6,876	20.55%	0.40	0	1
No Revolving Credit Accessed $_{t-1,\,t}$	6,876	31.91%	0.49	0	1
No Non-Revolving Credit Accessed $_{t-1,\,t}$	6,876	40.31%	0.50	0	1
Crowdlending Loan Amount $_{t-1}$	6,876	$8,211.95	5,537.23	0	35,000
Revolving Credit Extended $_{t-1,\,t}$	6,876	$9,307.39	16,174.16	0	311,900
Non-Revolving Credit Extended $_{t-1,\,t}$	6,876	$25,281.99	72,150.09	0	1,457,403
Crowdlending Borrowing Experience	6,876	1.20	0.42	1	6
Credit Line $_{t}$	6,876	$96,180.96	71,438.07	1,501	$657,487
Monthly Income $_{t}$	6,876	$9,011.27	5,484.59	808	$32,750
Employment History $_{t}$	6,876	151.11	121.59	0	500
Unemployment Rate $_{t}$	6,876	4.49%	0.02	1.8%	19.50%
Average County Income $_{t}$	6,876	$4,682.49	1,331.98	2,121.50	$14,170
Higher Education $_{t}$	6,876	62.04%	0.09	26.5%	93.3%
Time since last loan $_{t}$	6,876	1.15	0.74	0	3.61
COVID-19 $_{t}$	6,876	10.99%	0.31	0	1

Table 3. 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
Full Sample:				
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	
Matched Sample:				
Self Employed	Self Employed	1,231 (87.24%)	1,014 (71.86%)	***
Self Employed	Employee	180 (12.76%)	397 (28.14%)	***
		1,411	1,411	

Statistical significance at the 0.1%, 1%, 5%, and 10% level is indicated by ***, **, *, and † respectively.

Table 4. Δ Employment Status for Initially Self-Employed Loan Applicants (Self-Employed $_{t-1}$ = 1): Logistic Regression

	Dependent Variable: Δ Employment Status $_t$								
	(1) Matched Sample *dy/dx* (*s.e.*)	(2) Matched Sample *dy/dx* (*s.e.*)	(3) Matched Sample *dy/dx* (*s.e.*)	(4) Matched Sample *dy/dx* (*s.e.*)	(5) Matched Sample *dy/dx* (*s.e.*)	(6) Matched Sample *dy/dx* (*s.e.*)	(7) Matched Sample *dy/dx* (*s.e.*)	(8) Income Bottom Quartile *dy/dx* (*s.e.*)	(9) Income Top Quartile *dy/dx* (*s.e.*)
Credit Access:									
Crowdlending Loan Rejected $_{t-1}$				0.1326***	0.1146***	0.1043**	0.0691*	0.2515***	0.0869*
				(0.0236)	(0.0253)	(0.0366)	(0.0298)	(0.0579)	(0.0382)
No Revolving Credit Accessed $_{t-1,\,t}$			0.0786***		0.0677***	0.0669***	0.0011	0.0075	0.0399
			(0.0163)		(0.0164)	(0.0164)	(0.0278)	(0.0423)	(0.0258)
No Non-Revolving Credit Accessed $_{t-1,\,t}$		0.0739***			0.0413*	0.0347	0.0366†	0.0351	-0.0043
		(0.0175)			(0.0195)	(0.0270)	(0.0202)	(0.0447)	(0.0250)
Crowdlending Loan Rejection x No Revolving Credit Accessed							0.1341**		
							(0.0483)		
Crowdlending Loan Rejection x No Non-Revolving Credit Accessed						0.0187			
						(0.0486)			
Individual-Level:									
Crowdlending Borrowing Experience	0.0086	0.0049	0.0078	-0.0204	-0.0186	-0.0184	-0.0186	-0.0993	-0.0626†
	(0.0275)	(0.0274)	(0.0268)	(0.0322)	(0.0311)	(0.0311)	(0.0323)	(0.1063)	(0.0364)
Credit Line $_{t-1}$	0.0518***	0.0488***	0.0498***	0.0518***	0.0485***	0.0489***	0.0493***	0.0389†	0.0402*
	(0.0103)	(0.0103)	(0.0102)	(0.0102)	(0.0101)	(0.0101)	(0.0102)	(0.0218)	(0.0174)
Monthly Income $_{t-1}$	-0.1117***	-0.1086***	-0.1089***	-0.1127***	-0.1084***	-0.1088***	-0.1098***	-0.1744*	-0.0867**
	(0.0158)	(0.0159)	(0.0156)	(0.0157)	(0.0157)	(0.0156)	(0.0157)	(0.0688)	(0.0319)
Employment History $_{t-1}$	-0.0361***	-0.0364***	-0.0361***	-0.0362***	-0.0362***	-0.0362***	-0.0360***	-0.0368**	-0.0256**
	(0.0051)	(0.0051)	(0.0049)	(0.0051)	(0.0050)	(0.0050)	(0.0050)	(0.0123)	(0.0088)
County-Level:									
Unemployment Rate $_{t-1}$	-0.3326	-0.3344	-0.3210	-0.3072	-0.3011	-0.3051	-0.3812	-2.2663	1.8075
	(0.7584)	(0.7623)	(0.7416)	(0.7588)	(0.7439)	(0.7441)	(0.7549)	(1.8188)	(1.1316)
Average County Income $_{t-1}$	0.0445	0.0423	0.0491	0.0444	0.0463	0.0458	0.0493	-0.0889	0.0888†
	(0.0350)	(0.0353)	(0.0350)	(0.0349)	(0.0350)	(0.0350)	(0.0355)	(0.0915)	(0.0528)
Higher Education $_{t-1}$	-0.0301	-0.0264	-0.0448	-0.0286	-0.0391	-0.0387	-0.0386	0.0118	0.2222
	(0.1276)	(0.1268)	(0.1275)	(0.1265)	(0.1257)	(0.1256)	(0.1265)	(0.3142)	(0.1735)
Other Controls:									
Time since last loan	-0.1361***	-0.0931***	-0.0871***	-0.0417†	0.0108	0.0133	0.0296	0.0441	0.0248
	(0.0162)	(0.0194)	(0.0190)	(0.0235)	(0.0253)	(0.0265)	(0.0272)	(0.0538)	(0.0329)
COVID-19 $_t$	0.2413***	0.2323***	0.2146***	0.2054***	0.1827***	0.1824***	0.1803***	0.1142	0.1705*
	(0.0469)	(0.0461)	(0.0464)	(0.0452)	(0.0442)	(0.0441)	(0.0435)	(0.0942)	(0.0794)
Inverse Mills Ratio	-0.0044	-0.0030	-0.0016	0.0258	0.0245	0.0247	0.0252	0.1408†	0.0391
	(0.0265)	(0.0267)	(0.0260)	(0.0292)	(0.0286)	(0.0287)	(0.0288)	(0.0831)	(0.0379)
Quarter Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2,822	2,822	2,822	2,822	2,822	2,822	2,822	777	688
Pseudo R-squared	0.0902	0.0955	0.0964	0.1016	0.1083	0.1084	0.1124	0.0987	0.1114

This table exhibits the results of a logistic regression model with Δ Employment Status from self-employed to employee as the dependent variable. The marginal effects are reported. Standard errors are clustered at the county-level and are shown in parentheses. Statistical significance at the 0.1%, 1%, 5%, and 10% level is indicated by ***, **, *, and † respectively.

Table 5. Income Improvement for Initially Self-Employed Loan Applicants (Self-Employed $_{t-1}$ = 1)

	Dependent Variable: Δ Monthly Income $_t$				
	(1)	(2)	(3)	(4)	(5)
	β / s.e.	*β / s.e.*	*β / s.e.*	*β / s.e.*	*β / s.e.*
Credit Access:					
Crowdlending Loan Amount $_{t-1}$				0.0061***	0.0046**
				(0.0015)	(0.0016)
Revolving Credit Extended $_{t-1,\,t}$			0.0050**		0.0043**
			(0.0017)		(0.0017)
Non-Revolving Credit Extended $_{t-1,\,t}$		0.0042***			0.0028*
		(0.0011)			(0.0012)
Individual Level:					
Δ Employment Status $_t$	-0.0135	-0.0101	-0.0098	-0.0086	-0.0043
	(0.0198)	(0.0197)	(0.0194)	(0.0200)	(0.0196)
Crowdlending Borrowing	-0.0246	-0.0223	-0.0251	-0.0117	-0.0138
	(0.0157)	(0.0158)	(0.0153)	(0.0162)	(0.0157)
Employment History $_t$	-0.0121*	-0.0117*	-0.0119*	-0.0121*	-0.0117*
	(0.0048)	(0.0048)	(0.0049)	(0.0049)	(0.0049)
County-Level:					
Unemployment Rate $_t$	0.9143*	0.9112*	0.9505*	0.8997*	0.9325*
	(0.4163)	(0.4152)	(0.4105)	(0.4239)	(0.4164)
Average County Income $_t$	0.0160	0.0168	0.0125	0.0164	0.0138
	(0.0222)	(0.0222)	(0.0225)	(0.0221)	(0.0223)
Higher Education $_t$	0.0312	0.0287	0.0442	0.0289	0.0391
	(0.0808)	(0.0807)	(0.0807)	(0.0804)	(0.0804)
Other Controls:					
Time since last loan	0.2130***	0.1903***	0.1854***	0.1759***	0.1461***
	(0.0167)	(0.0171)	(0.0187)	(0.0182)	(0.0197)
COVID-19 $_t$	-0.0974*	-0.0977*	-0.0932*	-0.0901*	-0.0884*
	(0.0444)	(0.0450)	(0.0444)	(0.0447)	(0.0449)
Inverse Mills Ratio	0.0202	0.0189	0.0190	0.0072	0.0084
	(0.0167)	(0.0167)	(0.0165)	(0.0170)	(0.0167)
Quarter Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of Observations	2822	2822	2822	2822	2822
R-squared	0.1314	0.1351	0.1356	0.1358	0.1408
Adjusted R-squared	0.1265	0.1299	0.1304	0.1306	0.1350

This table presents OLS estimation models with change in Monthly Income as the dependent variable. Standard errors are clustered at the county-level and are shown in parentheses. Statistical significance at the 0.1%, 1%, 5%, and 10% level is indicated by ***, **, *, and Ϯ respectively.

Table 6. Credit Access Improvement for Initially Self-Employed Loan Applicants (Self-Employed $_{t-1}$ = 1)

Dependent Variable:	**Δ Credit Line $_t$**		**Δ Non-Revolving Credit Line $_t$**		**Δ Revolving Credit Line $_t$**	
	(1)	(2)	(3)	(4)	(5)	(6)
	β / s.e.	*β / s.e.*	*β / s.e.*	*β / s.e.*	*β / s.e.*	*β / s.e.*
Credit Access:						
Crowdlending Loan Amount $_{t-1}$		0.0067*		0.3805***		0.0926***
		(0.0029)		(0.0291)		(0.0255)
Individual Level:						
Δ Employment Status $_t$	-0.0271	-0.0217	-0.8100***	-0.5052**	-0.7460***	-0.6718***
	(0.0166)	(0.0164)	(0.1862)	(0.1829)	(0.1504)	(0.1497)
Crowdlending Borrowing Experience	0.0029	0.0170	-0.5368†	0.2667	0.1121	0.3078
	(0.0194)	(0.0198)	(0.3180)	(0.3514)	(0.3732)	(0.3853)
Employment History $_t$	-0.0195***	-0.0195***	-0.0993	-0.0986†	-0.0449	-0.0447
	(0.0057)	(0.0057)	(0.0616)	(0.0593)	(0.0541)	(0.0535)
County-Level:						
Unemployment Rate $_t$	-0.3865	-0.4026	0.7135	-0.1987	-7.2106	-7.4328
	(0.6023)	(0.6134)	(7.1278)	(7.0502)	(5.9666)	(6.0513)
Average County Income $_t$	0.0472	0.0476	-0.1771	-0.1546	0.6951*	0.7006*
	(0.0340)	(0.0340)	(0.4596)	(0.4176)	(0.3451)	(0.3494)
Higher Education $_t$	-0.1506	-0.1530	0.5896	0.4482	-2.5880*	-2.6224*
	(0.1221)	(0.1221)	(1.4292)	(1.3596)	(1.1110)	(1.1228)
Other Controls:						
Time since last loan	0.3117***	0.2710***	5.3511***	3.0349***	5.4918***	4.9278***
	(0.0164)	(0.0274)	(0.1786)	(0.2701)	(0.1608)	(0.2285)
COVID-19 $_t$	-0.0218	-0.0138	0.0702	0.5268	-0.8278	-0.7167
	(0.0626)	(0.0629)	(0.7474)	(0.7251)	(0.6747)	(0.6638)
Inverse Mills Ratio	-0.0174	-0.0317	0.2997	-0.5149	0.2360	0.0376
	(0.0262)	(0.0263)	(0.3248)	(0.3386)	(0.3350)	(0.3392)
Quarter Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2822	2822	2822	2822	2822	2822
R-squared	0.1743	0.1769	0.3760	0.4279	0.4197	0.4232
Adjusted R-squared	0.1695	0.1719	0.3724	0.4244	0.4164	0.4198

This table presents OLS estimation models with changes in Credit Lines, Non-Revolving Credit Lines, and Revolving Credit Lines as the dependent variable. Standard errors are clustered at the county-level and are shown in parentheses. Statistical significance at the 0.1%, 1%, 5%, and 10% level is indicated by ***, **, *, and † respectively.

Table 7. Employment Status and Successful Loan Amount: Panel Vector Auto Regression (PVAR) Model

Dependent Variable:	(1) Self-Employed $_t$ β/se		(2) Crowdlending Loan Amount $_t$ β/se	
Self-Employed $_{t-1}$	0.4651***	(0.0731)	-0.7813	(1.1522)
Crowdlending 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	

This table presents the coefficient estimates on *Self-Employed* and *Crowdlending 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 0.1%, 1%, 5%, and 10% level is indicated by ***, **, *, and † respectively.

Table 8. Causality between Employment Status and Successful Loan Amount: Panel Granger Causality Test

Eq (1)	Excluded	Chi ^{2}	Prob	Eq (2)	Excluded	Chi ^{2}	Prob
Self-Employed $_t$				**Crowdlending Loan Amount $_t$**			
	Crowdlending 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

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.