

## ORIGINAL ARTICLE

INTERNATIONAL  
REVIEW OF FINANCE

WILEY

# The impact of credit constraints and risk tolerance on self-employment: Accounting for the hidden majority

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**Abstract**

Small businesses are important drivers of economic activity and job creation but face significant credit constraints. This study examines the joint impact of credit constraints and risk tolerance on a household's decision to become self-employed using data from the 2022 Survey of Consumer Finance (SCF), and in a novel way. First, it uncovers and then accounts for the large numbers of households that are truly credit constrained yet systematically overlooked with traditional measures of credit constraints based on loan rejections. Three hidden groups are identified– underfunded borrowers, discouraged borrowers, and priced-out borrowers– which collectively make up an actual majority of credit constrained borrowers. Second, the study isolates and estimates the independent impact of credit constraints and risk tolerance on self-employment, avoiding a persistent common omitted variables problem in the literature. The results show that credit constraints and risk aversion significantly limit business activities. The exclusion biases are quantified.

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**KEYWORDS**

credit constraints, household finance, IV probit, risk analysis, risk tolerance, self-employment

**JEL CLASSIFICATION**

D14, D81, J24, M13

## 1 | INTRODUCTION

Credit markets are essential for small businesses (Evans and Jovanovic (1989), Holtz-Eakin et al. (1994), Kerr and Nanda (2009)). Would-be entrepreneurs often lack the personal wealth to finance their operations, especially in the critical first years of a new business venture, so they rely heavily on credit markets to invest and grow. If access to credit from banks or other lenders is restricted—whether it be from classic adverse selection or monitoring cost problems (Stiglitz and Weiss (1981))—even viable small businesses can fall short on money and fail, with obvious negative consequences to employment and to the economy (Beck et al. (2015), Bellon et al. (2021)). Not surprisingly, the smallest businesses—which are essentially self-employed individuals—are the most dependent on credit markets and most susceptible to problems in the credit market (Cai et al. (2018), Ngumkeu (2024)).

Given the importance of small businesses to the economy, and of credit markets to small businesses, we revisit the important question of how frictions in the credit market (i.e. the presence of credit constraints) affect small business formation (i.e. self-employment). There is a vast literature on the topic which generally finds that credit constraints reduce business formation, as one might expect. However, much of that literature suffers from two foundational issues that can substantially bias point estimates toward zero and understate the importance of the relationship. We are able to identify and correct for both of these issues here.

First, existing studies tend to rely on measures of credit constraints that are indirect or that are incomplete, leading to a potential endogeneity bias. In terms of indirect measures, studies with no direct information on credit constraints tend to rely on proxies for credit constraints, arguing that movements in a proxy are correlated with movements in credit constraints in an expected way. Most early studies and many newer ones fall into this category. A popular proxy is an individual's initial or inherited wealth (Holtz-Eakin et al. (1993) and Hurst and Lusardi (2004)). The idea with this proxy is that greater wealth implies greater availability of collateral for use in securing a loan, and hence a lower probability of running into a credit constraint problem. While this is perfectly reasonable, it also comes with an obvious endogeneity issue. We would expect wealth and self-employment to be positively correlated even if the wealth in question could not be used as collateral (e.g. retirement accounts), or even if credit markets did not exist at all. We will offer a direct measure here instead of a proxy.

In terms of incomplete measures of credit constraints, existing studies that use a direct measure tend to use measures that are incomplete and sometimes woefully incomplete, causing an endogeneity bias of its own. A common direct measure is whether an individual is rejected by a lender when applying for a loan (Jappelli (1990) and Cai et al. (2018)). We view credit constraints as broader than a simple count of outright rejections by a lender. At one end of the spectrum, an individual applying for a loan may not be outright rejected for a loan but approved for a fraction of the loan amount originally sought. We consider this to be a form of credit constraint, although a milder form, given that the individual falls somewhere in between full rejection and full approval. At the opposite end of the spectrum, an individual fearing she will almost surely be rejected for a loan if she tried to apply may well be discouraged from applying for that loan in the first place. We consider this to be a credit constraint as well, and a stronger form, given that the individual perceived a rejection to be so likely (or stressful, or disappointing) that she felt it not worth applying in the first place. This discouraged borrower essentially guarantees the credit constraint in advance, even if she might have been approved if she applied. Similarly, an individual fearing that the interest rate offered to her would be prohibitively high may also be discouraged from applying. We also

consider this to be a form of credit constraint, and a stronger form, given that the priced-out individual is too discouraged to apply.

With few exceptions, these three hidden groups of credit constrained borrowers are overlooked in the literature. In studies based on bank applications data, the latter two groups (discouraged and priced-out borrowers) are necessarily missed because they never actually apply for a loan and never appear in the dataset. More problematic, in studies based on survey data, discouraged and underfunded borrowers are in the data but miscategorized as not credit constrained (because they were not rejected on any loan) when in reality they were. The miscategorization means that the presumed “control group” of borrowers (which should consist only of not credit constrained individuals) becomes infected by treated individuals (credit constrained individuals). It sets up a comparison of the treated and the also-treated, creating an obvious bias in the estimated treatment effect. As we will discuss, the sign and magnitude of the bias depends on the relative proportion of discouraged and priced-out borrowers (who face the strongest credit constraint) on one hand, and underfunded borrowers (who face the weakest) on the other, and the relative strength of the within-group treatment effects.

The bias may be much larger than one might at first expect. In our survey data of U.S. households, we find that there are actually more credit constrained households contained in the three hidden groups of credit constrained households—underfunded, discouraged, and priced-out borrowers—than there are households that were outright rejected by a lender.

A second limitation of the literature that we can overcome here relates to a common omitted variables problem. Credit constraints are important to small business formation, but other factors matter as well, and perhaps the most significant is entrepreneurial risk tolerance. There is a large literature on risk tolerance and self-employment, which generally shows that more risk tolerant households are more likely to become entrepreneurs, and less risk tolerant households are more likely to accept paid employment (Cantillon (1979), Cramer et al. (2002), Caliendo et al. (2009, 2010), Choi et al. (2019)). The reason is straightforward—would-be entrepreneurs expose themselves to a series of significant personal financial risks in the event the business does not succeed (Knight (1921), Kan and Tsai (2006), Liu and Ren (2021)). But even though risk tolerance is shown to be a key driver for self-employment in that literature, it is rarely included as a control variable in the credit constraints literature when evaluating the effects of credit constraints on self-employment. This is a concern given that credit constraints and risk tolerance are correlated.<sup>1</sup> Absent a control for risk tolerance, the effects of both credit constraints and risk tolerance would be loaded onto the single credit constraints coefficient, biasing results. The credit constraints literature acknowledges the problem, citing that data availability limitations (Jappelli (1990), Cai et al. (2018)). In the current study, we can overcome this omitted variables problem by exploiting information not only on households' credit market experiences but also on those same households' appetite for risk, and including both variables in all our specifications.

With these issues in mind, we reexamine the empirical relationship between credit constraints and self-employment outcomes, using survey data from the 2022 Survey of Consumer Finances (SCF). The SCF includes a rich set of information about individual households' recent experience with credit markets—including whether they were rejected for a loan, underfunded, or discouraged from applying in the first place either from fear of rejection or fear of an unaffordable interest rate. It includes information on how that actual experience directly affected the likelihood that they will become self-employed. Moreover, it also includes direct information on a household's risk tolerance, enabling us to include that elusive control variable in our specifications. With the fine level of detail contained in the SCF, we require no proxies for credit constraints; we are not at risk of erroneously miscategorizing treated households in these three hidden groups as not credit constrained control households.

We make one additional contribution to the entrepreneurial risk tolerance literature. Just as risk tolerance is an omitted variable in studies of credit constraints and self-employment, credit constraints are an omitted variable in studies of risk tolerance and self-employment. The risk tolerance literature recognizes and acknowledges the problem, again citing data availability (Cressy (2000), Kan and Tsai (2006)). We overcome this by simultaneously estimating the effects of both credit constraints and risk tolerance on self-employment, for the same households and all in a single parsimonious specification.

In terms of mechanics, we test several hypotheses. Our first hypothesis is that greater credit constraints decrease the probability of becoming self-employed, taking into account all forms of credit constraints and controlling for risk tolerance. Said another way, we test whether better access to credit increases business formation and job creation. Along the way, we contrast our main results with those that would be had when using the incomplete measure of credit constraints based on loan rejections only. We will show that the bias from using the incomplete measure is significant. Our second hypothesis is that higher risk tolerance increases the probability of becoming self-employed, even after controlling for credit constraints. Using several different methods, we test whether higher risk-tolerant individuals are more likely to start a business while lower risk-tolerant individuals are more likely to look for steady employment.

To preview results, we find the relationship between credit constraints and self-employment is negative overall, consistent with the literature. Notably, we find that the effect is stronger once the more complete measure of credit constraints—that accounts for the hidden majority—is used in place of the incomplete one. Our findings further show that a credit constraint in any form reduces the probability of self-employment by 36.7%, which is almost 50% larger than the estimated effect when an incomplete definition of credit constraints based on rejections is used in the existing literature. Furthermore, this finding implies that, at the national level, approximately 1.45 million individuals may have become self-employed and potentially started businesses if these broader forms of credit constraints, what we refer to as the “hidden majority,” did not exist. This not only underscores the importance of our expanded definition but also highlights the broader economic implications of credit accessibility. The implication of our findings is clear—a reliance on a too-narrow measure of credit constraints misses much—and in fact most—of the credit constrained households of concern. We also find a positive relationship between risk tolerance and self-employment after controlling for the impact of credit constraints, as expected. Notably, we find an interesting convexity in the risk tolerance–self-employment relationship that becomes apparent only once the more complete measure of credit constraints is used.

The remainder of the study is organized as follows: Section 2 describes the existing literature on credit constraints, risk, and self-employment. Section 3 presents the data, variables, and methodology; Section 4 presents the results. Section 5 concludes with policy implications and scope for further research.

## 2 | BACKGROUND AND LITERATURE REVIEW

Small business is critical to the economy. Small businesses accounted for 44% of the private non-farm US economy from 1998 to 2014, and grew an average of 3.3% per year (Kobe and Schwinn (2018)). They are the primary source of new jobs (Berkowitz and White (2004)), creating two out of every three new jobs in the U.S. (National Economic Council (2012)), and have the highest productivity per payroll dollar (Kobe and Schwinn (2018)). They provide positive externalities throughout the economy and form a feedback loop between new businesses, new jobs, and economic growth (Beck et al. (2007, 2015), Li et al. (2021), Beck and Demircuc-Kunt (2006)).

Yet in recent years, the share of Small Bank Lending (SBL), a primary funding source of funds for small businesses, has shrunk (Jagtiani and Lemieux (2016), Cornelli et al. (2024)). A 2017 Federal Reserve Survey shows that while 62% of all online lending went to small businesses (businesses with annual revenues of less than \$1 million) in 2016, a full two-thirds of these small businesses faced credit constraint problems (Kothari (2020)).<sup>2</sup> The figure is high and especially problematic given that small businesses are key drivers of job growth and economic activity (Hvide and Møen (2007), Carter et al. (2017), Kobe and Schwinn (2018)).

### 2.1 | Credit constraints and self-employment

There is a vast literature on credit constraints and their effects on self-employment and other factors. Much of the early literature relies on proxies for credit constraints, but provides the earliest insights into the credit constraint—

self-employment relationship. In the early seminal study of Evans & Jovanovic, 1989, the authors use the National Longitudinal Survey of Young Men from 1976 to 1978 to investigate the relationship between own wealth and small business formation, and find a correlation between wealth and small business formation. They argue that a lack of access to credit, although unobserved, is probably the latent binding constraint preventing less wealthy young men from starting businesses to the same extent as wealthier young men. Essentially, wealth is used as a proxy for credit availability, as credit constraints are not directly observed. Meyer (1990) builds upon this and uses the Survey of Income and Program Participation (SIPP) for 1984 and 1985 to show that the problem is even more severe for minority would-be entrepreneurs, taking into account both wealth and potentially discriminatory and other social hurdles. Holtz-Eakin et al. (1993, 1994) and Blattman et al. (2014) find that wealth matters too, and argue that own wealth and presumed better access to credit markets due to that wealth can lead to more self-employment.

An interesting strand of more current research exploits policy shocks in a regression discontinuity or natural experiment framework. In these papers, the policy shock itself is the proxy for credit constraints, and it is assumed that the policy will shock credit constraints in expected ways. One concern with this strand of literature is that some of the policy shocks are actually wealth shocks, meaning that the effects of wealth and the effects of credit constraints cannot be separated, leading to some of the same endogeneity concerns discussed above. Bellon et al. (2021) show that increased wealth from oil and gas royalties leads to increases in self-employment, while Wang (2012) finds that an increase in property rights and subsidized home ownership in China (more wealth) also increases self-employment. In a few studies, the policy shock is tied closer to a credit constraint shock, even though still by proxy. For example, Lastrapes et al. (2022) exploit an amendment to the Texas constitution to show that a new ability to use home equity as loan collateral leads to more business activity, and Herkenhoff et al. (2021) use actual credit information to show that bankruptcy flag removals from credit reports increase self-employment.

Other studies examine how credit constraints affect outcomes other than self-employment, such as general job market outcomes. Acemoglu (2001), for example, argues that frictions arising from credit market imperfections make it more difficult for entrepreneurs to hire workers. Still, other studies focus on the causes of credit constraints rather than their effects. Adverse selection and moral hazard are common themes as would-be entrepreneurs and above-average risk takers self-select into applying for loans and, once funded, can be difficult to monitor (Knight (1921), Stiglitz and Weiss (1981), LeRoy et al. (1987)). Buera et al. (2015) argue that a lack of personal collateral significantly contributes to credit constraints.

Many studies use proxies for credit constraints, but fewer use direct information, as we do here. Two key exceptions, and the two papers most closely related to our study in terms of approach, are Jappelli (1990) and Cai et al. (2018). Jappelli (1990) was among the first to use direct data on households' individual efforts to access credit, using an early wave of the SCF from 1983. Respondents were asked a series of questions about their recent experiences in attempting to secure loans. Although the set of questions was substantially more limited than those in the more recent wave that we use, Jappelli exploits the data to directly analyze the actual credit constraints that respondents faced, without the need to resort to wealth-based proxies. The purpose of that study is very different from our own, however. Its focus is simply to understand the nature and characteristics of households that either received or were denied credit, whereas our focus is to estimate the actual effects of those constraints on self-employment outcomes.

The second closely related paper is the excellent work of Cai et al. (2018), who use micro level data from the 2011 and 2013 China Household Finance Survey (CHFS) to argue that credit constraints had a dampening effect on self-employment in China. We are able to improve upon this study in several ways. First, our data enables us to distinguish between underfunded and rejected applications, which is an important distinction since these two groups represent different degrees of credit constraint. Second, our data enables us to identify discouraged and priced out borrowers, which is important as these groups make up a large proportion of credit constrained households. Third, our data enables us to explicitly control for the traditionally omitted risk tolerance variable. The two studies are also very different in terms of timing and geography—Cai et al. (2018) examine Chinese borrowers in 2013 whereas we examine a large cross-section of U.S. borrowers in 2022. It is unlikely that the experience of Chinese borrowers in the Chinese credit market will closely match the experience of U.S. borrowers in the U.S. credit market, so we explore the U.S. experience here.

## 2.2 | Risk and self-employment

Just like lenders take on risk when lending to new businesses, business owners take on risk when starting or expanding their businesses. Risk tolerance varies across individuals and projects, and there is a vast literature examining the relationship between risk tolerance and entrepreneurship. Knight (1921) and Cantillon (1931) were among the first to claim that risk attitudes play a significant role in start-up formation, while Schumpeter (1934), Menger (1950), and Kirzner (1979) downplayed its relative importance. Kihlstrom and Laffont (1979) develop a theoretical model to show how risk tolerance influences a household's choice to enter self-employment, while Chell et al. (1991) argue that the relationship between risk attitude and entrepreneurial survival is a U-shaped one—both the most risk averse and the most risk loving are more likely to fail. Cressy, 2000 develops a model of wealth and absolute risk that endogenizes risk aversion and argues that risk tolerance depends primarily on the proportion of one's wealth placed at risk.

Empirically, Cramer et al. (2002) test the risk-wealth-entrepreneurship relationship using data on lottery winners and, from this, conclude that risk aversion can deter entrepreneurship. Kan and Tsai (2006) show that risk aversion has a similarly negative impact on self-employment using the 1995 to 1997 waves of the Panel Study of Income Dynamics (PSID). Caliendo et al. (2010) show that intermediate degrees of risk attitude lead to the longest lasting businesses, consistent with the work of Chell et al. (1991), using the German Socio-Economic Panel (SOEP). Lopera and Marchand (2018) examine entrepreneurial choices in the presence of social interaction and peer pressure while Riepe et al. (2020) extend the analysis to consider the interaction of financial literacy and risk aversion, showing that financial literacy promotes entrepreneurship. Liu and Ren (2021) similarly conclude that risky markets and economic conditions have a negative impact on entrepreneurship in China using data from the CHFS. There are many others.

The literature is vast but suffers from a common limitation—studies rarely have information on credit constraints to use as a control when testing the relationship between risk tolerance and business formation (Cressy (2000), Kan and Tsai (2006)). Because we expect (and observe) that risk tolerance and credit constraints are themselves negatively correlated, omitting the credit constraint variable in a study about risk tolerance leads to an obvious omitted variables bias. Any effect of the omitted credit constraint variable is necessarily loaded onto the risk tolerance coefficient. In our study, we have matched data on credit constraints and risk tolerance for the same households, and can control for the credit constraints variable that has been elusive in the risk tolerance and self-employment literature. With so many studies on credit constraints and self-employment, and so many studies on risk tolerance and self-employment, it is perhaps surprising that so little work has been done to estimate these two relationships simultaneously. We fill this gap in the literature here.

## 3 | DATA AND METHODOLOGY

Our study utilizes data from the 2022 wave of the Survey of Consumers Finances (SCF),<sup>3</sup> a triennial cross-sectional survey of U.S. households administered by the Federal Reserve Board in cooperation with the U.S. Department of Treasury. The 2022 SCF data contain 6,500 random households with information on 22,975 individuals about their demographics, finances, lending and borrowing activities, and labor market decisions including the decision to become self-employed.

It contains a wealth of information on credit markets, including information on who applies for credit, who is funded, who is rejected, and who is accepted but underfunded. It also asks who was discouraged from applying in the first place for fear of rejection or for fear of being priced out by a high interest rate. The data contains information on self-reported risk tolerances as well. We use this detailed information to jointly examine the credit market experiences of entrepreneurs and their risk tolerances on the likelihood of becoming self-employed. Additionally, the SCF provides rich information on the different types of household assets and liabilities, and household demographics, which we use as additional controls. The richness of the information contained in the SCF is a key reason why the

data is so extensively used to analyze various household outcomes, including credit constraint and self-employment experiences (Perraudin and Sørensen (2000)).

The main limitations of the SCF are the usual ones. Like all voluntary surveys, it is subject to the usual issues of potential self-selection bias, memory bias, and exaggeration bias. We do not expect these to be a meaningful problem in this context, but it is noted. The dataset is also not longitudinal, meaning that we cannot track the same households over time from one survey to the next. A longitudinal dataset would be ideal; although a non-longitudinal one means that attrition bias is not a concern.

Our dependent variable is *SelfEmployed*, an indicator variable taking on a value of one if a household owns or starts a business and zero otherwise. The same basic variable has been used in numerous other studies (Hurst and Lusardi (2004), Elfenbein et al. (2010), Nguyen and Nordman (2018), Cai et al. (2018), Li et al. (2021)) as a measure of entrepreneurship or business start-up. In the 2022 SCF that we use here, 2.73% of households report owning their own business. Summary statistics on this and other variables appear in Table 1.

We have two primary right-hand-side variables of interest—credit constraints and risk tolerance. We expect that credit constraints—the inability of a household to borrow funds to finance a business—will negatively impact the probability that a household will start up a business and become self-employed. The reason is straightforward—getting a business off the ground can require significant capital investments for obtaining workspace, equipment, staffing, and inventory, and absent sufficient own wealth, it is often financially prohibitive. Even small single-person freelancer or independent contractor businesses, those without physical locations or inventory needs, still have significant capital needs for items such as basic equipment and advertising, and simply for living expenses as they forgo regular income to work full-time on growing their business to the point of self-sustainability.

While we expect credit constraints to play a vital role, the connection between credit availability and self-employment is not always easy to pin down. As noted by Cai et al. (2018), it can be difficult to measure the effect of credit constraints on self-employment because of an obvious selection problem that keeps many would-be borrowers out of the standard databases used for this purpose. Datasets based on actual loans, by construction, do not include borrowers who are rejected. Datasets based on loan applications, also by construction, do not include the potentially large number of discouraged borrowers who did not apply for a loan in the first place because they either feared rejection or feared that the interest rate attached to that loan would be too high. All these cause selection issues.

Broad-based surveys presumably include all would-be borrowers, but contain a completely different kind of bias if the survey questions asked are not sufficiently detailed. A survey that asks only if one applied for a loan and if one was accepted or rejected on that loan would erroneously dump all discouraged borrowers, priced-out borrowers, and an unknown amount of underfunded borrowers into the control group of not credit constrained borrowers. This would set up a meaningless comparison of the treated to the also-treated; instead, a meaningful comparison of the treated to a treatment-free control.

We circumvent these issues here by making use of the rich series of questions that the 2022 SCF asks of all households about their borrowing or desired borrowing behavior. These questions include whether they applied for a loan, whether they received the loan, whether they received the full amount of the loan, or if they were capped at a lesser amount. The SCF also asks respondents if they thought about applying for a loan but did not apply, and if they did not apply, why they did not apply. If they did not apply, the SCF asks whether it was because they did not need the credit, they thought they would be rejected, or they thought their interest rate would be too high to manage.

We create a series of right-hand-side indicator variables to describe these situations. We define the indicator variable *Rejected* to be equal to one if a household states they applied for credit in the last twelve months but was rejected. This variable would, by itself, be a typical measure of credit constraints in the literature.

The indicator variable *Underfunded* is equal to one if a household's application was accepted but only for a lesser amount. The indicator variable *Discouraged* is equal to one if the household wanted to apply but did not apply for the loan specifically because they felt they would probably be rejected. The indicator variable *PricedOut* is equal to one if

**TABLE 1** Description of variables.

| Variable                             | Definition                                                                               | Mean   |
|--------------------------------------|------------------------------------------------------------------------------------------|--------|
| Employment Status:                   |                                                                                          |        |
| Self Employed                        | = 1 if household owns a business                                                         | 2.73   |
| Credit Constraints:                  |                                                                                          |        |
| Credit Constrained                   | = 1 if household was credit constrained in any way                                       | 17.74  |
| Rejected                             | = 1 if household's initial credit application was rejected                               | 8.82   |
| Underfunded                          | = 1 if household's initial credit application was approved but underfunded               | 2.54   |
| Discouraged                          | = 1 if household did not apply for credit for fear of being rejected                     | 3.88   |
| Priced Out                           | = 1 if household did not apply because expected interest rate too high                   | 2.56   |
| Credit Constrained (Alternate)       | = 1 if household was still credit constrained after all application attempts             | 14.53  |
| Rejected (Alternate)                 | = 1 if all household's credit applications were rejected or underfunded                  | 8.80   |
| Financial Institution Distance (FID) | mean (miles)                                                                             | 104.05 |
| Risk Tolerance:                      |                                                                                          |        |
| Low Risk Tolerance                   | = 1 if household scores its risk tolerance between -1 and 2                              | 23.52  |
| Medium Risk Tolerance                | = 1 if household scores its risk tolerance between 4 and 7                               | 59.35  |
| High Risk Tolerance                  | = 1 if household scores its risk tolerance between 8 and 10                              | 17.13  |
| Willingness to Take Risk             | = 1 if household responds generally that it is willing to take risk (alternate question) | 68.24  |
| Wealth:                              |                                                                                          |        |
| Home Ownership                       | = 1 if household owns their own home                                                     | 61.13  |
| Auto Ownership                       | = 1 if household owns their own automobile                                               | 85.27  |
| Indebtedness:                        |                                                                                          |        |
| Credit Cards                         | =1 if household holds a credit card                                                      | 82.12  |
| Mortgage                             | = 1 if household applied for mortgage last 12 months                                     | 2.71   |
| Auto Loan                            | = 1 if household applied for an automobile loan last 12 months                           | 26.39  |
| Student Loan                         | = 1 if household applied for a student loan last 12 months                               | 17.67  |
| Other Loan                           | = 1 if household applied for another type of loan last 12 months                         | 8.91   |
| Business Finance:                    |                                                                                          |        |
| Inherited Business                   | = 1 if household has inherited a business                                                | 1.04   |
| Start Up Business                    | = 1 if household has initiated a new business                                            | 16.43  |
| Business Collateral                  | = 1 if household used personal assets as collateral for business loan                    | 0.59   |
| Socioeconomic Variables:             |                                                                                          |        |
| Age                                  | mean (years)                                                                             | 51.71  |
| Household Size                       | mean (number of people)                                                                  | 2.36   |
| ln(Income (in Thousands))            | mean (natural log of thousands of dollars)                                               | 11.66  |
| Gender (omitted: Male)               |                                                                                          |        |
| Female                               | = 1 if head of household is female                                                       | 23.89  |
| Marital Status (omitted: Single)     |                                                                                          |        |
| Married                              | = 1 if head of household is married                                                      | 54.60  |

**TABLE 1** (Continued)

| Variable                                   | Definition                                                          | Mean  |
|--------------------------------------------|---------------------------------------------------------------------|-------|
| Separated                                  | = 1 if head of household is separated                               | 17.12 |
| Widowed                                    | = 1 if head of household is widowed                                 | 6.72  |
| Race and Ethnicity (omitted: White)        |                                                                     |       |
| Black                                      | = if head of household is Black                                     | 15.59 |
| Asian/Indian/Hawaiian                      | = if head of household is Asian / American Indian / Native Hawaiian | 8.77  |
| Hispanic/Latino                            | = if head of household is Hispanic                                  | 13.59 |
| Education (omitted: Less than High School) |                                                                     |       |
| High School                                | =if head of household has high school diploma only                  | 19.68 |
| Bachelors Degree                           | =if head of household highest degree is a bachelors degree          | 47.21 |
| Post Graduate                              | =if head of household has some post-graduate education              | 23.76 |

the household did not apply for the loan in the first place specifically because it felt that the loan, if funded, would be too expensive to maintain at the expected interest rate. The latter three categories—Underfunded, Discouraged, and Priced Out, are collectively referred to as the hidden majority, as they represent households facing credit constraints that are not always captured through formal rejections. To our knowledge, this detailed breakdown of credit constraints into all these components is new. Combining them all together, we generate the indicator variable *CreditConstrained* equal to one if any of the four above variables above are equal to one. We consider those that did not apply because they did not need credit, and those that applied and were fully funded, as not credit constrained.

With this more complete set of information on borrower situations, our measure of credit constrained households is more comprehensive and better delineated than measures commonly found in the literature. Underfunded borrowers are not technically rejected for a loan, so they can be miscategorized as not credit constrained even though they are. It is hard to know how a bank, or a respondent in a survey, would code an underfunded loan in any given dataset when the only two allowable choices are 'rejecte' and 'not rejecte'. In reality, the loan is neither 'rejecte' nor 'not rejecte' but some unknown mix of the two.

Discouraged borrowers are rarely identified in the literature (Jappelli (1990) being an example) and, to our knowledge, Priced Out borrowers have not been identified previously. These borrowers do not appear in datasets of bank loans or bank loan applications, and in surveys that do not explicitly ask about these situations, they would be miscategorized into the not credit constrained control group (as they never applied and were never rejected). Jappelli (1990), using an earlier version of the SCF, first quantified the importance of discouraged borrowers; though not in the context of self-employment decisions.

Table 1 shows just how much information is lost or misplaced when the measure of credit constraints, based on bank rejections only, is adopted. Overall, we find that 17.74% of households in the sample report being credit constrained in some form—either by being rejected on a loan, underfunded on a loan, discouraged from applying for a loan because they expected to be rejected, or priced out of a loan. When we break this down further, we see that not even half of those credit constrained households—8.82% in all—were outright rejected by a bank. Better than half of the total number of credit constrained households were credit constrained in ways other than outright rejection: 2.54% of households were underfunded, 3.88% were discouraged from applying for fear of rejection, and 2.56% did not apply for credit because they expected to be priced out, for a total of 8.98%. In other words, these three hidden groups of credit constrained would-be borrowers, missed or miscategorized in the literature, actually comprise a hidden majority of credit constrained households. They would all be miscategorized into the presumed control group of not credit constrained households if the incomplete measure of credit constraints based on

rejections only was used. The control group would actually be infected with more treated households than exist within the treatment group itself. This was surprising to us given the lack of discussion about these hidden groups in the literature, and a key contribution of the current effort is to identify this hidden majority and return them to the treatment group for analysis.

Representing approximately a quarter, a half, and a quarter of all hidden credit-constrained households respectively, these three hidden groups of credit-constrained households are each substantial in their own right. Importantly, they are not randomly drawn from the credit constraint severity distribution. Underfunded borrowers face the weakest credit constraints and will be concentrated in the left tail of the credit constraint severity distribution. Discouraged and priced-out borrowers face the strongest credit constraints and will be concentrated in the right tail of the credit constraint severity distribution. In other words, one miscategorized group (about a quarter of the total miscategorized households) received a weak treatment, and two miscategorized groups (about three-quarters of the total) received an especially strong treatment. The miscategorization suggests a potentially significant composition bias that skews in a direction and by an amount that depends on the size of the respective hidden groups and the strength of the credit constraint—self-employment relationship within each group. We discuss this in more detail below. For now, given the relative size of the groups, we expect the bias is likely to drive our coefficient of interest towards zero and understate the effect of credit constraints on self-employment.

Our second key set of right-hand side variables relates to a household's risk tolerance. As is well known, self-employment tends to be more risky than paid employment at a fixed wage or salary; thus, a higher expected return is needed (Cramer et al. (2002)). But just how high a return is needed depends largely on a household's risk tolerance, with risk tolerant households more willing to start a business than risk averse households for any given expected return. For this reason, we expect greater risk tolerance to be associated with a higher likelihood of self-employment, all else equal (Cramer et al. (2002))<sup>4</sup> As noted, risk tolerance is a perpetually omitted variable in the literature on credit constraints and self-employment.

The SCF asks households directly about their risk tolerance. It asks households to self-rate their tolerance for taking financial risks on an 11 point scale, from  $-1$  to  $10$ , with  $-1$  being “not at all willing to take any financial risk” and  $10$  being “completely willing to take financial risks”. Following the work of Caliendo et al. (2010), we build three risk categories based on households' responses to this question—households with scores from  $-1$  to  $2$  inclusive we call “Low Risk Tolerance” households, households with scores from  $3$  to  $7$  inclusive we call “Medium Risk Tolerance” households, and households with scores from  $8$  to  $10$  inclusive we call “High Risk Tolerance” households. Table 1 shows that 23.52% of households have low risk tolerance, 59.35% of households have medium risk tolerance, and 17.13% of households have a high risk tolerance. We create separate indicator variables for medium and for high risk tolerance households, with low risk tolerance households serving as the omitted reference group.

In addition to our main right-hand side variables, we include a large set of control variables. They consist of demographic and socio-economic variables, including age, gender, marital status, income, education level, race and ethnicity, collateral availability, credit card debt, and auto ownership. Summary statistics are shown in Table 1. While we are interested in these only as background controls, other studies have examined the effects of these variables in their own right. It is seen that older individuals tend to take fewer risks and remain as paid employees, whereas younger individuals are more likely to take more risks and start up a business (Holtz-Eakin et al. (1994)). Marital status and the number of children also matter, but in a more nuanced way. On one hand, individuals with large families and more expenses can become more risk averse and more likely to retain paid employment. On the other hand, the fact that individuals choose to have large families in the first place means they may be inherently more open to taking risks. The evidence is mixed—Holtz-Eakin et al. (1994) find a negative relationship between family size and self-employment, while Hout and Rosen (2000) find a positive one. The effect of education on self-employment is also nuanced. On one hand, greater education leads to higher entrepreneurship both because graduates learn skills useful in business and because higher education tends to attract smarter and more motivated individuals in general (Hurst and Lusardi (2004)). On the other hand, a significant student loan balance can directly affect the credit constraints a potential entrepreneur faces and the ability to start a business. In addition, especially motivated entrepreneurs may

skip the remaining years of education to start their business sooner, as numerous famous examples in tech industries attest. The effects of the wealth variables are also in general ambiguous. We have two wealth-related variables, similar to Cai et al., 2018, on whether the household has credit card debt and on whether the household owns at least one vehicle. On one hand, greater initial wealth can make it easier to avoid credit constraints and easier to start a new business. On the other hand, wealth-related variables based on physical assets tend to be less liquid than savings or financial instruments and could themselves be considered a substitute for business investment. We also include a business collateral variable, defined as whether a household has personal assets used as collateral in a business loan, which, all else being equal, should make loans easier to get.

Of key interest is our credit constraint variables, but as these may be endogenously determined, we employ instrumental variables techniques. Credit constraints are potentially endogenous for a number of reasons. First, macroeconomic shocks can affect both the choice to become self-employed and the probability that credit constraints will be binding at the same time. Second, credit constraints can be correlated with income or time-varying factors that banks but not individuals may be aware of (Rossi and Trucchi (2016)). Third, credit constraints can be determined in part by the demographic and socioeconomic characteristics of households which themselves are potential predictors of self-employment (Perraudin and Sørensen (2000)). Fourth, the decision to be self-employed is jointly determined by both credit access and risk tolerance (Miniati and Pastorello, 2010), though we explicitly control for risk tolerance here. Fifth, and more importantly, there is the potential for reverse causality since individuals that are self-employed and successful are less likely to be credit-constrained exactly because they are successful (Cai et al. (2018)). Sixth, and inversely, it may be harder to get a loan if a household is already self-employed, or about to become self-employed, since self-employed individuals lose their verifiable future income stream and can no longer offer that as collateral.

To address endogeneity, we look for an instrument that is correlated with the probability of being subject to a credit constraint but uncorrelated with an individual's self-employment status except indirectly through its effect on credit constraints. A prime candidate for this, and one that is used by Cai et al. (2018), is the physical distance between the potential borrower (based on the census tract of the surveyed household) and the nearest branch of the lending institution. The idea is that awareness of local business conditions and a personal banking relationship can affect a bank's willingness to fund a new would-be entrepreneur in a (risky) new small business venture. At the same time, proximity should not meaningfully affect self-employment status except through this channel.<sup>5</sup> We build this instrument using the distance between a respondent and the nearest financial institution branch, based on the Haversine Method of calculating distances between the geocoordinates of the respondent and the branch. Distance measures such as these for use with instruments are common in the literature across a variety of different applications. To maintain consistency with Cai et al. (2018), we call our instrument Financial Institutional Distance.

We find that 8.73% of respondents report a distance less than half a mile to the nearest financial institution, and 88.44% of respondents reported a distance of more than half a mile. The remaining 2.85% do not report a distance to the nearest financial institution.

We begin our empirical set-up with the underlying latent variable model given by:

$$\begin{aligned} SelfEmployed_i^* = & \alpha + \beta CreditConstrained_i + \theta^M MediumRiskTolerance_i \\ & + \theta^H HighRiskTolerance_i + \sum_{j=1}^N \eta_j X_j + \varepsilon_i \end{aligned} \quad (1)$$

where  $SelfEmployed_i^*$  is a continuous, but latent, variable that measures a household's desire and ability to become self-employed.  $CreditConstrained_i$  is equal to one if a household is either (i) Rejected, (ii) Underfunded, (iii) Discouraged from applying because they think they will be rejected, or (iv) discouraged from applying because they felt they would be Priced Out at the interest rate offered. The variable  $MediumRiskTolerance_i$  is equal to one for medium risk tolerant households and  $HighRiskTolerance_i$  is equal to one for high risk tolerant households, with  $LowRiskTolerance$  being the omitted indicator variable. The matrix  $X$  contains all other control variables. The omitted

indicator variables within each set of related control variables is noted in Table 1. The  $\varepsilon_i$  is a normally distributed error term.

Since we do not observe *SelfEmployed\**, but only a dichotomous variable *SelfEmployed<sub>t</sub>* equal to one when the self-employment option is chosen, we use a Probit model in the estimation.<sup>6</sup>

More specifically, we use a two-stage Probit instrumental variables model (Probit IV) to correct for endogeneity using the first stage regression given by:

$$\text{CreditConstrained}_i = \gamma + \omega \text{FID}_i + \sum_{j=1}^N \psi_j X_{ij} + v_i \quad (2)$$

where *FID* is the Financial Institutional Distance variable, the matrix *X* is as before, and  $v_i$  is an independent and normally distributed error-term.

## 4 | RESULTS

### 4.1 | Preliminary results

We begin by analyzing the raw data on self-employment, credit constraints, and risk tolerance, and establish some general correlations among our key variables. We find substantial differences between self-employed households and non-self-employed households in terms of their experience with credit constraints and their degree of risk tolerance. We present these early results in Table 2. In the first column of the table, we see that 8.76% of self-employed households overall report having been credit constrained in some way. In sharp contrast, in the second column, we see that a much higher 17.99% of non-self-employed households report having been credit constrained in some way. While our main question will be whether there is a causal relationship here—whether an increase in credit constraints makes households less likely to become self-employed—we already see a substantial correlation in the raw data with the expected negative sign. Greater credit constraints appear strongly associated with less self-employment when accounting for all credit constrained would-be borrowers. The correlation in the raw data is strong—credit constraints are more than twice as likely with households that did not or could not start a business compared to households that could and did.

What is even more striking about the table is how much stronger this correlation is when we account for all forms of credit constraints, instead of relying on the incomplete measure based on rejections only. When all credit

**TABLE 2** Correlation of Credit Constraints and Risk Tolerance by Employment Status.

|                                       | Self employed | Not self employed |
|---------------------------------------|---------------|-------------------|
| Credit Constraints:                   | 8.76          | 17.99             |
| Rejected                              | 6.37          | 8.89              |
| Underfunded                           | 0.00          | 2.54              |
| Discouraged                           | 1.59          | 3.95              |
| Priced Out                            | 0.80          | 2.61              |
| Risk Tolerance:                       |               |                   |
| Low Risk Tolerance (Scores –1 to 2)   | 8.92          | 23.93             |
| Medium Risk Tolerance (Scores 3 to 7) | 58.92         | 59.36             |
| High Risk Tolerance (Scores 8 to 10)  | 32.17         | 16.71             |
| Willingness to Take Financial Risk    | 92.20         | 67.57             |

Note: Cells contain percentages of the column group that have the row item.

constraints are considered, the proportion of non-self-employed households that faced credit constraints was basically double the proportion of self-employed households that faced credit constraints (%17.99 versus %8.76), a substantial amount. We see some correlation between rejections and self-employment as well, but the correlation is muted—the proportion of non-self-employed households that faced outright rejections was 8.89% while the proportion of self-employed households that faced outright rejections was moderately lower at 6.37%.

This early comparison foreshadows a key contribution of our study—the incomplete measure of credit constraints based on bank rejections masks the strength of the relationship between credit constraints and self-employment. While non-self-employed households are only modestly more likely to be outright rejected than self-employed households, they are much more likely to experience other forms of credit constraints, i.e. be underfunded, discouraged, or priced out. A total of 2.54% of non-self-employed households report having been underfunded compared to essentially zero self-employed households. A total of 3.95% of non-self-employed households report having been discouraged to apply for fear of rejection compared to only 1.59% of self-employed households. A total of 2.61% of non-self-employed households report having been priced out of the credit market compared to only 0.80% of self-employed households. Overall, 9.1% of non-self-employed individuals experienced these other hidden forms of credit constraints, whereas only 2.39% of self-employed households experienced them. In short, a high proportion of non-self-employed households gave up on a loan even before the application stage began, and still more settled for less money than they sought. More than half of all credit constrained households experienced one of these hidden credit constraints.

The correlation can also be seen in aggregate data. Figure 1 shows the quarterly growth rate of total private non-financial-sector business credit on one hand (GCPNFS), with the quarterly growth rate of self-employed businesses on the other (GSelfEmp), in the United States, from 1970 to 2020. The total credit series is taken from the Bank for International Settlements (BIS) and the self-employment series is taken from the U.S. Bureau of Labor Statistics. The timing of U.S. recessions is also shown. The figure shows a positive correlation between the two time series over the long term.

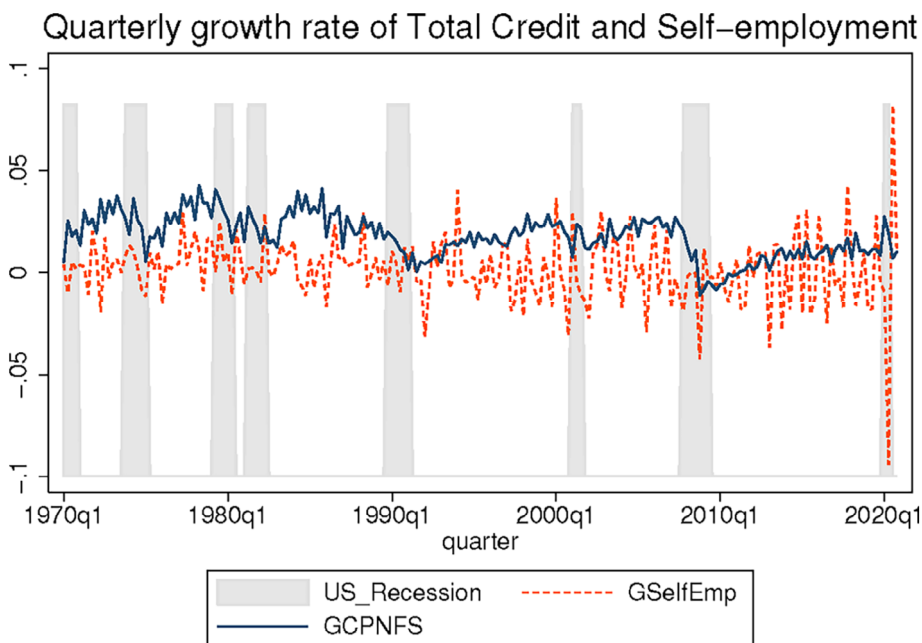


**FIGURE 1** Quarterly growth rate of total credit and self-employment.

The bottom part of Table 2 focuses on risk tolerances and foreshadows another key contribution of our study. The table shows that households that describe themselves as highly risk tolerant are indeed more likely to be self-employed. In all, 32% of self-employed households described themselves as having a high risk tolerance on financial matters, but only 17% of non-self-employed households did. Only 9% of self-employed households described themselves as having low risk tolerance on financial matters, but 24% of non-self-employed households did. Approximately 59% of each type of household described themselves as having a medium risk tolerance. The raw correlation is consistent with findings in the literature (for example, Caliendo et al. (2010), for Germany) and suggests that more risk tolerant households are more likely to enter self-employment.

An interesting feature of our data is that, for those who applied for loan but were rejected or underfunded on that loan, the SCF asks them why.<sup>7</sup> Table 3 lists the reasons given and the percentage of potential borrowers who were given each of the listed reasons, separately for rejected borrowers and for underfunded borrowers. There are some interesting differences. Not surprisingly, the most frequent reason given for rejecting an applicant (48.5%) is a poor credit rating or past bankruptcy. The second most frequent reason is the somewhat generic concern that the applicant is a bad creditor (10.1%). The third most frequent reason is insufficient income (9.3%) and the fourth most important reason is lack of credit history (8.54%). The fifth is the amount of debt or size of payments (7.6%). The most frequent reason for underfunding an applicant is again a poor credit rating or past bankruptcy (34.9%), followed by the amount of debt or size of payments (14.3%), insufficient income (10.4%), and lack of credit history (10.0%), setting aside the “no reason given” category. We see that underfunded borrowers are less likely to be considered a “bad creditor,” which is sensible given that the applicant was at least partially funded. The amount of debt or size of payments appears to be the key limiting factor in how much the lender is willing to lend to an underfunded applicant. Perhaps surprisingly, a lack of assets for collateral is the reason given for only 3% to 4% of rejections.

A curious side note is that a disproportionately large percentage of underfunded borrowers stated they were not given a reason for the underfunding (11.4%); whereas fewer rejected borrowers were not given a reason for the rejection (4.8%). We think this is an interesting behavioral result in its own right. We hypothesize that rejected borrowers—simply because they are rejected and have nothing left to lose—would be more demanding of the bank

**TABLE 3** Reasons for rejections or underfunding.

|                                    | Rejected borrowers | Underfunded borrowers |
|------------------------------------|--------------------|-----------------------|
| Credit rating or bankruptcy        | 48.47              | 34.86                 |
| Amount of debt or size of payments | 7.60               | 14.26                 |
| Insufficient income                | 9.33               | 10.39                 |
| No or little credit history/age    | 8.34               | 10.04                 |
| No reason given                    | 4.84               | 11.44                 |
| Lack of assets/collateral          | 2.81               | 3.87                  |
| Bad creditor                       | 10.07              | 4.75                  |
| Error in credit report/fraud       | 1.28               | 0.18                  |
| Marital status/gender/race/health  | 0.25               | 0.00                  |
| Previous bad experience            | 0.25               | 0.00                  |
| Need checking/savings account      | 0.54               | 0.00                  |
| Type of job or no job              | 2.12               | 5.46                  |
| Time at current address            | 0.54               | 0.88                  |
| Other                              | 0.00               | 0.00                  |
| Number of Observations             | 2026               | 568                   |

Note: Cells contain percentages of the column group that have the row item (except the last row).

officer for the specific reason for the rejection. In contrast, underfunded borrowers, having gotten at least some of what they asked for, have more of an incentive to “play nice” and may ask fewer demanding or confrontational questions to stay on the safe side of the lender. A second reason may be that underfunded borrowers, having received much of the money they asked for and probably happier with their experience than rejected borrowers would be, may have weaker recall about the negative aspects of their experience by the time of the survey.

We expect that personal and financial characteristics will play an important role in determining self employment status and credit constraint experiences. Table 4 breaks down households' wealth, indebtedness, and the availability of personal collateral for use in obtaining a business loan, by self-employment status and credit constraint experiences. The first column looks at wealth and indebtedness for the self-employed. We find that 73.4% of self-employed households own their own home, and 92.2% own their own vehicle. Many self-employed households report debt (taken on within the last 12 months): 4.8% recently applied for a mortgage, 23.7% recently applied for an auto loan, 9.2% recently applied for a student loan, and 4.4% recently applied for another type of loan. The vast majority, 94.1%, carry some credit card debt. A total 12.3% of self-employed households stated that they had personal assets to use as collateral in getting a business loan.

The second column looks at wealth and indebtedness for the non-self-employed. We see that fewer non-self-employed households own a home (61.3%) and fewer own a car (85.1%). They are less likely to have credit card debt or a mortgage (81.8% and 2.7%); but more likely to have an auto loan (26.5%, in spite of owning fewer automobiles), a student loan (17.2%), or another type of loan (9.0%).

In the third column of Table 4, which looks at households that experienced any form of credit constraint, we see that 35.1% of households that reported a credit constraint owned a home, and 76.0% of such households owned a vehicle. In addition, 1.1% recently applied for a mortgage; 32.4% recently applied for an auto loan; 28.3% recently applied for a student loan; and 19.4% recently applied for another type of loan. A smaller majority, 61.7%, carry some credit card debt. A very small proportion, just 2.9% of those reporting being credit constrained, report having had personal assets to use as collateral.

The fourth through eighth columns of Table 4 examine wealth and indebtedness by credit constraint, but with a finer breakdown, and here some interesting patterns emerge. Among those households that experienced credit constraints, the percentage of home ownership is highest among those who would ultimately be underfunded (48.2%), second and third highest among those who were either priced out (43.3%) or rejected (37.3%), and smallest among

**TABLE 4** Correlation of employment status and credit constraints by wealth and indebtedness.

|                         | Self<br>employed | Not self<br>employed | Credit<br>constrained | Rejected | Underfunded | Discouraged | Priced<br>out |
|-------------------------|------------------|----------------------|-----------------------|----------|-------------|-------------|---------------|
| Wealth:                 |                  |                      |                       |          |             |             |               |
| Home Ownership          | 73.41            | 61.3                 | 35.09                 | 37.31    | 48.2        | 16.26       | 43.29         |
| Auto Ownership          | 92.2             | 85.07                | 76.02                 | 80.21    | 88.4        | 60.87       | 72.67         |
| Indebtedness:           |                  |                      |                       |          |             |             |               |
| Credit Card             | 94.11            | 81.79                | 61.72                 | 75.27    | 85.9        | 23.09       | 50.25         |
| Mortgage                | 4.78             | 2.65                 | 1.1                   | 1.23     | 0.88        | 0.56        | 1.7           |
| Auto Loan               | 23.73            | 26.47                | 32.44                 | 39.98    | 46.1        | 17.38       | 16.13         |
| Student Loan            | 9.24             | 17.19                | 28.32                 | 34.55    | 33.3        | 19.62       | 15.28         |
| Other Loan              | 5.41             | 9.01                 | 19.41                 | 24.73    | 20.3        | 14.01       | 8.49          |
| Collateral for Business | 12.26            | 3.56                 | 2.92                  | 3.65     | 5.28        | 0           | 2.55          |
| Number of Observations  | 628              | 22,347               | 4075                  | 2026     | 568         | 892         | 589           |

Note: Cells contain percentages of the column group that have the row item (except the last row).

those who were discouraged for fear of being rejected (16.3%). A similar pattern is present in terms of the percentage of auto ownership as well, with the percentage of auto ownership highest among underfunded households (88.4%), second highest among rejected households (80.2%), third highest among priced out households (72.7%), and lowest among those who were discouraged for fear of being rejected (60.9%). It forms an interesting ranking that is consistent with our notion of the severity of the credit constraint. We argue that the underfunded group experiences the weakest credit constraint (as they were partially funded), the rejected group experiences the next strongest credit constraint (noting that, although rejected, they felt they had a reasonable enough chance to apply), and the often-ignored groups of priced out and discouraged borrowers collectively experience the strongest credit constraint of all (as they had so little hope in getting a loan that there was little point in applying). The percentage of credit constrained households that own homes and autos follows this same ranking, from the highest percentage with the weakest credit constraint to the lowest percentage with the strongest credit constraint.

A similar pattern arises when examining indebtedness among the four groups, even though indebtedness is a form of negative wealth in the short run. The highest percentages of indebtedness usually belong to households that would ultimately be underfunded or rejected, and the lowest percentages of indebtedness belong to households that were either priced out or discouraged. The correlations, at a minimum, suggest that those who have used credit markets in the past are likely to continue to try to use credit markets in the future.

The availability of personal assets to use as collateral in securing a business loan also varies meaningfully across the four groups, in ways one would expect. Of those households that were credit constrained, the percentage of households with personal collateral is highest for the group that would ultimately be underfunded (5.3%); second highest for the group that ultimately applied but was rejected (3.7%) and lowest for the discouraged and priced out groups who wanted the loan but could not see the value in trying to get it.

## 4.2 | Main results

We now turn to our main results, reported in Table 5. We present four specifications that build up and conclude with our preferred specification, Specification (4). Specification (4) is the full model using IV and based on the more complete measure of credit constraints. We report marginal effects for all specifications in the table.

We focus first on our first dependent variable of interest, credit constraints, and then return to our second dependent variable of interest, risk tolerance, later. For completeness, all four specifications include both credit constraints and risk tolerance explanatory variables, plus a full set of demographic and socioeconomic controls.

The earlier specifications help us better understand the direction and magnitude of the biases at work. We present them here for comparison with our preferred specification. We build Specifications (1) and (2) using the common but incomplete measure of a credit constraint, based on rejected borrowers only. Specification (1) presents the basic Probit model without instruments, and Specification (2) presents the full Probit IV model (including both first and final stages), using FID as our instrument. As noted, we expect a bias in these specifications, and a potentially significant one, given that they focus narrowly on rejected borrowers and ignore the hidden majority of credit constrained borrowers. By ignoring the three 'hidden' groups of credit constrained borrowers—underfunded borrowers, discouraged borrowers, and priced out borrowers—the specifications *de facto* miscategorize them into the not-credit-constrained 'control' group of households. This inverts the very notion of treatment and control.

We begin with Specification (1) that counts only rejected borrowers and assumes strict exogeneity of the rejections variable. Sure enough, we find a completely counterintuitive *positive* sign on the rejections variable (coefficient = 0.009), and statistically significant at that. Taken at face value, the significant positive sign suggests that stronger credit constraints are *good* for business formation. This is obviously anomalous on its face, but it is also obviously unreliable for two reasons. The first is that Specification (1) does not make any effort to control for endogeneity through instrumentation; which we will do next. The second is that Specification (1) is essentially a

TABLE 5 Impact of credit constraints and risk tolerance on self-employment.

|                                      | (1)                         | (2)                           |                             | (3)                         | (4)                           |                             |
|--------------------------------------|-----------------------------|-------------------------------|-----------------------------|-----------------------------|-------------------------------|-----------------------------|
|                                      | Probit<br>model             | Probit IV<br>1st stage        | Probit IV<br>final stage    | Probit<br>model             | Probit IV<br>1st stage        | Probit IV<br>final stage    |
| <i>Dependent Variable</i>            | <i>Self-<br/>Employment</i> | <i>Rejected<br/>Borrowers</i> | <i>Self-<br/>Employment</i> | <i>Self-<br/>Employment</i> | <i>Credit<br/>Constraints</i> | <i>Self-<br/>Employment</i> |
| Rejected                             | 0.009**<br>(0.004)          |                               | −0.247**<br>(0.125)         |                             |                               |                             |
| Credit Constrained                   |                             |                               |                             | −0.001<br>(0.004)           |                               | −0.367*<br>(0.216)          |
| Distance to Financial<br>Institution |                             | 0.00003***<br>(0.000)         |                             |                             | 0.00002***<br>(0.000)         |                             |
| Medium Risk Tolerance                | 0.010***<br>(0.004)         | −0.002<br>(0.005)             | 0.009**<br>(0.004)          | 0.010***<br>(0.004)         | −0.013**<br>(0.006)           | 0.005<br>(0.005)            |
| High Risk Tolerance                  | 0.020***<br>(0.004)         | 0.006<br>(0.006)              | 0.021***<br>(0.004)         | 0.020***<br>(0.004)         | −0.000<br>(0.008)             | 0.020***<br>(0.005)         |
| Credit Card                          | 0.004<br>(0.004)            | 0.019***<br>(0.006)           | 0.010*<br>(0.005)           | 0.005<br>(0.004)            | −0.120***<br>(0.007)          | −0.039<br>(0.026)           |
| Auto Ownership                       | 0.002<br>(0.004)            | −0.005<br>(0.006)             | 0.001<br>(0.004)            | 0.002<br>(0.004)            | −0.020***<br>(0.007)          | −0.005<br>(0.006)           |
| Business Collateral                  | 0.013<br>(0.010)            | 0.019<br>(0.024)              | 0.017<br>(0.012)            | 0.013<br>(0.010)            | 0.109***<br>(0.030)           | 0.053*<br>(0.028)           |
| Log of Income                        | 0.007***<br>(0.001)         | −0.014***<br>(0.001)          | 0.004**<br>(0.002)          | 0.007***<br>(0.001)         | −0.016***<br>(0.002)          | 0.001<br>(0.004)            |
| Age                                  | 0.005***<br>(0.001)         | −0.001<br>(0.001)             | 0.004***<br>(0.001)         | 0.005***<br>(0.001)         | −0.000<br>(0.001)             | 0.005***<br>(0.001)         |
| Age Squared                          | −0.000***<br>(0.000)        | −0.000<br>(0.000)             | −0.000***<br>(0.000)        | −0.000***<br>(0.000)        | −0.000***<br>(0.000)          | −0.000***<br>(0.000)        |
| Household Size                       | −0.001<br>(0.001)           | 0.006***<br>(0.002)           | 0.000<br>(0.001)            | −0.001<br>(0.001)           | 0.018***<br>(0.002)           | 0.005<br>(0.004)            |
| Female                               | −0.003<br>(0.004)           | −0.009<br>(0.006)             | −0.005<br>(0.004)           | −0.002<br>(0.004)           | 0.012*<br>(0.007)             | 0.002<br>(0.005)            |
| Married                              | 0.020***<br>(0.005)         | 0.001<br>(0.007)              | 0.020***<br>(0.005)         | 0.020***<br>(0.005)         | −0.042***<br>(0.008)          | 0.004<br>(0.011)            |
| Separated                            | 0.031***<br>(0.005)         | 0.041***<br>(0.006)           | 0.041***<br>(0.007)         | 0.031***<br>(0.005)         | 0.039***<br>(0.008)           | 0.045***<br>(0.010)         |
| Widowed                              | 0.010<br>(0.008)            | 0.030***<br>(0.009)           | 0.018**<br>(0.009)          | 0.010<br>(0.008)            | −0.004<br>(0.012)             | 0.008<br>(0.009)            |
| Black                                | −0.014***<br>(0.004)        | 0.085***<br>(0.006)           | 0.008<br>(0.012)            | −0.012***<br>(0.004)        | 0.158***<br>(0.007)           | 0.045<br>(0.035)            |
| Hispanic/Latino                      | −0.025***<br>(0.005)        | 0.015**<br>(0.006)            | −0.021***<br>(0.006)        | −0.024***<br>(0.005)        | 0.043***<br>(0.008)           | −0.009<br>(0.011)           |

(Continues)

TABLE 5 (Continued)

|                           | (1)                 | (2)                    |                          | (3)                 | (4)                    |                          |
|---------------------------|---------------------|------------------------|--------------------------|---------------------|------------------------|--------------------------|
|                           | Probit<br>model     | Probit IV<br>1st stage | Probit IV<br>final stage | Probit<br>model     | Probit IV<br>1st stage | Probit IV<br>final stage |
| Asian/Indian/Hawaiian     | −0.005<br>(0.004)   | 0.008<br>(0.007)       | −0.003<br>(0.004)        | −0.005<br>(0.004)   | 0.004<br>(0.009)       | −0.004<br>(0.005)        |
| High School               | −0.013**<br>(0.006) | 0.025***<br>(0.008)    | −0.006<br>(0.007)        | −0.012**<br>(0.006) | −0.049***<br>(0.010)   | −0.030**<br>(0.013)      |
| Bachelors Degree          | −0.010*<br>(0.005)  | −0.005<br>(0.007)      | −0.011*<br>(0.006)       | −0.010*<br>(0.005)  | −0.086***<br>(0.009)   | −0.041**<br>(0.020)      |
| Post Graduate             | −0.012**<br>(0.006) | −0.017**<br>(0.008)    | −0.016**<br>(0.006)      | −0.013**<br>(0.006) | −0.096***<br>(0.011)   | −0.047**<br>(0.022)      |
| Pseudo R-squared          | 0.109               |                        |                          | 0.108               |                        |                          |
| Wald Chi-squared          |                     |                        | 1991.1                   |                     |                        | 6150.23                  |
| Endogeneity Test          |                     |                        | 7.49 (0.006)             |                     |                        | 8.33 (0.003)             |
| Number of<br>Observations | 22,975              |                        | 22,975                   | 22,975              |                        | 22,975                   |

Note: Standard errors in parentheses. \*\*\* Significant at the 1% level, \*\* Significant at the 5% level, \* Significant at the 10% level.

regression of the treated on the also-treated, so that the comparison actually being made is not the comparison one would think is being made. We will fix this as well.

Once we add our instrumental variable and estimate the Probit IV model of Specification (2), we fix part of the problem, even while keeping the incomplete credit constraints measure. In the final stage regression (the rightmost of the two columns) under Specification (2) the coefficient on our “rejected” variable now has an expected negative sign (coefficient = −0.247) and is statistically significant at better than the 1% level.<sup>8</sup> These results are qualitatively similar to the existing literature, including Cai et al. (2018) and Li et al. (2021). They are qualitatively similar to even Evans and Jovanovic (1989) and Hurst and Lusardi (2004), who focused on liquidity constraints rather than credit constraints.<sup>9</sup>

However, Specification (2) is still biased because it is still essentially a comparison of the treated on the also-treated. To address this, Specifications (3) and (4) incorporate the more complete measure of credit constraints based on all four groups of constrained households—underfunded, rejected, discouraged and priced out borrowers. Specification (3) is based on a standard Probit model without instruments, and is included for comparison with Specification (1). Specification (4) is our preferred specification, based on the Probit IV model, and using FID as an instrument.

Accounting for all four groups of credit constrained borrowers, to our knowledge, is new. In the two studies most closely related to our own, Jappelli (1990) defines credit constraints to include rejected and discouraged borrowers but not underfunded or priced out borrowers; Cai et al. (2018) defines credit constraints to include rejected and underfunded borrowers but not discouraged or priced out borrowers. Here, we account for all four groups of constrained borrowers, including all the hidden majority.

A quick comparison of Specification (3) with Specification (1) reveals that, even before we control for endogeneity, the simple expansion of our credit constraints variable to include the three hidden groups of credit constrained households is sufficient on its own to remove the counterintuitive positive sign on the credit constraints variable of Specification (1). We find no statistically significant effect of credit constraints on the self-employment decision in Specification (3); the negative point estimate is very close to zero.

This is an important result with a takeaway of its own. In Specification (1), the treated households were erroneously spread out almost equally between the so-called treatment group and the so-called control group, with the most and the least affected households miscategorized into that control group, biasing the result. In general, the direction of that bias is unknown; however, in our case, it is positive. Once we return the large number of discouraged and priced out households, previously mixed up into the control group, back into the treatment group in Specification (3), it removes the inherent upward bias in that coefficient for that reason. As seen in the raw data, relatively few discouraged and priced out households started a business, so once these households are categorized properly, the underlying correlation comes through clearly enough to remove the unintuitive positive sign.

Specification (3) still does not control for endogeneity and is not determinative for that reason, but Specification (4) does, and is. Specification (4) is our full model and preferred specification, taking into account all four groups of credit constrained households and incorporating IV techniques to control for endogeneity. This specification removes both sources of bias and provides the cleanest estimate. Looking at this specification, our first main result is that we find a strong and statistically significant negative relationship between credit constraints and the decision to become self-employed (coefficient =  $-0.367$ ). This is the largest (negative) coefficient of any of our specifications—the estimated coefficient is fully 50% larger than the estimated effect when an incomplete definition of credit constraints based on rejections only is used, even with IV. It shows that a credit constraint in any form reduces the probability of self-employment by 36.7%. Furthermore, our findings suggest that, on a national scale, an estimated 1.45 million additional individuals could have pursued self-employment and potentially started their own businesses if the broader credit constraints, what we term the “hidden majority” had not been present. This highlights not only the significance of our expanded definition but also the wider economic impact of limited credit access.<sup>10</sup>

Essentially, when discouraged and priced-out borrowers (and underfunded borrowers) are removed from the control group where they do not belong and placed back into the treatment group where they do belong, and the control group is no longer infected with the also-treated, the estimated effect is more negative and stronger.

The reason why the bias is upwards in this case, i.e., towards zero, is interesting. Discouraged and priced out borrowers face the strongest credit constraints, and their miscategorization works towards an upward bias of the estimates (i.e. towards no relationship, assuming a true inverse relationship). Essentially, these would-be borrowers receive the strongest treatments of all, so by miscategorizing them into the control group and then comparing the nominal treatment group to the nominal control group, the borrowers subtract from, rather than add to, the overall estimated treatment effect. That biases the result towards zero, or no relationship.

Underfunded borrowers are more nuanced. They face the weakest form of credit constraints and are an intermediate case between the rejected/discouraged/priced-out borrowers in the treatment group and the unconstrained borrowers in the control group. The sign of the bias from their exclusion then depends on the curvature of effects and is in general ambiguous. Essentially, if underfunded borrowers are more like rejected borrowers, they bias the result upwards (i.e. towards zero) and reinforce the bias above. If they are more like unconstrained borrowers, they bias the result downwards (i.e. away from zero) and offset the bias above. If they are 'midwa' between the two, the bias from this group goes to zero.

In our case, we found many more discouraged and priced out borrowers miscategorized into the control group (6.44%) than we found underfunded borrowers miscategorized into the control group (2.54%). The discouraged and priced out borrower groups dominated the underfunded group in size and in strength, causing a large and negative but hidden 'treatment effect' inside that control group. Since this hidden treatment effect had been counted in the control group, it was subtracted from the treatment effect of rejected borrowers, and we got the bias toward zero (since subtracting a negative number is equivalent to adding a positive one).

The policy implications are clear. A reliance on an incomplete measure of credit constraints would lead one to infect the control group with the also-treated and—in our case—substantially understate the importance of credit on small business formation. Once one adopts a more complete measure of credit constraints and the control group is no longer infected with the also-treated, the effect of interest is better isolated, and the strength of the relationship becomes more evident.

Our analysis is based on a broad sample of U.S. households in 2022, but the miscategorization concern is present in any dataset, time period, or geography, whenever relying on an incomplete measure of credit constraints. The direction of bias depends on the relative size of the hidden groups and the relative strength of the effects for those borrowers; the only way to gauge the true magnitude and direction of the bias from using an incomplete measure of credit constraints is to do the empirical analysis, as we do here for U.S. households. Further research is needed to quantify the bias in other datasets, time periods, and geographies.

Even if the bias would be small, we would argue that this is still not a justification for excluding hidden groups whenever data capturing these groups is available. First, one generally cannot know the degree of bias until the bias is actually estimated. Second, one has to estimate the model using the complete measure of credit constraints to gauge that bias; and, once done, it is difficult to justify reverting back to the incomplete measure with all its known miscategorizations. Third, even if it turns out that the two sets of coefficients of interest are not statistically significantly different, the central point estimate from the complete measure is still the best estimate and is more reliable than the central point estimate of the incomplete measure. The confidence intervals from the complete measure would be the correct confidence intervals to use.

We now turn to our second right hand side variable of interest, risk tolerance. In each specification in Table 5, we include indicator variables for medium risk tolerance and high risk tolerance, with the low risk tolerance indicator variable omitted. In every specification, we find that the effect is strong—households that are more risk tolerant are more likely to become self-employed. This is consistent with many of the findings in the literature (Cramer et al. (2002), Skriabikova et al. (2014) and Cai et al. (2018)), on a general level. We are unable to find evidence of any U-shaped relationship between risk tolerance and self-employment, as suggested by Caliendo et al. (2010).

However, we do uncover an interesting non-linearity in our preferred specification that is new. According to our first three preliminary specifications, the effect of risk on self-employment appears to be roughly linear, with the coefficient on high risk tolerance approximately double that of the coefficient on medium risk tolerance. However, in our preferred Specification (4), which uses the complete measure of credit constraints and controls for endogeneity via IV, we find a pronounced convexity. The coefficient on the high risk tolerance is equal to 0.020, statistically significantly different from zero, i.e., statistically significantly different from low risk tolerance households, and the coefficient on the medium risk tolerance households is 0.005, no longer statistically significantly different from zero, i.e., no longer statistically significantly different from low risk tolerance households. The medium risk tolerance coefficient is only a quarter of its high risk tolerance counterpart, rather than the half it was in previous specifications. This convexity in the coefficients {0, 0.005, and 0.02} has an interesting meaning. Rather than drawing more entrepreneurs in a linearly increasing fashion as we move left to right in the risk tolerance distribution, we see relatively few entrepreneurs at all until we reach the roughly 17% of households that call themselves high risk takers. At that point, we see a more dramatic increase in the number of self-employed households. This makes intuitive sense considering only 2.7% of households in the full dataset are self-employed, and we would naturally expect these households to be heavily concentrated in the far upper tail of the risk tolerance distribution.

In terms of other control variables, several patterns emerge. Older, single, and non-white persons are less likely to be self-employed, consistent with the results of Cai et al. (2018) and Li et al. (2021) on age, and Weng et al. (2020) on household structure. The impact of education on self-employment is not stable across specifications, consistent with the ambiguous effects of education noted by Bates (1995). There are no significant differences between households headed by women versus men or households that are smaller versus larger, consistent with Cai et al. (2018).

Table 6 presents a series of robustness checks on our main results. In this table, we consider several alternate definitions to our main variables and reperform the analysis with them. First, we consider an alternate definition of what it means to be a “rejected” borrower. Our original rejected borrower variable is based on the standard SCF question asking respondents if they applied for a loan in the last twelve months and if that loan application had been rejected. If they responded that they were rejected, they were classified as a rejected borrower.

**TABLE 6** Robustness check—alternate definitions of credit constraints and impacts on self-employment.

|                                       | (1)                  | (2)                  | (3)                  | (4)                  | (5)                  | (6)                  |
|---------------------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| Rejected Borrowers (Alternate)        | −0.265**<br>(0.131)  |                      | −0.285**<br>(0.133)  |                      |                      |                      |
| Rejected Borrowers (Original)         |                      | −0.264**<br>(0.125)  |                      |                      |                      |                      |
| Credit Constrained (Alternate)        |                      |                      |                      | −0.185**<br>(0.087)  |                      | −0.195**<br>(0.086)  |
| Credit Constrained (Original)         |                      |                      |                      |                      | −0.368*<br>(0.201)   |                      |
| Medium Risk Tolerance                 | 0.007*<br>(0.004)    |                      |                      | 0.005<br>(0.004)     |                      |                      |
| High Risk Tolerance                   | 0.020***<br>(0.004)  |                      |                      | 0.019***<br>(0.004)  |                      |                      |
| Willingness to Take Risks (Alternate) |                      | 0.025***<br>(0.004)  | 0.027***<br>(0.007)  |                      | 0.015**<br>(0.004)   | 0.025***             |
| Credit Card                           | 0.007<br>(0.005)     | 0.007<br>(0.005)     | 0.004<br>(0.005)     | 0.001<br>(0.005)     | −0.041*<br>(0.024)   | −0.003<br>(0.005)    |
| Auto Ownership                        | 0.004<br>(0.004)     | 0.001<br>(0.004)     | 0.003<br>(0.004)     | −0.001<br>(0.004)    | −0.005<br>(0.006)    | −0.002<br>(0.004)    |
| Business Collateral                   | 0.043**<br>(0.019)   | 0.017<br>(0.012)     | 0.044**<br>(0.019)   | 0.032**<br>(0.014)   | 0.054**<br>(0.027)   | 0.033**<br>(0.015)   |
| Log of Income                         | 0.004**<br>(0.002)   | 0.004**<br>(0.002)   | 0.004**<br>(0.002)   | 0.004***<br>(0.001)  | 0.002<br>(0.003)     | 0.004***<br>(0.001)  |
| Age                                   | 0.004***<br>(0.001)  | 0.005***<br>(0.001)  | 0.004***<br>(0.001)  | 0.004***<br>(0.001)  | 0.005***<br>(0.001)  | 0.004***<br>(0.001)  |
| Age Squared                           | −0.000***<br>(0.000) | −0.000***<br>(0.000) | −0.000***<br>(0.000) | −0.000***<br>(0.000) | −0.000***<br>(0.000) | −0.000***<br>(0.000) |
| Household Size                        | 0.002<br>(0.002)     | 0.001<br>(0.001)     | 0.002<br>(0.002)     | 0.002<br>(0.002)     | 0.006<br>(0.004)     | 0.003<br>(0.002)     |
| Female                                | −0.000<br>(0.004)    | −0.005<br>(0.004)    | 0.000<br>(0.004)     | 0.002<br>(0.005)     | 0.001<br>(0.005)     | 0.002<br>(0.005)     |
| Married                               | 0.020***<br>(0.005)  | 0.019***<br>(0.005)  | 0.019***<br>(0.005)  | 0.013**<br>(0.006)   | 0.003<br>(0.011)     | 0.011*<br>(0.006)    |
| Separated                             | 0.039***<br>(0.007)  | 0.042***<br>(0.008)  | 0.040***<br>(0.007)  | 0.034***<br>(0.005)  | 0.045***<br>(0.010)  | 0.035***<br>(0.006)  |
| Widowed                               | 0.020**<br>(0.009)   | 0.019**<br>(0.009)   | 0.022**<br>(0.010)   | 0.008<br>(0.008)     | 0.009<br>(0.009)     | 0.009<br>(0.008)     |
| Black                                 | 0.015<br>(0.014)     | 0.011<br>(0.012)     | 0.020<br>(0.015)     | 0.018<br>(0.015)     | 0.047<br>(0.032)     | 0.022<br>(0.015)     |
| Hispanic/Latino                       | −0.018***<br>(0.006) | −0.018***<br>(0.006) | −0.015**<br>(0.006)  | −0.014*<br>(0.007)   | −0.007<br>(0.010)    | −0.011<br>(0.007)    |

(Continues)

**TABLE 6** (Continued)

|                        | (1)                 | (2)                  | (3)                  | (4)                  | (5)                  | (6)                  |
|------------------------|---------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| Asian/Indian/Hawaiian  | −0.005<br>(0.004)   | −0.001<br>(0.004)    | −0.003<br>(0.004)    | −0.004<br>(0.004)    | −0.002<br>(0.005)    | −0.002<br>(0.004)    |
| High School            | −0.008<br>(0.006)   | −0.007<br>(0.007)    | −0.010<br>(0.006)    | −0.008<br>(0.006)    | −0.031***<br>(0.012) | −0.010<br>(0.006)    |
| Bachelor's Degree      | −0.009<br>(0.006)   | −0.015***<br>(0.006) | −0.015**<br>(0.006)  | −0.009*<br>(0.006)   | −0.044**<br>(0.018)  | −0.015***<br>(0.006) |
| Post Graduate          | −0.012**<br>(0.006) | −0.021***<br>(0.007) | −0.018***<br>(0.006) | −0.016***<br>(0.006) | −0.050***<br>(0.019) | −0.022***<br>(0.006) |
| Model                  | IV Probit           | IV Probit            | IV Probit            | IV Probit            | IV Probit            | IV Probit            |
| Wald Chi-squared       | 2019.77             | 2276.2               | 2318.01              | 1429.62              | 6247                 | 1566.35              |
| Endogeneity Test       | 7.05<br>(0.007)     | 9.03<br>(0.002)      | 8.46<br>(0.003)      | 6.05<br>(0.013)      | 9.82<br>(0.001)      | 7.29<br>(0.006)      |
| Number of Observations | 22,975              | 22,975               | 22,975               | 22,975               | 22,975               | 22,975               |

Note: Standard errors in parentheses. \*\*\* Significant at the 1% level, \*\* Significant at the 5% level, \* Significant at the 10% level. First stage F-statistics (available upon request) significant in each case.

The newer waves of the SCF ask a set of follow-up questions about respondents' post-rejection experience. They ask previously rejected respondents if they tried again to get the same basic loan from somewhere else and if they had any success in doing so. As a robustness check, we redefine a rejected borrower to include only those borrowers who were rejected on all such attempts to get funding for a particular loan, rather than a borrower who was rejected each time. Since our definition of "rejected borrower" changes, our definition of "credit constrained" borrowers, which include rejected borrowers, also changes.

Second, we consider an alternate definition of risk tolerance. Our original risk tolerance variables—low risk tolerance (omitted), medium risk tolerance, and high risk tolerance—are based on a question in which respondents are asked to score their risk tolerance on a scale from −1 to 10. It turns out that the SCF asks a similar and probably older legacy question in which it asks the respondent if they would be willing to take "substantial financial risks," "above average financial risks," "average financial risks," or potentially "not take any type of financial risk" in their investing activities. As a robustness check, we redefine an alternate risk tolerance variable, "Willingness to Take Risks", to be equal to one if the respondent answers affirmatively to one of the first three descriptions of its risk tolerance level, and zero if she responds affirmatively with the fourth.<sup>11</sup> Specifications (1) through (3) of Table 6 are based on the narrower definition of credit constraints that counts rejected borrowers only, and Specifications (4) through (6) are based on our more comprehensive credit constraints measure. All specifications are from the Probit IV model.<sup>12</sup> Specification (1) uses the alternate definition of a rejected borrower and keeps the original definition of risk tolerance. Specification (2) keeps the original definition of a rejected borrower and uses the alternate definition of risk tolerance. Specification (3) uses the alternate definitions of both rejected borrowers and risk tolerance. Specifications (4), (5), and (6) of Table 6 are similar to Specifications (1), (2), and (3) respectively except they use our more comprehensive definition of credit constraints, which includes not only rejected borrowers but also underfunded, discouraged, and priced out borrowers.

The coefficients on Rejected Borrowers or on Credit Constrained Borrowers, based on the new and alternate definition of rejected borrowers, continues to be negative and statistically significant, showing that stronger credit constraints significantly and negatively impact self-employment. The coefficients on Willingness to Take Risks, based on the new and alternate definition of risk tolerance, continues to be positive and statistically significant, showing that greater risk tolerance positively impacts self-employment. In short, all of the signs and significance levels

**TABLE 7** Breakdown of the impact of credit constraints on self-employment.

|                                  | (1)                 | (2)                 | (3)                 | (4)                |
|----------------------------------|---------------------|---------------------|---------------------|--------------------|
| Rejected                         | −0.264**<br>(0.125) |                     |                     |                    |
| Rejected/Underfunded             |                     | −0.239**<br>(0.111) |                     |                    |
| Rejected/Underfunded/Discouraged |                     |                     | −0.313**<br>(0.159) |                    |
| Credit Constrained (All)         |                     |                     |                     | −0.368*<br>(0.201) |
| Willingness to Take Risks        | 0.025***<br>(0.004) | 0.025***<br>(0.004) | 0.020***<br>(0.005) | 0.015**<br>(0.007) |
| Model                            | IV Probit           | IV Probit           | IV Probit           | IV Probit          |
| Standard Control Variables       | YES                 | YES                 | YES                 | YES                |
| Wald Chi-squared                 | 2276.20             | 2204.62             | 4240.62             | 6247.00            |
| Endogeneity Test                 | 9.03 (0.002)        | 8.59 (0.003)        | 9.71 (0.001)        | 9.82 (0.001)       |
| Number of Observations           | 22,975              | 22,975              | 22,975              | 22,975             |

Note: Standard errors in parentheses. \*\*\* Significant at the 1% level, \*\* Significant at the 5% level, \* Significant at the 10% level. Control variable coefficients omitted from table to conserve space.

continue to hold. We performed a battery of additional robustness checks as well, using various sets of control variables, and find our main coefficients of interest to be significant and robust to these variations.

The degree of bias between the narrower and broader measure of credit constraint changes (though not significantly) as expected, given that we are recategorizing many once-rejected borrowers (who were present in the original rejected category) and many once-underfunded borrowers (who were not present in the original rejected category but were present in the original credit-constrained measure) back into the not credit constrained category. These recategorized borrowers all pull estimates in different directions and, as discussed, the degree and direction in general depend on the size and strength of effects within the different groups of recategorized households.

Finally, in Table 7, we go deeper inside our measure of credit constraints to examine how the exclusion and then reinclusion of our three hidden groups of credit constrained borrowers pull on our estimates. We adopt a nesting approach and present four specifications in order from the least complete to the most complete measure of credit constraints. Specification (1) counts only rejected borrowers as credit constrained borrowers and miscategorizes all other credit constrained borrowers into the non-credit constrained control group. As noted, this places more treated credit constrained households in the control group than in the treatment group and is the most unreliable, in our view. Specification (2) expands the definition of credit constrained borrowers to include underfunded borrowers, who face a weaker form of credit constraint, while the large numbers of underfunded and priced out borrowers are still miscategorized in the control group. Specification (3) expands the definition to include discouraged borrowers, who face a stronger form of credit constraint, while only priced-out borrowers are still miscategorized in the control group. Finally, Specification (4) expands the definition to include all credit constrained borrowers, now including priced-out borrowers who face a strong form of credit constraint as well. Specification (1) and (4) have been seen before, but are included here as benchmarks and bookends to our nesting exercise. We include controls for risk tolerance and the full set of demographic and socioeconomic factors, though we exclude the latter controls from the table to save space.<sup>13</sup>

In Specification (1), we see that the Rejected variable is negative and significant, with a coefficient of −0.26. Once we remove underfunded borrowers from the control group and add them to the treatment group in

Specification (2), the estimate falls (in magnitude) to  $-0.24$ , consistent with our prior that these borrowers face a relatively weaker form of constraint. Said another way, the overall impact of “credit constraints” on self-employment falls because the average treatment intensity of the new treatment group is lower. Once we also remove the large number of discouraged borrowers from the control group and add them to the treatment group in Specification (3), the estimate rises substantially (in magnitude) to  $-0.33$ , consistent with our prior that this large group of borrowers faces a relatively strong credit constraint. Said another way, our overall estimated impact rises because the average treatment intensity of this new treatment group is now higher. Finally, once we also remove priced-out borrowers from the control group and add them to the treatment group in Specification (4), the estimate rises again (in magnitude) and reaches our final estimate of  $-0.37$ . The average treatment intensity of the treatment group is even higher, and so the effects of the credit constraint treatment on self-employment outcomes grow even stronger. The pattern of coefficients is interesting and consistent with our priors.

Households that were credit constrained even though they were strictly speaking not outright rejected by a lender are a heterogeneous group. Their exclusion biases results in both directions, with the net effect depending on the size and relative strength of treatment of the different groups.

## 5 | CONCLUSIONS AND POLICY IMPLICATIONS

In this article, we examined the effects of credit constraints and risk tolerance, in addition to standard demographic and socioeconomic controls, on the decision to become self-employed.

In one of the main contributions of our study, we addressed a systematic bias in the credit constraints literature in which measures of credit constraints are often narrowly based on only bank rejections and are incomplete. We discussed three “hidden” groups of credit constraints that are necessarily missed by this narrow measure—underfunded borrowers, discouraged borrowers, and priced-out borrowers. These represent substantial numbers of credit-constrained households and should not be missed. Yet, in a database of bank applications, these households do not appear in the dataset at all because they never apply, and in a survey database, these households are effectively miscategorized into the not credit-constrained group of households, infecting the control group and biasing the treatment-control comparison.

We found that the bias can be significant. It was not just that some treated households were miscategorized into the control group under the narrow measure; we found that there were actually more treated households miscategorized into the control group than there were in the treatment group itself, a hidden majority, including 100% of those households that faced the strongest credit constraints of all (discouraged and priced-out borrowers). Underfunded borrowers—who were rejected for part but not all of a loan and faced a weaker form of credit constraint—were miscategorized there as well. With a substantially infected control group, any purported comparison of the self-employment experience of the nominal treatment group with the nominal control group would be unreliable. It is essentially a comparison of the treated with the also-treated. In our study, we pointed out this bias inherent in using an incomplete measure of credit constraints, and we quantified that bias in the case of U.S. households. Under our more complete measure of credit constraints, being subject to a credit constraint cut the likelihood of becoming self-employed by about a third.

There is a large literature on the effects of credit constraints on small business formation, and another large literature on the effects of risk tolerance on small business formation; yet relatively few studies combine these two literatures to simultaneously estimate the effects of both credit constraints and risk tolerance on small business formation in a single specification. As noted by past authors, it can be difficult to control for risk tolerance when examining credit constraints and business formation, or to control for credit constraints when examining risk tolerance and business formation, especially with macro-level or bank-level data, leading to obvious omitted variable problems. In this study, we were able to overcome these issues by exploiting micro data on the same households that included information on both their credit market experiences and their risk tolerances, in addition to their self-employment

decisions, and estimate both effects simultaneously. We find that greater risk tolerance leads to more self-employment, and we found an interesting convexity in effects that becomes apparent only when the complete measure of credit constraints is used.

Credit constraints significantly cut into a household's entrepreneurial potential, with obvious implications for the economy, income, and jobs. While some marginal business ventures do not merit funding, many promising business ideas are often left unfunded or inefficiently unfunded. Asymmetric information between the would-be borrower and the lender will inevitably lead to many viable business ventures failing simply because the borrowers could not get the funds to get what would be a promising business venture off the ground. This is likely to be even more true in higher-tech pursuits or innovative industries, where a bank's lending officers rarely have the expertise to fully vet the business idea. The issue was even more acute during the Great Recession of the late 2000s or the COVID-19 pandemic of the early 2020s, when access to credit from banks or alternate lenders was limited in a bout of bank-level risk aversion, leaving high-potential, viable small businesses without funds (Colak & Öztekin, 2011). Inefficient small business investment has obvious negative consequences not only for these businesses, but for the businesses that would work with them, the employees that would work for them, the taxes that would be paid, and economic activity as a whole. We add to the large literature on credit constraints and small business formation, with a view towards potential future policy that would make credit for financially viable small businesses easier to find.

Risk tolerance is primarily an innate characteristic of individuals and households, but certain policies can help more risk-averse individuals apply for a loan, reapply if needed, and start their own viable-in-expectation businesses. The most obvious is a risk-sharing policy, via the tax code, in which new entrepreneurs are given an incentive, credit, or reduced tax rate when starting up a new business. If the new business fails, the loss to the entrepreneur is moderated. If the new business is successful, the tax authority shares in the benefit through higher tax revenue in subsequent years. Any new revenue can further fund any such policy initiative.

Ultimately, small businesses are the key to economic growth, jobs, and tax revenue. Accordingly, it is important to ensure that viable-in-expectation small businesses are able to secure the funding they need to start up and operate efficiently.

Our research also has a few limitations. First, the SCF data does not directly differentiate between incorporated and unincorporated self-employment in its primary self-employment variable. As an alternative strategy, researchers could either use a different dataset that includes this distinction or redefine the self-employment variable using the SCF's business ownership information, which provides details on the type of business established. Secondly, our focus is primarily on the hidden dimensions of credit constraints, which limits our ability to fully explore the interaction between race and access to credit—and, consequently, its impact on self-employment. In short, this study does not directly examine the role of racial discrimination in financial constraints as a barrier to self-employment.

Our research suggests several directions for future research. The first is the effects of the new wave of Fintech financing. Fintech lending is an important tool for would-be entrepreneurs and is arguably an emerging pillar in support of small businesses. Recently, the Small Business Administration (SBA) has authorized Fintech lending to support small businesses (Small Business Administration (2024)). Our data cannot distinguish between traditional banking and Fintech, but we think it would be interesting to see to what extent Fintech does a superior or inferior job in identifying and funding viable small businesses than traditional funding sources. If effective, the government can introduce more flexible policies to allow Fintech lenders to participate more fully in SBA loan programs in the future.

A second direction for new research would be to analyze self-employment, credit constraints, and risk tolerance using data at the firm level, instead of, or in addition to, the household level. The challenge here, of course, would be to utilize firm-level data while at the same time not losing sight of discouraged and priced-out borrowers that may disappear from firm-level data. Linked household and firm-level datasets would be ideal for this purpose. Data at a firm level could give us further insights about how to help lenders become more responsive to small businesses and more welcoming to otherwise discouraged borrowers who are hesitant in making a financial commitment. A third direction for new research relates to the efficiency of so-called green loans. The U.S. government recently approved more than \$33 million for green investment through SBA loans, given increasing concern about the speed of climate

change. It is an open question how effective these and similar monies will be used, making this an important and pressing area for new research. A fourth potential direction for future research involves distinguishing between incorporated and unincorporated forms of self-employment. Incorporated self-employment typically involves establishing a separate legal entity, such as a corporation or LLC, while unincorporated self-employment refers to operating without a formal legal structure, such as through a sole proprietorship or partnership. This distinction can have important implications for understanding differences in credit needs, risk exposure, and business dynamics. While beyond the scope of the current study, this represents a valuable avenue for future investigation.

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## ENDNOTES

- <sup>1</sup> For example, more risk tolerant individuals are more likely to apply for a loan (and not be discouraged) and more likely to appeal a loan decision if they are at first rejected, hence they are less likely to be credit constrained.
- <sup>2</sup> Private credit became exceptionally scarce in the recent COVID-19 pandemic and many small businesses lost viability altogether (Hackney (2022), Federal Reserve (2020), Kothari (2020), Pham et al. (2018)).
- <sup>3</sup> We have included a robustness check using the 2019 SCF data and found that the main results remain consistent across both waves.
- <sup>4</sup> The psychology literature argues for an inverse U-shaped relationship between risk and observed reward since the probability of success first increases and then eventually decreases with increased risk-taking (Chell et al. (1991), Caliendo et al. (2010)). We take a household's risk tolerance to be largely predetermined, consistent with other studies of risk taking with household level data (Cai et al. (2018), Skriabikova, Dohmen, and Kriechel (2014), Caliendo et al. (2010)).
- <sup>5</sup> Controlling for location-specific characteristics, such as urban or rural status, could serve as a proxy for local economic activity and may help strengthen our current instrument. However, this is a minor concern, as we already control for income, which serves as a more direct indicator of economic opportunity—individuals in areas with greater economic opportunities are likely to earn higher incomes, while those in less advantaged areas tend to earn less. Additionally, the SCF does not provide detailed geographic identifiers at this level of granularity due to confidentiality constraints.
- <sup>6</sup> We also ran LPM and logit models and the results remain consistent across all specifications. We present Probit model for a few reasons: (i) the Linear Probability Model (LPM) natively produces marginal effects estimates, which is nice, but has its well known issues (the predicted probabilities can easily fall outside the [0,1] range and the standard errors by construction cannot be normally distributed with a discrete dependent variable); (ii) The logits are best when one wants specifically to read and interpret odds ratios, which is less relevant for us here. So we find the Probit (with marginal effects instead of raw coefficients reported) to be the most natural way to present. But empirically, none of it changes anything meaningful.
- <sup>7</sup> Jappelli (1990) showed a similar chart for rejected borrowers for the 1982 SCF. Here, we are able to update that table and expand it to include underfunded borrowers as well.
- <sup>8</sup> The first stage regression uses rejected borrowers as the dependent variable, and regresses it on the instrument, FID. We find that FID is strongly significant in the first-stage regression and not a weak instrument as that term is used (Hurst and Lusardi (2004)). We further performed a Wald test on the exogeneity of our suspected endogenous rejections variable and rejected the null hypothesis of no endogeneity, suggesting the IV Probit, and not the Probit, is the appropriate model.
- <sup>9</sup> We also incorporate “inheritance received” as an additional instrumental variable in the analysis. Table 5 has been tentatively revised to reflect this instrument and the results remain broadly consistent with our original findings.
- <sup>10</sup> The estimate of 1.45 million additional self-employed individuals is calculated using the U.S. working-age population (ages 15 to 64), which totals approximately 211,554,500 as of April 2025 (FRED). Based on the current self-employment rate of 2.73% (as shown in Table 1), this corresponds to approximately 5.77 million self-employed individuals. Our findings suggest that in the absence of hidden credit constraints, the self-employment rate could have reached to 9.12 million self-employed individuals. In reality, the number is only about 7.67 million. This difference implies that approximately 1.45 million individuals may have been prevented from pursuing self-employment due to hidden financial barriers.
- <sup>11</sup> Our results and takeaways do not meaningfully change with other breakdowns.
- <sup>12</sup> In each case, the first stage regressions yield a statistically significant coefficient on the FID instrument.

- <sup>13</sup> We use the “Willingness to Take Risks” variable as a measure of risk tolerance in this table for space, though results are very similar with the low/medium/high risk tolerance indicator variable set as well.

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**How to cite this article:** Nawaz, M., & Noel, M. D. (2025). The impact of credit constraints and risk tolerance on self-employment: Accounting for the hidden majority. *International Review of Finance*, 25(3), e70038.

<https://doi.org/10.1111/irfi.70038>