Credit Access: Implications for Sole-Proprietor Household Production

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Abstract

The objective of this study is to explain the determinants of farm and non-farm sole-proprietorship households access to credit as well as the extent their credit constraints impact their value of production. A propensity, kernel-based matching estimator was employed to provide unbiased estimates of the production impacts of being denied credit. Prior research efforts have used inferior methods, including the two-stage Heckman estimator to deal with estimation issues (selection bias and endogeneity) inherent in determining impacts of credit access and use. Results suggest that credit constrained sole-proprietorships, farm and non-farm, have a significantly lower value of production, but this drop in production, when aggregated to a national level, is small.

Keywords: farm credit, credit constraint, debt

Credit has become a staple of U.S. households. Growth in the availability and use of consumer credit over the past 40 years has been astonishing. In 1956, a little more than half of U.S. households had some type of mortgage or consumer installment (non-mortgage) debt. In contrast, by 2004 over 75 percent of U.S. households held some type of debt (Bucks, Kennickel, and Moore 2006). Credit bureau reporting has brought lower prices, more equitable treatment, and more differentiated credit products to millions of households who would have been turned down as too risky just a generation ago. The U.S. credit reporting system also has made consumers (and workers) more mobile by reducing the cost of severing established financial relationships and seeking better opportunities elsewhere. Several other factors have encouraged broader access to credit products such as improvements in the speed and accuracy of data processing and information retrieval, changes in legal requirements for the collection and sharing of personal credit information, the removal of interest rate ceilings that prevented lenders from pricing loans according to risk, and the emergence of a wide variety of credit providers (Lyons 2003; Weinberg 2006; and Tallman 2001).

Given that credit is ubiquitous, what are the implications of credit use by a U.S. household who owns and operates a business? Households use credit to finance purchases of homes and durable consumer goods. They can also use it to bridge temporary drops in income. Access to credit has direct implications for household welfare and business performance, since credit can be used to increase the equity in the business. An individual may also benefit from mere access to credit, even if it is not borrowing, because with the option of borrowing the individual can avoid adopting risk-reducing, but inefficient, income diversification strategies or engaging in precautionary savings with negative returns.

A central assumption of the life cycle-permanent income hypothesis is that capital markets are perfect, where individuals can borrow freely at the current interest rate. When capital markets are imperfect (for example, when the borrowing rate is higher than the deposit rate or when the credit limit of individuals is low), individuals will not be able to borrow freely, and changes in an individual's current income may have a significant impact on consumption. Self-employed households are unique in that they engage in the role of both consumer and producer. Therefore, whether capital markets are perfect or imperfect drastically alters theoretical predictions concerning consumption behavior, but production as well.

Thus, our study aims to quantify the extent and determinants of sole-proprietorship households' access to credit as well as the severity of their credit constraints on production. In doing so, we examine the extent to which credit use and availability issues for farm sole-proprietorships are distinct and similar to non-farm sole-proprietorship households. It is hypothesized that unique types of credit constrained farm and non-farm sole-proprietorships can be identified based on a household's demand for credit and the supply of credit provided by creditors. To the knowledge of the authors, no study has examined the credit use and constraint differences in farm and non-farm sole-proprietorships. Examining these two different types of households is unique because it combines data from two nationally based surveys: the Survey of Consumer Finances (SCF) and the Agricultural Resource Management Survey (ARMS). Since the data considers directly elicited credit constraints, we split the sample based on the value of production for each household type and use matching methods to control for endogenity and selection bias. The matching method we employ validates using directly elicited credit constraints because the impact of being credit constrained has similar results across the two household types. The final, and perhaps more policy relevant objective, is to measure the effect of credit constraints on the behavior and financial performance of sole-proprietorships. It is hypothesized that the credit constrained sole-proprietorship, farm and non-farm, has a significantly lower value of production but this drop in production, when aggregated to a national level, is small. The policy implications of imperfect capital markets are wide ranging in agriculture such as the relative market distortion created by subsidies to the implications for trade from decoupled payments (Burfisher and Hopkins 2004; OECD 2001).

The remainder of this paper is structured as follows. Previous studies of credit constraints are discussed in the next section. The third section presents an empirical framework for credit supply and demand. Data sources are discussed in the fourth section. The fifth section contains variable definitions and descriptive statistics for non-farm sole-proprietors based on the 2004 SCF and farm sole-proprietor households from the 2005 ARMS. This is followed by a discussion of the multinomial logistic regression for both farm and non-farm household across the five distinct categories of credit use and availability. The seventh section provides background on the method of propensity score matching. This is followed by a presentation of the results of the matching approach to estimating the production impacts of being credit constrained. The final section provides conclusions and implications for further study.

Previous Studies

The analysis of the determinants of credit constraints answers important questions in and of itself. It also corresponds to the first stage of many studies aimed at evaluating the impact of credit constraints on household-specific outcomes. In order to control for potential selection bias in the estimation of the "impact equation," a selection model needs to be estimated. Feder et al. 1990, Carter and Olinto 2003, and Foltz 2004 provide examples of this general approach in studies analyzing impacts of credit constraint on investment or productivity.

For example, Jappelli 1990, Cox and Jappelli 1990, and Cox and Jappelli 1993 used the SCF to study the characteristics of liquidity constrained consumers in the U.S. Credit constraints can be directly observed in their micro data as the SCF provides information on which consumers had their request for credit rejected by financial institutions. Jappelli 1990 shows that economic characteristics (such as current income, wealth and unemployment) are important determinants of whether a household is credit-constrained. However, Jappelli also shows that demographic characteristics (such as age, marital status and household type) are highly significant in determining whether a household is credit-constrained.

Studies that examine the existence and implications of credit constraints in agricultural production have largely been confined to developing countries or countries in economic transition with immature markets. For example, Petrick 2004 examined credit rationing in Poland using cross-section data in the context of the microeconomic farm household model. He found demographic characteristics and collateral were important determinants of credit rationing. The analysis for Poland found 40 percent of borrowers experienced credit rationing - - obtaining less credit than they originally wanted - - while a minority of farms were completely denied credit. Foltz 2004 examined credit access and its effects on investment for rural Tunisian households. His results suggest that the presence of credit constraints hinders farm profitability, but have smaller consequences for investment.

Guirkinger and Boucher 2005 employed a more robust definition of being credit constrained and the impacts on productivity in Peruvian agriculture. They distinguished between formal and informal credit markets showing that the impact on productivity of farmers who were constrained in formal credit markets depended primarily on their endowment in productive inputs. Blancard et al. 2006 developed a nonparametric profit frontier model to asses various efficiency measures of being internally or externally credit constrained. Their results indicate that long-run credit constraints vastly decrease the financial efficiency or investment of a French farm. Thus, policy makers could use this information to design programs that would allow French farmers to increase their access to external credit.

A limitation of the Blancard et al. 2006 study is that household preferences are ignored when assessing whether or not a credit constraint is binding. Barry and Robison 2001 found that household preferences, in their case risk characteristics and business practices, significantly influenced the credit terms and availability of credit by a lender. Feder et al. 1990 also found that household preferences significantly impacted the likelihood a household would be credit constrained and the subsequent impact on consumption and production for Chinese farm households. Thus, our aim is to directly consider the impact of these different household preferences on whether or not a household is credit constrained and compare these preferences across farm and non-farm sole proprietorships and their subsequent impact on production.

Theoretical Inferences on Modeling Differing Credit Constraints

In theory, households will pursue credit up to some credit limit if the deposit rate is greater than the borrowing rate. This limit may be imposed by a lender or the result of self limiting behavior. These limits may or may not be mutually exclusive. The maximum amount lenders are willing to provide is a function of available resources and is independent of the interest rate that can be charged and of the likelihood of default. Asymmetry of information between the borrower and lender gives rise to the differences in these two limits. For example, a household may not apply for credit because of the fear of denial. Another situation where asymmetry of information exists is when borrowers wish to borrow more than their credit limit allows. This is commonly known as credit rationing. Also, credit rationing creates the situation where some borrowers may receive credit while other borrowers with similar financial characteristics do not. The potential of adverse selection arising from the asymmetry of information between the lender and the borrower will also discourage lenders from using the interest rate as a way to ration credit (Stiglitz and Weiss 1981). Credit limits and credit rationing influence the household's credit decision and are further discussed relative to the supply and demand forces that influence credit.

Supply of credit, C^S, is a quantity controlled by lenders. To determine how much credit to issue to a borrower, lenders assess the creditworthiness of a borrower. Credit scoring models are the standard way lenders control the supply of credit by analyzing the repayment capacity, solvency, liquidity, and collateral position of a potential borrower. Solely relying on the supply of credit as determining whether a household is credit constrained is incorrect. Demand for credit, C^D, is a household's desire to supplement consumption and/or investment through credit. Phimister 1995 and Jefferson 1997 found that farms and entrepreneurs, respectively, benefit from relaxed borrowing constraints.

Unfortunately, C^S and C^D are not observable. What is observable is the total amount of credit or debt held by the household, C. Similar to Grant 2003, we assume that C^S and C^D are functions of a set of household characteristics that impact the supply and demand for credit,X^S and X^D, respectively. Furthermore, it is difficult to identify if C^S and/or C^D generated C. Through a simplifying assumption, we illustrate how C is determined:

$$C = \begin{cases} min(C^S(X^S), C^D(X^D)) & C^S(X^S)>0, C^D(X^D)>0 \\ 0 & Otherwise \end{cases} \tag{1}$$

From equation (1), we know that the supply and demand for credit represents the minimum amount of credit. Thus, the decision to acquire credit and the decision to provide credit both influence the observed C. This is an important assumption because it highlights the importance of capturing both C^S and C^D when identifying the underlying determinants and the probability of a household being credit constrained.

The classic method for modeling if a household is credit constrained is to estimate the probability of the household being credit constrained, π_i (Jappelli 1990). Typically, π_i is a dichotomous variable where a household is credit constrained when $\pi_i = 1$ if $C^S = 0$ and $C^D > C^S$ and $\pi_i = 0$ otherwise. This is a simplistic method of modeling whether or not a household is credit constrained. Cox and Jappelli 1993 considered that constrained and non-constrained households may or may not desire debt, i.e. C^D may equal zero in both cases. Therefore, being credit constrained extends beyond whether or not $\pi_i = 1$ or 0 because both supply and demand factors impact π_i.

Similar to Jappelli, Pischke, and Souleles 1998, we consider a direct method of assessing whether or not a household is credit constrained. Our paper extends their work by analyzing different categories of credit constrained households and then estimate and compare the different impacts those categories have on the value of production. To properly account for different credit constraint classifications, it is assumed that each situation is distinct and observable. The five credit constraint classifications are: credit constrained, obtained credit after multiple attempts, not credit constrained, did not apply for credit, and discouraged credit applicants. Jappelli 1990 argues that discouraged credit applicants and credit constrained applicants are not different. Therefore, these two groups comprise $\pi_i = 1$ and the other three groups fall into $\pi_i = 0$. We contend that this classification underestimates the impact of being credit constrained on the value of production. Therefore, segmenting the data by the five groups described earlier is necessary. The SCF and the ARMS data pose questions that allow the identification of the five credit constrained groups.

Data

To meet our objectives, a comparable sample of non-farm households who own and operate sole-proprietorships and farm households relative to credit constraints must be created. The SCF and the ARMS each contain the necessary information to construct such a comparable sample. The SCF is a cross-sectional survey conducted every three years by the Board of Governors of the Federal Reserve System (Blancard et al. 2006). The SCF provides a wide array of household and business characteristics and uses a dual frame sample design to improve coverage of all households in the U. S. Similar to the SCF, the ARMS data set contains all of the necessary information to compare farm households and non-farm households. ARMS is a complex survey design where each observation in the ARMS data set represents a number of similar farm households or the inverse probability of the surveyed household being selected for the survey.

Unfortunately, creating a comparable sample is not a straightforward task given the types of questions asked in the 2004 SCF and the lack of direct correspondence between business ownership and self-employed status (Carroll and Samwick 1997; Hurst and Lusardi 2004). In the 2004 SCF, self-employment status results from a question asking whether the household head works for herself or someone else. Excluding farms, there are over 12 million self-employed households whose business owners have either an active or passive role in the management of the business. Applying the restriction of business owners with an active management role to the original population of non-farm self-employed further reduces the

2004 sample to 1,727 representing 6.5 million households. A comparable set of farm sole proprietorships is identified in the 2005 ARMS with a sample of 6,870 representing 2.04 million farm households.

The 2004 SCF, similar to past SCF, directly elicits the credit constraint status of a household. The same sets of credit constraint status questions were added to the 2005 ARMS. Advantages of this approach are that a simple, unambiguous method for identifying credit constraints can be established for each household. In addition, the questions are designed to capture all aspects of credit use and sources of constraints on credit access providing a more comprehensive assessment than theoretical measurement approaches. Others have considered the implications of using directly elicited credit constraints and found support for using this method to model credit constrained households and businesses (see Jappelli 1990; Feder et al. 1990; Cox and Jappelli 1990; Cox and Jappelli 1993; Jappelli, Pischke, and Souleles 1998). Now our focus is on the difference between the five credit constraint categories in the data in order to see if the groups are indeed different and plausible.

Descriptive Statistics of the Differing Credit Constrained Households

Households were classified into the following five observable situations based on their responses to the survey questions: (1) not credit constrained; (2) no debt or did not apply for credit in the last 5 years; (3) obtained credit after multiple attempts; (4) discouraged credit applicants; (5) denied credit. The proportions of households that use credit without issue (group 1) are nearly identical at 54 percent for farm and non-farm proprietorships (figure 1). There were more than two times as many farm households that had no debt or did not apply (group 2) as for non-farm proprietorship households (15 percent). Seven percent of non-farm proprietorship households obtained credit after multiple attempts (group 3) compared with 5 percent of farm households. The share of discouraged borrowers (group 4) was substantially higher for non-farm proprietorship households at 16 percent compared with only 2 percent of farm households. Finally, 3 percent of farm households reported being denied credit (group 5) compared with 8 percent of non-farm proprietorship households.[1]

Comparing the means of selected variables in table 1 for farm and non-farm sole proprietorship households, yield some striking similarities and differences. The average household income (*HHINC*) was about $9,000 higher for non-farm proprietorship households than for farm households, while household debt (*DEBT*) was nearly $36,000 higher. Discouraged credit applicants and credit constrained households had the lowest *HHINC* within each farm and non-farm household groups. *DEBT* for both household types who did not apply for credit in the last five years is much smaller than for the other categories. This further supports the assertion that this group's demand for credit is zero or near zero. It has been well documented that farm households have more business equity (*BUSEQ*) relative to their non-farm counterparts. The results in table 1 are no different given that all types of credit constrained farm households have a higher *BUSEQ*. The proxy for liquidity used in this study is the liquidity reserve ratio (*LIQRES*). This ratio measures how much cash and liquid assets a household has available after paying current debts relative to its monthly expenditures. It is interesting to note that all credit constraint classifications for farm households have a larger amount of liquidity reserve relative to their non-farm counterparts. This may be a product of precautionary saving that is more prevalent for a farm household relative to a non-farm household (Mishra et al. 2002).

CHROFF is the combined non-business related work weeks for both the household head and spouse. Diversity of household income sources may be viewed favorably by lenders when evaluating credit worthiness. Farm households had much greater participation in the off-farm workplace averaging 25 full-time weeks per year compared with 17 weeks for non-farm proprietors. Among both farm and non-farm sole-proprietor households, the lowest amount of labor devoted to non-business wage employment occurred for the group that does not utilize credit and the group consisting of discouraged borrowers. Farm households that used credit without issue (group 1) had the highest average weeks of non-farm wage employment, while those in the group that obtained credit after multiple attempts had the highest weeks of wage employment for non-farm sole-proprietor households.

The average years of owning and operating the business (*YRBUS*) is lower for all credit constrained types of non-farm households relative to farm households. Since production agriculture is highly capitalized, there are few new entrants, farm families have fewer children, and farming has a highly specialized business operations and regulatory environment that influences this result. Also, the age of farm household operators has been increasing over time (Hoppe et al. 2001). This result may explain why the average household head's age (AGE) for a farm household is higher than non-farm households.

Twenty four percent and fourteen percent of all non-farm and farm households, respectively, had a major capital purchases ($CAPPUR$). The largest $CAPPUR$ for both farm and non-farm households was non-farm discouraged credit applicants; over half had a major capital purchase. Farm households have the highest average of household heads or spouses who do not have a college education ($COLLEGE$). However, non-farm discouraged credit applicants and credit constrained households have similar averages relative to their farm counterparts or have the highest amount of household heads and spouse without a college education. Fewer non-farm household heads are not married ($MARRIED$) while the largest amount of farm and non-farm household heads who are not married are classified as being a discouraged credit applicant. Finally, a majority of the sample is of a white, non-hispanic ethnic background based on the dummy variable all other races except white ($OTHRACE$) being around 8 percent for both farm and non-farm sole-proprietor households.

The means of the selected variables show that each group of credit constrained households is unique and distinct, while similarities do exist across farm and non-farm household types. The results of the multinomial regression model show that these differences and similarities do indeed hold within and across farm and non-farm household types.

Determinants of Credit Use and Credit Constraints

Earlier it was assumed that π_i is observable and directly impacted by C^D and C^S. Since the researcher cannot directly observe the impact of C^D and C^S on π_i, further structure is assumed. The observed amount of C was assumed to be the minimum C^D and C^S; thus, observable household characteristics, X, that impact C capture X^D and X^S. To estimate π_i, a multinomial logistic regression is used to compare the probability of a sole proprietorship falling into a credit constrained classifications to an omitted classification. Using borrowers who had no difficulty obtaining the full amount of credit requested as the base, the model estimates the following probability:

$$\pi_i = \frac{exp(\beta_j' X_i)}{1 + \sum_{l=1}^{m-1} exp(\beta_l' X_i)} \tag{2}$$

This represents the probability the i^{th} household falls into the j^{th} credit use classification. The β_j coefficients represent the effects of household characteristics, X, on the probability of the i^{th} household falling into the j^{th} credit use classification over the omitted alternative. Finally, estimation is for *m-1* sets of regression coefficients. Because of the multiple implicate design of the SCF, the repeated imputation inference (RII) method was used with the multinomial logistic regression (Montalto and Yuh 1996). Complex sample estimation issues for the ARMS data were handled using delete-a-group jackknife procedures (Kott 1998).

As income increases for both types of sole proprietorships, there is a lower probability that a household will fall into the credit constrained or discouraged credit applicant group relative to not being credit constrained. This result is similar to Cox and Jappelli 1993. Statistical significance on debt was noted for both farm and non-farm sole proprietorships. Increasing amounts of debt leads to a lower probability of a farm falling into the no debt or did not apply for credit group. This is not surprising given that this group deals directly with the demand for credit. Higher debt levels negatively impacts the probability of being in the multiple attempts group for farm households and the discouraged borrower group for non-farm proprietorship households.

One would expect that larger amounts of equity would reduce the probability of a sole proprietorship being a discouraged borrower and the results in table 2 confirm this contention. Higher business equity is also positively associated with the probability of not having debt or not applying for credit for farm households. A higher liquidity reserve position decreases the probability a non-farm sole proprietorship will be a discouraged borrower or credit constrained. Conversely, an increase in liquidity increases the probability a farm household will not apply for credit. Since these two measures deal directly with business and financial risk, a more financial stable sole proprietorship is more likely to not apply for credit.

Working off the farm by the household head and spouse reduces the likelihood that a farm sole proprietorship will not apply credit. This result relates to the findings of Mishra and Goodwin 1997. They found that off farm work is a response to farm income pressures and a means to stabilize household income. The longer a sole proprietorship operates a business the less likely they will be credit constrained and younger operators are less likely to apply for credit. This result fits the life cycle hypothesis in terms of debt usage relative to age.

If a non-farm sole proprietorship had a capital purchase, then they were more likely to be a discouraged borrower. Contrary to this result, farm sole proprietorships that made a capital purchase were less likely to be a discouraged borrower. Recent capital purchases have differing outcomes because the purchases may have exhausted unused credit capacity and therefore lowered the borrowers perception of their own creditworthiness. However, those with little or no borrowing experience may discover they have more credit capacity than perceived upon the completion of a successful transaction. It is interesting that the latter effect seems more prevalent for farm proprietors than non-farm proprietor households suggesting that farmers may be more likely to undervalue their credit capacity.

Farm and non-farm sole proprietorships that do not have a college education are more likely to be credit constrained, which is similar to the results of Jappelli 1990. Those non-farm household heads that do not have a spouse are more likely to fall into the obtained credit after multiple attempts group. This may be product of fewer amounts of labor hours available to the household, which may negatively impacts cash flow. If this is the case, this explains why farm and non-farm household heads that are not married are more likely to apply for credit. Finally, white household heads are less likely to be a discouraged borrower or credit constrained, which is similar to the findings of Blanchflower, Levine, and Zimmerman 2003.

These multinomial logit results explain differences and similarities among farm and non-farm sole proprietorships relative to the five credit use groups. Having identified distinct groups with varying degrees of credit use and credit access issues, a more fundamental question is whether household decisions and the resulting economic outcomes measured by value of production are affected by credit use and availability. In order to properly estimate a set of regressions to answer these questions, two key econometric issues must be dealt with: self selection bias and endogenity. Sample selection bias or the firms with and without access may be inherently different, and measures of their behavior and performance may determine the extent to which firms have credit. As made clear by the dynamic limited enforcement models of Albuquerque and Hopenhayn 2004, Hart and Moore 1998, and Monge 1990, the characteristics of firms in any point in time are the result of their previous behavior and access to credit. Those models also imply that the value of productivity and profits of a firm determine explicitly the credit that they can obtain. Thus, anyone interested in estimating the effect of credit constraints on dimensions of firm's behavior, must necessarily face the identification problem of controlling for the effect of those observable characteristics on the credit received. Propensity score matching econometric models are employed to alleviate these two issues.

Propensity Score Matching

As mentioned previously we test our hypothesis in the context of a non-random selection problem. In this framework, we wish to test for, and measure, our treatment effect where the observation of interest is a sole proprietorship, either farm or non-farm. The treatment is the denial of credit in the past 5 years, and the outcome of interest is the value of production from the business entity. This is a non-random selection process because, as we have argued, sole proprietorships that are credit constrained are likely to have, on average, different characteristics than sole proprietorships not constrained and these characteristics may alter the dollar value of output produced.

Conventional analyses, such as least squares regression model, attempt to control for these characteristics by entering them, together with the treatment variable, into a regression-type model that seeks to explain the outcome. But criticisms of this type of approach are now common. Unlike OLS, the maximum likelihood Heckman procedure controls for selection bias by jointly estimating the outcome and treatment equations, but the procedure relies on a joint normality assumption between the residuals. In the last decade an alternative for improving the rigor of the statistical test called matching has gain popular support. The procedure estimates treatment effects by matching treated and untreated observations controlling for distributional differences using conditioning variables. Such matching methods allow non-parametric estimation of treatment effects, removing sensitivity to functional form and exposing violations of the common support - cases where treated observations are substantially different from untreated observations. In the context of regression-type analysis, such violations remain undetected and can result in treatment effects being extrapolated solely on the basis of functional form because non-treated observations that are similar to treated ones do not exist.

Here we draw on a class of estimators called propensity score matching estimators, first suggested by Rosenbaum and Rubin 1983. Applications of propensity score matching are now quite prevalent in the literature, especially in labor economics where the evaluation of job training programs represents a significant challenge (e.g. Smith and Todd 2005a; Dehejia and Wahba 2002). Before explaining the specifics of our own application, we lay out the general form of the matching estimation procedure following such standard references as Heckman and Robb 1986; Heckman 1974; Heckman, Ichimura, and Todd 1997); Heckman et al. 1998; and Smith and Todd 2005a.

Our task is to determine the difference in the value of production between credit constrained sole proprietorships and not credit constrained sole proprietorships while controlling for differences in the distribution of covariates. In the evaluation literature the outcome variable, Y, is value of production and the treatment is denial of credit, $D = 1$, is the treatment indicator. Following common notation Y_1 is the outcome under treatment and Y_0 is the outcome with no treatment. For any observation only one of these outcomes is observed. Also Z is a vector of K conditioning variables which include variables likely to impact value of production and the probability of treatment. These latter variables are the ones included in the vector X of previous sections.

The usual task set out by propensity score matching procedures is to estimate the average treatment on the treated (ATT). For our problem this is the dollar value of the difference in value of production averaged over all treated sole proprietorships. Specifically, we want an estimate of

$$\Delta_{ATT} = E(Y_1 - Y_0|Z, D = 1) = E(Y_1|Z, D = 1) - E(Y_0|Z, D = 1) \tag{3}$$

where Δ_{ATT} is the average treatment effect. This equals the expected value of the difference between the treated outcome and the non-treated outcome, conditional on exogenous explanatory factors, Z, for the group that are treated. The first term in the last expression in (3) is easily obtained, as it is the average actual outcome for the treated observations - in our case, the mean value of production from treated sole proprietorships. However, the second term which is called the counterfactual is not observable, this is referred to as the evaluation problem. It is the expected outcome for the treated observations had they not been treated. The task of propensity score estimators is to define an estimator for $E(Y_0|Z, D = 1)$, using an appropriate subset of the $D = 0$ data.

Matching estimators pair each treated observation with one or more observationally similar non-treated observations, using the conditioning variables, Z to identify the similarity. This procedure is justified if it can be argued that conditional on these $Z's$, outcomes are independent of the selection process. That is, if those observations found in the set $D = 0$ were actually treated, the expected value of their outcomes, once conditioned on the $Z's$, would not differ from the expected value of outcomes in the treated group. More precisely, conditional mean independence is required, such that

$$E(Y_0|Z, D = 1) = -E(Y_0|Z, D = 0) \tag{4}$$

Direct implementation of the above would be difficult for a large number of conditioning variables, yet ensuring that (4) holds would typically require a rich set of these variables. [2] Rosenbaum and Rubin defined the propensity score matching estimator by showing that instead of conditioning on all K elements of the Z vector, one can equivalently condition on a one-dimensional function of that vector. They show that if outcome Y_0 is independent of selection when conditioned on the $Z's$, then it is also independent of selection when conditioned on the propensity score which is defined as the probability of selection conditioned on the $Z's$. Defining

$$P(Z) = Pr(D = 1|Z), \tag{5}$$

the treatment effect in (3) can now be rewritten as:

$$\Delta_{ATT} = E(Y_1 - Y0|P(Z), D = 1) = E(Y_1|P(Z), D = 1) - E(Y_0|P(Z), D = 1) \tag{6}$$

In practice, (5) is estimated as a binary probit or logit, with the treatment dummy as the dependent variable. Explanatory variables include factors that are expected to affect the probability of treatment and those that are expected to affect outcomes directly and may be correlated with treatment. The last term in (6) is illustrates the conditional independence condition outlined in equation (4). With these propensity scores in hand there are several ways to construct the counter factual, including nearest neighbor and kernel estimates which we use in this study. Nearest neighbor matching compares one treated observation to a single control observation while kernel estimates use a weighted average of all or a subset of control observations to construct the counter factual for each treated observation.

One strength of propensity score matching is that it exposes regions in which the support of Z does not overlap for treated and untreated observations. For example, there may be no untreated observations with propensity scores in the range of high values of $P(Z_i)$. When this is the case, the matching procedure is defensible only over the region of the common support. Treated observations outside the common support are dropped from the analysis, and Δ_{ATT} is an estimate of the effect of treatment on the treated only over the range of the common support.

Estimating production impacts from credit constraints

We first estimate production impacts using the most common approach in the literature; the maximum likelihood Heckman procedure for treatment effects.

We perform a propensity score matching estimate using the ARMS dataset and the SCF dataset separately due to differences in data collection procedures. The first step of the procedure requires estimation of the propensity score by estimating the probability that a sole proprietorship is treated as a function of factors that affect the likelihood of treatment and factors that affect the outcome(i.e. value of production). We drop outliers defined as observations over two standard deviations from the weight mean value of production[3], we then estimate the propensity score using a survey weighted logit model for the SCF and for the ARMS data.

We use the multinomial logit results which verify the credit classification differences across covariates are used as the base set of covariates to predict the probability of treatment. Determinants of the value of production are added to the propensity score estimator as suggested by the theory. These include the expected sales price of the primary home of the operator (*EXPSALESPRICE*), a count of the number of dependants in the household (*HHSIZE*), the number of floating loans open (*NUMFLOAN*), the number of employees (*EMPLYNUM*), and a series of dummy variables representing production speciality for the farm data and industry codes for the business data. Additionally, we include (*ACRES*) and regional dummies in the farm estimates because we have the additional data available.

We estimate the ATT using those households who received credit with no issue as the control group and those who were denied credit as the treatment group. By not collapsing the identified credit constrained groups, potentially biased estimates are avoided. In addition, we expect comparisons between these two groups to exhibit the largest production impact, an upper bound, of being credit constrained. Since we have subset each dataset to a level where these sole proprietorships are expected to interchange household and business assets we include several more variables to exploit the sole proprietorship's credit situation.

The results of the initial specifications of the logit models are given in Table 3. Parameter estimates in both models are generally in line with expectations although the significance of variables differ between data sets. Significant variables from the ARMS data suggest that being married, greater net worth($LNBUSNW$), and more years in business($YRBUS$) lower the probability of being denied credit. Significant variables from the SCF data suggest that a greater net worth($LNBUSNW$), more savings($LIQRESV$), and more employees($EMPLYNUM$) lessen the probability of being denied credit. The lack of college education is positive and significant in both data sets suggesting that the human capital payoff of education is capitalized in sole proprietorships. Measures of financial well being including household income ($LNHHINC$), expected sales price of home($EXPSALP$), and business net worth ($LNBUSNW$) are consistently negative in both models.

Before calculating the ATT, the outcome must be shown to be mean independent of the treatment, conditional on the propensity score. Given the conditional independence assumption set out in (5) above, this requires insuring the set of $Z's$ meet this condition, which is equivalent to achieving 'balance' between treatments and their controls. Several balancing tests exist in the literature. The test we use is suggested by Smith and Todd 2005a and explained in more detail in Smith and Todd 2005b commonly called regression based balancing. The intuition behind this test is that after conditioning on $Pr(D = 1|Z)$, any further conditioning on the Z vector should not provide new information on D. In other words, we test whether there are differences in Z between the treatment and control groups after conditioning on the propensity score.[4] If differences remain, then this suggests the propensity score model is mis-specified. Following Dehejia and Wahba 2002 we add cross products and squares of covariates are added to the specification until balancing is achieved.

The balancing test assures that any conditioning power of the selected variables is removed, i.e. pickup up by the propensity score. The final specifications we use pass the balancing tests when applied to the observations in the common support. The common support is the region of the propensity scores where untreated observations exist to match the treated observations. Recall that regression techniques ignore this support condition.

Table 4 reports the results for a kernel matching estimate using the Epanechnikov kernel, the maximum likelihood Heckman results, and an ATT for the traditional treatment classifications. We focus on the kernel estimate since these estimates are most likely to contain the least bias when using a global bandwidth and with the sample size of the SCF data as suggested by Frölich's Monte Carlo study (Frölich 2004). In the ARMS dataset we have adequate observations to construct the counterfactual using other approaches but we do not have a large sample from the SCF data. The bandwidths for the kernel estimates are selected by leave one out cross validation using a range of bandwidths suggested by Frölich. [5]

The columns marked "unmatched" report the full sample means for value of production by treatment category. For example, the raw means for treated businesses from the SCF data are \$154,146 in the control group and \$78,615 for the treated group. Similarly, in the ARMS data the control group raw mean is \$225,114 and the treated group mean is \$163,169. The matched weighted means are presented in the next column using the Epanechnikov kernel estimates. In both farm and non-farm cases the matching estimate eliminated non-comparable observations from the counterfactual, 9 observations were off the common support in the farm data and 2 in the business data.

The difference in means for the matched data are \$44,099 for the farm sole-proprietorships and \$65,442 for businesses. In general, the Heckman procedure tends to overestimate the treatment effect while the impact based on the traditional treatment definition is smaller in both cases, as expected. The difference between the preferred measure and the Heckman may be due to the reliance of the Heckman procedure on functional form restrictions and the inclusion of all observations that fall off the common support. While the difference between the preferred measure and the traditional treatment measure illustrates a form of sample bias present in the previous literature.

To test differences between the outcomes for the treated groups and the constructed counterfactual we calculate bootstrapped standard errors. Using these standard errors, we find across both datasets and estimators that the treatment effect is negative and significantly different from zero at 95%. The results from these matching estimators suggest that credit constraints significantly impact the value of production in both farm and business sectors.

Aggregating these results to a national level for observations on the common support suggests a total loss of output of 12 percent for business sole-proprietorships and 3 percent for farms organized as sole-proprietorships. Output loss over the entire population of non-farm and farm sole-proprietorships would only be 8 percent, and 1 percent respectively. [6]

Conclusions and Policy Implications

This study provides an analysis of credit use for both farm and non-farm proprietor households that unlike previous analysis of directly elicited questions, allows for 5 distinct groupings of credit use including those considered to be credit constrained. For both farm and non-farm sole proprietor households, a majority, and similar share (54 percent) used credit without issue. A much higher share of non-farm sole proprietorship households were either denied credit or were discouraged enough not to apply for additional credit. The 3 percent of farm households that were denied credit accounted for a slightly smaller share of total agricultural production and slightly higher share of total household living expenses. The 2 percent of farm households that did not apply for additional credit for fear of denial (discouraged borrower) accounted for only 1 percent of total production and household consumption expenditures. Taking the boarder definition of credit constrained to include denied credit and discouraged borrower (as in Jappelli 1990), suggests that credit constraints do exist in today's production agriculture, although there are limited to only 5 percent of farm households. And, when compared to other non-farm proprietor households where nearly one in four report having been denied (8 percent) or a discouraged borrower (16 percent), the incidence of credit constraints in farming are much less significant.

A propensity, kernel-based matching estimator was employed to provide unbiased estimates of the production impacts of being denied credit. Prior research efforts have used inferior methods, including the two-stage Heckman estimator to deal with estimation issues (selection bias and endogeneity) inherent in determining impacts of credit access and use. Moreover, the specification of 5 distinct categories or credit use allowed for a succinct definition of the control group-those who willingly borrow with no credit issues. Previous studies collapse households who have obtained credit after multiple attempts and those that have no demand for credit into the control group, thus confounding the comparison and potentially biasing estimates of economic impacts. By controlling for these issues, the empirical evidence suggests that the total U.S. value of production decreases slightly due to farm and non-farm sole proprietorships being turned down for credit. This small decrease is possibly due to the wide availability of credit and programs in place through the Farm Service Agency and the Small Business Administration to assist farm and non-farm sole proprietorships just starting or facing financial adversity.

Notes

[1] Many other studies use the debt-to-asset ratio as a proxy for being credit constrained. Except for the did not apply for credit group, all other groups vary widely on their respective debt-to-asset ratio. There is not a direct correspondence between the debt-to-asset ratio and how sole proprietorships answered the credit constraint questions. Therefore, the proposed groupings of credit constrained households more accurately depict the credit constraint because other factors influence being credit constrained than just leverage (e.g. repayment capacity, character, etc.)

[2]We also need the additional condition that there is no single Z_k or combination of $Z_{k's}$ that guarantees treatment. Put another way, for any set of the $Z's$, the probability of treatment is strictly less than 1, i.e. $Pr(D = 1|Z) < 0$. This must be true for each treated observation to have the potential of an analogue among the untreated.

[3]Farm Data are cut at \$785,339 (15% of the sample) and the SCF cut is at \$672,873 (16% of the sample)

[4]Operationally, we regress each covariate on the propensity score, the treatment dummy, the propensity score squared and cubed, and the propensity score, squared and cubed, interacted with the treatment dummy. The likelihood ratio test of all variables containing the treatment dummy equal to zero provides the test statistic.

[5]For kernel matching the bandwidth grid is $0.01 \times 1.2^{g-1}$ for $g = 1, ..., 29$.

[6]Note that the estimates of supply response are partial equilibrium, not general. Under general equilibrium procedures they would be less.

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Table 1: Variable definitions and descriptive statistics for farm and non-farm sole-proprietorships by credit use category

Definition/Units	Variable	All Business	Debt Constraint Category for Small Business Owners (1)	(2)	(3)	(4)	(5)	All Farm	Debt Constraint Category for Farm Owners (1)	(2)	(3)	(4)	(5)
Household income[1/]	LNHHINC	$81,426	$97,236	$85,952	$63,347	$45,579	$51,190	$72,541	$83,473	$61,571	$67,211	$46,918	$37,761
		(7.479)	(7.539)	(28.364)	(28.472)	(11.622)	(15.715)	(6.179)	(4.310)	(5.326)	(57.800)	(22.700)	(15.420)
Household debt[1/]	LNDEBT	$115,481	$148,924	$26,701	$127,652	$78,999	$117,607	$79,998	$129,841	$829	$58,680	$116,094	$136,590
		(6.923)	(7.539)	(35.196)	(20.720)	(21.637)	(22.376)	(14.950)	(4.982)	(8.799)	(200.100)	(31.460)	(12.210)
Business equity[1/]	LNBUSNW	$152,596	$193,611	$178,176	$84,438	$65,920	$54,339	$596,608	$627,087	$555,377	$821,814	$429,872	$299,115
		(27.181)	(29.999)	(73.205)	(61.116)	(26.905)	(35.712)	(4.067)	(4.643)	(5.920)	(50.710)	(14.100)	(11.460)
Months of current equity (current household assets minus current household debt)	LIQRESV	4.91	3.68	15.51	4.52	1.23	0.55	9.18	7.64	12.07	6.66	11.35	5.66
		(16.293)	(11.626)	(20.975)	(33.581)	(28.995)	(25.993)	(6.433)	(7.359)	(5.509)	(49.760)	(20.110)	(12.800)
Total operator and spouse labor hours	LABHR	3,099	3,320	2,108	3,719	3,012	3,106	3,799	4,444	2,936	3,559	2,583	3,761
		(5.086)	(3.177)	(11.265)	(6.997)	(8.256)	(9.487)	(4.050)	(1.962)	([3.260)	(44.23)	(17.54)	(6.365)
Combined weeks of household head or respondent and spouse off-farm wage hours per 40 hour work week	CHROFF	17	20	10	28	12	16	25	31	17	24	16	25
		(6.425)	(7.289)	(24.843)	(19.401)	(20.019)	(25.283)	(5.659)	(4.117)	(7.400)	(46.230)	(29.090)	(12.210)
Number of years owning and operating the business	YRBUS	13	14	18	11	9	7	24	22	30	23	15	13
		(4.688)	(5.785)	(10.228)	(12.847)	(12.629)	(17.202)	(2.335)	(2.683)	(2.075)	(18.150)	(15.270)	(10.980)
Household head's age in years	AGE	50	51	60	43	42	45	57	54	64	56	59	51
		(1.521)	(1.753)	(3.153)	(5.292)	(4.816)	(5.958)	(0.833)	(1.032)	(0.653)	(4.123)	(7.103)	(3.331)
Number of dependents	HHSIZE	1.1	1.1	0.4	1.0	1.6	1.3	1.4	1.5	1.2	1.4	1.3	1.8
		(5.956)	(8.493)	(24.762)	(28.161)	(15.412)	(17.910)	(1.830)	(2.944)	(2.068)	(14.51)	(13.08)	(9.954)
The number of employees of the business	EMPLNUM	2.5	2.8	1.8	2.6	2.0	2.7	1.2	1.2	1.1	1.2	1.4	1.2
		(14.657)	(21.041)	(14.626)	(25.638)	(14.445)	(38.078)	(33.66)	(1.957)	(0.963)	(323.3)	(13.63)	(6.100)
Number of loans	NUMFLOAN	5.0	6.3	3.7	4.2	3.3	2.9	1.4	2.1	0.0	1.0	3.5	3.2
		(4.784)	(5.100)	(15.177)	(14.215)	(17.173)	(20.219)	(4.707)	(2.297)	(na)	(49.46)	(8.129)	(9.494)
Expected sale price of dwelling	EXPSALP	227,973	280,538	239,739	152,750	78,637	205,513	135,262	142,961	124,630	149,139	128,152	107,925
		(7.674)	(8.058)	(23.078)	(30.407)	(26.105)	(33.255)	(14.657)	(21.041)	(14.626)	(25.638)	(14.445)	(38.078)
Dummy variable with the base category being respondent and spouse with college education	COLLEGE	73.5%	66.2%	77.5%	68.1%	90.0%	88.4%	87.0%	84.7%	89.3%	85.4%	91.9%	97.8%
		(3.467)	(5.270)	(7.446)	(14.647)	(6.089)	(8.308)	(1.169)	(1.395)	(1.940)	(9.426)	(5.623)	(1.204)
Dummy variable with the base category being married	MARRIED	28.8%	21.9%	34.7%	44.3%	47.5%	19.4%	18.5%	15.7%	22.3%	17.6%	28.3%	18.6%
		(9.231)	(14.220)	(18.957)	(23.999)	(19.198)	(46.827)	(8.298)	(11.040)	(9.808)	(51.490)	(36.500)	(34.130)
Dummy variable with the base category being white ethnic background	RACE	8.6%	6.2%	10.0%	1.0%	20.9%	4.6%	7.8%	5.8%	5.3%	7.1%	48.6%	43.3%
		(19.582)	(28.614)	(41.544)	(208.478)	(35.509)	(103.946)	(11.790)	(11.000)	(28.970)	(65.440)	(19.100)	(13.090)
Sample size	TOTAL	1,560	924	267	114	155	100	5,411	3,423	1,390	299	105	194
Population estimate, households	SVWGT	5,855,852	3,175,040	890,159	412,673	909,354	468,627	1,915,726	1,029,329	684,676	99,088	38,812	63,821
Value of production	VPROD	$108,712	$131,053	$115,660	$75,085	$63,796	$60,920	$58,914	$83,559	$24,642	$53,665	$40,369	$48,531

1/ Variable is presented in natural form since this aids in interpretation of the differences across groups; however, the regression equation variable is the log of the respective number.
Note: the number in parenthesis below the estimate is the standard error.
Categories 1-5 are represented as follows: (1) Not credit constrained (2) Did not apply for credit in the last 5 years (3) Obtained credit after multiple attempts (4) Discouraged credit applicants (5) Turned down for credit

Table 2: Multinomial logit estimates of credit use for farm and non-farm sole-proprietorships

	Coefficient estimate		Standard error		T-value		Marginal	
Variable name	Non-farm	Farm	Non-farm	Farm	Non-farm	Farm	Non-farm	Farm
INTERCEPT_4	12.811	-2.968	3.981	1.954	3.218(∗∗)	−1.519	**1.593**	-0.916
INTERCEPT_3	11.356	-3.821	3.676	4.263	3.089(∗∗)	−0.896	**1.156**	-0.917
INTERCEPT_2	4.458	6.400	3.734	3.599	1.194	1.778(∗)	-0.209	**1.022**
INTERCEPT_1	-2.329	6.115	2.867	2.953	−0.812	2.071(∗)	-1.530	**0.987**
LNHHINC_4	-1.283	-0.043	0.362	0.041	−3.549(∗∗)	−1.044	**-0.169**	-0.005
LNHHINC_3	-0.768	-0.062	0.316	0.062	−2.430(∗∗)	−1.003	**-0.051**	-0.008
LNHHINC_2	-0.498	0.035	0.340	0.483	−1.465	0.073	0.002	0.010
LNHHINC_1	0.132	-0.023	0.206	0.063	0.639	−0.369	0.125	-0.001
LNDEBT_4	0.067	0.114	0.126	0.097	0.533	1.182	0.026	0.120
LNDEBT_3	-0.147	0.020	0.078	0.246	−1.874(∗)	0.082	**-0.019**	0.081
LNDEBT_2	0.040	-0.730	0.124	0.284	0.319	−2.572(∗∗)	0.018	**-0.062**
LNDEBT_1	-0.228	-1.508	0.041	0.159	−5.507(∗∗)	−9.477(∗∗)	**-0.035**	**-0.212**
LNBUSNW_4	-0.066	-0.099	0.059	0.088	−1.105	−1.125	-0.006	-0.045
LNBUSNW_3	-0.145	0.008	0.056	0.097	−2.583(∗∗)	0.083	**-0.021**	-0.016
LNBUSNW_2	0.054	0.035	0.066	0.259	0.813	0.136	0.018	-0.011
LNBUSNW_1	-0.026	0.554	0.055	0.178	−0.467	3.110(∗∗)	0.002	**0.088**
LIQRESV_4	-0.962	-0.014	0.410	0.017	−2.344(∗∗)	−0.847	**-0.155**	-0.005
LIQRESV_3	-0.250	0.036	0.135	0.023	−1.853(∗)	1.572	**0.000**	0.005
LIQRESV_2	0.007	-0.010	0.029	0.048	0.256	−0.215	0.052	-0.003
LIQRESV_1	0.032	0.029	0.020	0.014	1.556	2.123(∗)	0.055	**0.004**
CHROFF_4	-0.003	-0.018	0.014	0.010	−0.249	−1.870(∗)	0.000	**0.000**
CHROFF_3	-0.024	-0.024	0.016	0.013	−1.540	−1.903(∗)	-0.004	**-0.001**
CHROFF_2	0.020	-0.021	0.012	0.037	1.643	−0.578	0.005	-0.001
CHROFF_1	-0.021	-0.019	0.015	0.011	−1.405	−1.758(∗)	-0.003	**0.000**
YRBUS_4	-0.078	-0.036	0.040	0.011	−1.925(∗)	−3.191(∗∗)	**-0.013**	**-0.005**
YRBUS_3	-0.010	-0.046	0.031	0.022	−0.334	−2.117(∗)	0.002	**-0.006**
YRBUS_2	0.004	0.000	0.030	0.029	0.117	0.005	0.005	0.003
YRBUS_1	-0.010	0.009	0.020	0.012	−0.475	0.755	0.002	0.005
OP_AGE_4	0.011	-0.010	0.026	0.014	0.414	−0.666	0.005	-0.001
OP_AGE_3	-0.054	0.024	0.026	0.035	−2.095(∗)	0.691	**-0.009**	0.006
OP_AGE_2	-0.046	-0.028	0.027	0.029	−1.678(∗)	−0.984	**-0.007**	-0.004
OP_AGE_1	0.036	-0.022	0.022	0.013	1.613	−1.696	0.009	-0.003
CAPPUR_4	-0.264	0.522	0.679	0.384	−0.389	1.360	-0.105	0.166
CAPPUR_3	1.735	-1.287	0.539	0.601	3.220(∗∗)	−2.139(∗∗)	**0.299**	**-0.212**
CAPPUR_2	0.209	-0.108	0.537	0.659	0.390	−0.163	-0.001	0.014
CAPPUR_1	-0.569	-0.193	0.638	0.325	−0.893	−0.593	-0.154	-0.002
COLLEGE_4	0.934	1.887	0.833	0.648	1.122	2.915(∗∗)	0.147	**0.320**
COLLEGE_3	0.745	0.168	0.629	0.987	1.184	0.170	0.096	-0.069
COLLEGE_2	-0.666	-0.157	0.538	0.684	−1.238	−0.230	-0.187	-0.127
COLLEGE_1	0.207	0.374	0.456	0.483	0.454	0.773	-0.010	-0.028
MARIED_4	-0.437	-0.230	0.711	0.628	−0.615	−0.366	-0.148	0.040
MARIED_3	0.874	0.145	0.576	0.518	1.516	0.280	0.124	0.105
MARIED_2	1.045	-1.010	0.582	0.652	1.797(∗)	−1.550	**0.162**	-0.114
MARIED_1	-0.232	-0.950	0.551	0.387	−0.422	−2.451(∗∗)	-0.093	**-0.105**
RACE_4	-0.183	2.328	1.168	0.313	−0.157	7.450(∗∗)	-0.114	**0.295**
RACE_3	1.853	2.216	0.690	0.446	2.686(∗∗)	4.964(∗∗)	**0.298**	**0.220**
RACE_2	-0.465	0.256	1.090	0.681	−0.426	0.376	-0.163	-0.152
RACE_1	0.551	0.196	0.737	0.481	0.748	0.409	0.041	-0.167

* indicates statistical significance at 0.10 levels. ** indicates statistical significance at 0.05 level.

Log-likelihood function	SCF	ARMS
Constant only	754.28	4011592.4
Convergence	539.29	1903460.0
Pseudo-R2	0.29	0.53

Table 3: Logit estimates for credit constrained farm and non-farm sole-proprietorships

	Farm		Non-Farm	
Variable	Coefficient	p-val	Coefficient	p-val
COLLEGE	3.0909†	0.000	1.4478*	0.089
MARRIED	-2.3756†	0.004	1.6851	0.355
HHSIZE	.0092	0.934	.4327	0.576
AGE	.0096	0.648	- .0935	0.294
NUMFLOAN	.0729	0.495	- .1268	0.276
LNBUSNW	- .3152†	0.002	- .4459†	0.005
LNHHINC	- .0840	0.067	- .9475	0.454
LIQRESV	.0180	0.282	- 1.5381**	0.034
LABHR	- .0001	0.328	.0001	0.910
CHROFF	- .0002	0.229	- .0006	0.232
YRBUS	- .0711†	0.000	- .1555*	0.066
EMPLYNUM	.0074	0.938	.0473	0.741
EXPSALP	- .0006	0.661	- .0032	0.209
INTERCEPT	1.5096	0.440	20.9565	0.268
ACRES	- .0004	0.186		
Spec dummies /1	YES		YES	
Region dummies	YES			

Significance levels: $\dagger$: 1% $**$: 5% $*$: 10%

/1 -Spec dummies are industry codes for non-farm data and production types for farm data.

Table 4: Propensity score matching results for farm and non-farm proprietorships

Farm Data - ARMS					
	On Support	Off Support		Unmatched	Epan
Treated	90	9		225,114	211,289
Controls	1,614	0		163,169	167,190
		Preferred Measure	ATT	-61,945	**-44,099***
			Heckman		-100,443**
		Traditional Treatment Definition			
			ATT		- 33,878*
			Heckman		- 80,330**
Non-Farm Data - SCF					
	On Support	Off Support		Unmatched	Epan
Treated	16	2		154,146	148,471
Controls	154	0		78,615	83,029
		Preferred Measure	ATT	-75,531	**-65,442***
			Heckman		-34,849
		Traditional Treatment Definition			
			ATT		-14,763
			Heckman		-56,878*

Significance levels: † : 1% $**$: 5% $*$: 10%

Bandwidth - 0.184 SCF, 0.013 ARMS

ATT - Average Treatment on Treated

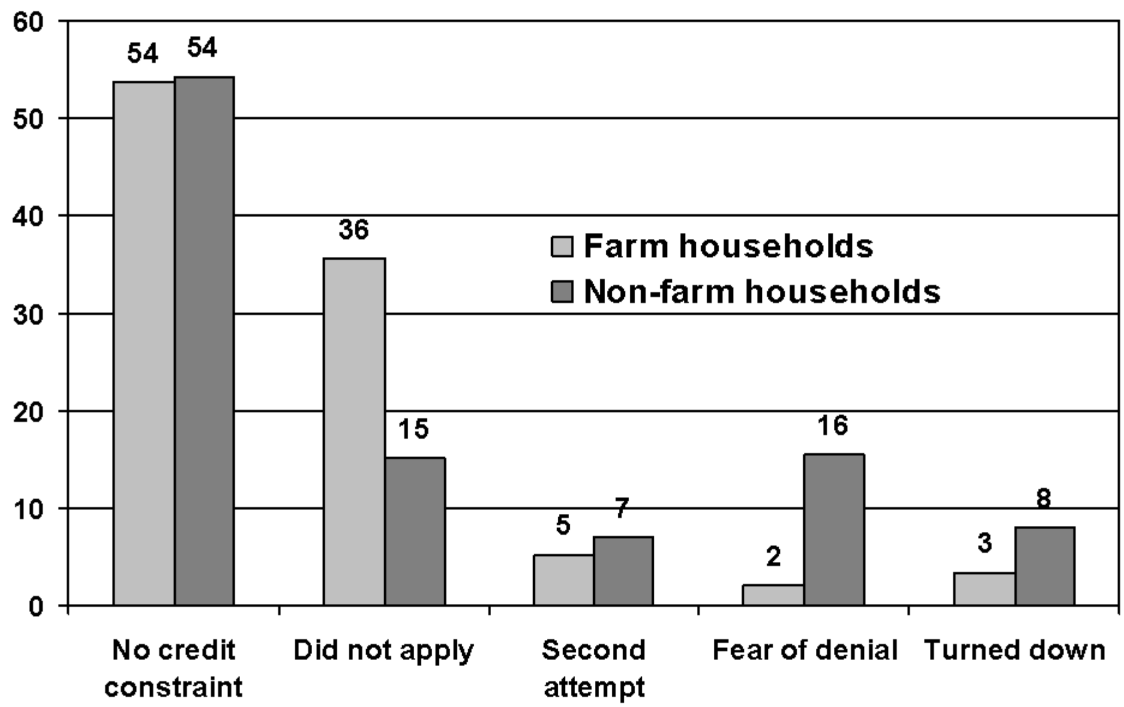

Figure 1: Distribution of farm and non-farm sole-proprietorship households by credit use categories